The Role of Abnormal Stock Trading Volume in the Equity Option Market

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Abstract

This paper investigates the effect of underlying stocks' abnormal trading volume on equity options. We document significant negative relations between daily-rebalanced delta-hedged option returns and abnormal stock trading volume. The abnormally high stock trading volume captures the attention of investors (especially retail investors), and some investors bet in the equity option market. Consistent with the demand-based option pricing theory, both call and put options of stocks with abnormally high trading volume become more expensive because of high demand from end-users. Our results cannot be explained through informed trading or risk channel, and we provide evidence for the investor attention channel. Our paper extends the literature of abnormal trading volume to the equity option market and highlights the importance of investor attention shock on the pricing and trading behaviors of equity options.

Keywords: high-volume anomaly, investor attention, delta-hedged option returns, option trading behaviors, retail investors

JEL Classification: G11, G12, G14, G41

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1. Introduction

Motivated by the influential work of Kahneman (1973), researchers have linked the attention effect with financial markets and asset prices in several aspects. Among various investor attention proxies, the abnormal trading volume (ATV) has been widely accepted and studied. The seminal work of Gervais, Kaniel, and Mingelgrin (2001) document that stocks with higher abnormal trading volume will have higher returns over the next month, known as the *high-volume return premium* (HVP hereafter). This anomaly has been affirmed in the international stock markets later (Kaniel, Ozoguz, and Starks 2012) and shown to be linked with economic fundamentals (Wang 2021) and firms' real corporate activities (Israeli, Kaniel, and Sridharan 2021).

Gervais et al. (2001) explain the HVP under the framework built by Merton (1987). The positive shock to a stock's trading activity can increase its visibility, leading to higher demand and subsequent price rise. Barber and Odean (2008) support this view by documenting that investors are net buyers of stocks experiencing unusually heavy trading volume. Conducting comprehensive analyses in the international stock market, Kaniel et al. (2012) provide more detailed evidence that helps explain the HVP through the investor recognition hypothesis in Merton (1987). They find that the magnitude of HVP heavily depends on characteristics related to the investor base.

Previous studies about the abnormal trading volume mainly focus on the stock market and leave the equity option market untouched. Whether underlying stocks' abnormal trading volume affects the pricing of their options, and if so, through which channel? In this paper, we extend the study about the abnormal trading volume to the equity option market and show that the pricing and trading activities of equity options are also affected by the abnormal trading volume of their underlying stocks through the investor attention channel.

The equity option market has grown steadily since its launch and has seen a dramatic increase since 2020 because retail investors poured into the financial market, caused by the rise of new retail trading platforms with zero commission and the COVID-19 lockdown. As a result, equity options play increasingly important roles in investors' investment decisions, and it is natural for investors to make their bets in the equity option market when some stocks attract them. After noticing a stock, many retail investors trade equity options to maximize their potential gains instead of purchasing the stock directly. According to an analysis by CBOE, when a stock captures investors' attention by becoming one of the "meme" stocks, the median increase of its option trading volume is 48.9%, compared with the median increase of 16.2% for the underlying stock.[1] However, since the stock market and the equity option market have different characteristics, and stocks and equity options also have different structures, the effect of attention-grabbing events on equity options needs to be dug deeper. Some pioneer studies have highlighted the importance of investor attention to option pricing. For example, Choy and Wei (2022) document that investors buy more options written on daily winners and losers because these stocks receive more attention from investors. Boulatov, Eisdorfer, Goyal, and Zhdanov (2022) show that options written on low-priced stocks are relatively overpriced because of the demand pressure generated by investors' inattention to the underlying stock prices. Although both examine investor attention's effect on equity options, these studies implement attention proxies that do not necessarily represent the attention shock. Therefore, we use the abnormal trading volume of the underlying stock as a proxy for the shock to investors' attention and directly test its impacts on equity option pricing and trading activities. Specifically, we use the standardized unexpected volume (SUV) to measure the abnormal trading volume in our main analysis, following Israeli et al. (2021).

We begin our study by sorting options into portfolios based on SUV and showing its predictability on the daily-rebalanced delta-hedged option returns. We find that both call options and put options written on stocks with high abnormal trading volumes have significantly lower delta-hedged returns over the next month. For example, the return to the 5-minus-1 spread portfolio of daily-rebalanced delta-hedged options is -0.48% (-0.34%) per month for call (put) options when the weighting scheme is equally weighted. The predictive power of SUV remains significant when the weighting scheme changes to stock-value weighted or option-value weighted.

There are many proxies for investors' attention in the finance literature. Chen, Tang, Yao, and Zhou (2021) list several of them and form a market-level attention index based on these proxies. To investigate whether other investor attention proxies can absorb the effect of SUV on delta-hedged option returns, we do the dependent double portfolio sorting on selected alternative investor attention proxies and SUV. We choose six alternative investor attention proxies: extreme return, past return, nearness of stock price to its 12-month high, media coverage, analyst coverage, and abnormal Google Search Volume Index. We discover that none of these attention proxies have a significant impact on the predictability of SUV on delta-hedged option returns. Besides investor attention proxies, we do similar tests on several stock or option characteristics and also find that

[1] https://www.cboe.com/insights/posts/how-meme-stocks-impact-options-trading/

none of these characteristics can fully subsume the effect of SUV.

To control multiple variables simultaneously, we test the relation between SUV and the delta-hedged option returns in the Fama and MacBeth (1973) regression setting. In the univariate regression, the coefficient of SUV is -0.170 (-0.124) with a t-statistics of 8.92 (7.54) for call (put) options. Moreover, after controlling a comprehensive list of control variables, including several alternative attention proxies and various stock or option characteristics, the coefficient on SUV remains -0.124 (-0.099) for call (put) options, which is still statistically and economically significant. The dependent double portfolio sorting and the Fama-Macbeth regression test show that SUV provide significantly incremental information for predicting the delta-hedged option returns.

After documenting the predictability of SUV on the delta-hedged option returns, we try to identify the economic channel through which SUV influences the pricing of equity options. The trading volume of a stock can be abnormally high (low) when the stock has some positive (negative) private information, while the abnormal trading volume is also treated as a signal of the increasing risks by some studies. Therefore, we start by ruling out two potential channels: the informed trading channel and the risk channel. To rule out the informed trading channel, in addition to the fact that SUV contains less fundamental information by construction, we show that SUV has little to do with the option implied informed trading measure and is positively associated with both the demand pressure of call options and put options. As for ruling out the risk channel, we prove that the risks of stocks with higher SUV are decreasing and document that the delta-hedged option return spreads generated by SUV remain significant after being adjusted by a broad set of common risk factors.

Second, we show that the investor attention channel is the most likely economic channel by linking SUV with the trading activities of equity options. Guided by the demand-based option pricing theory by Gârleanu, Pedersen, and Poteshman (2009), we consider that the demand pressure exerted by investors attracted by SUV causes the temporary overpricing and future lower returns of equity options. Using the option Open/Close data from Chicago Board Options Exchange (CBOE) and International Securities Exchange (ISE), we document significant positive contemporaneous relations between SUV and the order imbalance (OIB) for both call options and put options. From the portfolio with the highest SUV to the lowest SUV, the option OIB increases monotonically, and the spread is 0.22 (0.15) for call (put) options. In addition, we decompose the option OIB by orders from retail and non-retail investors and find that only the retail OIB has significant positive relations with SUV, consistent with previous findings that retail investors contribute more to the attention-driven trading in the equity option market. (Choy and Wei 2022 and Eisdorfer, Goyal, Zhdanov, and Boulatov 2022). Furthermore, on the daily basis, we show that the daily unexpected volume is positively associated with the intraday option OIB and can predict the option OIB for at least 5 days. Similarly, the significant relations only appear for the retail OIB. This finding provides more direct and clear evidence that investors, especially retail investors, react to the abnormal trading volume and choose to trade in the equity option market.

Last, we investigate the heterogeneity of the SUV's impact on options' trading activities. Proxying the stock market short-sale constraints by the lending fee and the utilization rate, we show that the effect of SUV on put option OIB is significantly stronger among stocks with higher stock market short-sale constraints, while that on call option OIB is similar across each group. In contrast, we do not find similar results for different levels of margin requirements, which we treat as the short-sale constraints in the equity option market. We consider that the buying inclination of investors may root in their lottery preference since the potential gains of long option positions are unlimited while those of short option positions are bounded. We show that the effect of SUV on the option OIB is significantly stronger among more lottery-like stocks, providing evidence for this argument. If a stock has already received much attention from investors, any new attention shocks should have less impact on it. Consistently, we find that SUV has weaker impacts on the option trading activities of larger stocks and stocks with higher prices, which are often considered with high attention levels. These findings lend more support to the hypothesis that SUV influences equity options through the investor attention channel

As for the robustness of our findings, first, we find that the predictability of SUV remains significant across option samples with different moneyness and maturity (except for the ATM put option sample with 3.5-month maturity). Second, we also show that our findings are not restricted to the SUV but robust to different measures of the abnormal trading volume. Employing the binary measure from Gervais et al. (2001) and the ratio measure from Barber and Odean (2008), we find similar relationships between the abnormal trading volume and the delta-hedged option returns. Third, we show that our results still hold whether we use SUV constructed based on buyer-initiated or seller-initiated trades.

Our paper is related to three strands of literature. First, our study stands on the literature about the *abnormal trading volume*. Motivated by the HVP documented in Gervais et al. (2001), researchers have followed and contributed to this literature continuously. Kaniel et al. (2012) provide evidence for the HVP from the international stock market, and Akbas (2016) turns his attention to the abnormally low volume before firms' earnings announcements. Wang (2021) and Israeli et al. (2021) link this anomaly to macroeconomic indicators and firms' real activities, respectively. Complementing their research, we extend this literature to the equity option market. We show that the delta-hedged option returns and the abnormal trading volume of the underlying stocks are closely associated and provide a possible economic channel about how the abnormal trading volume affects the equity options' trading and pricing. Our study highlights the importance of examing the effect of volume-related anomalies in different markets.

Second, we contribute to the growing literature about the effect of investor attention on equity options. The effect of investor attention on the pricing of assets has been investigated thoroughly in the stock market from both cross-sectional and time-series perspectives. However, the influence of investor attention on equity options has just begun. Choy and Wei (2022) document that options written on daily winners and losers over the month are overpriced and have lower future returns. Theoretically and empirically, Boulatov et al. (2022) show that investors' inattention to the underlying stock prices exerts higher demand pressure on options written on low-priced stocks, thus making them overpriced. Our study implements the abnormal stock trading volume to proxy for the attention shock and shows that investors, especially retail investors, also trade equity options when attracted by the attention-grabbing in the stock market. In addition to the contemporaneous relations, we directly show that investors react to the abnormal stock trading volume in the equity option market on the daily basis to avoid endogeneity issues.

Third, our paper contributes to the literature about option return predictability. Goyal and Saretto (2009) find that the difference between the historical volatility and the implied volatility is a strong predictor of straddle returns and delta-hedged call option returns. Cao and Han (2013) show that idiosyncratic volatility is negatively associated with delta-hedged option returns. Christoffersen, Goyenko, Jacobs, and Karoui (2018) provide evidence that options' liquidity can predict future option returns. Zhan, Han, Cao, and Tong (2022) document several important stock characteristics that can predict future option returns. Ramachandran and Tayal (2021) show that put options written on overpriced stocks tend to have significantly lower returns over the next month. Jeon, Kan, and Li (2019) present findings that the return autocorrelation of underlying stocks can positively predict future option returns. We provide evidence that the abnormal trading volume of the underlying stock provides incremental information in predicting the cross-section of option returns. We document robust negative relations between the abnormal trading volume and the cross-section of delta-hedged option returns.

The remainder of this paper proceeds as follows. Section 2 describes the data and variables. Section 3 documents our empirical findings. Section 4 study the economic channel about how the abnormal trading volume affects the equity options. Section 5 test the robustness of our findings. Section 6 concludes the paper.

2. Data and Variables

This section introduces the data and key variables used in the empirical analyses.

2.1. Sample

We obtain data from both equity and option markets. Our sample period is from January 1996 to November 2021. We collect individual equity option data from the Ivy DB database provided by OptionMetrics. The data we obtain include the daily closing bid and ask quotes, trading volume, and open interest of each option. Implied volatility, options' delta, vega, and other Greeks are computed by OptionMetrics based on standard market conventions. We collect stock prices, returns, and trading volume from the Center for Research on Security Prices (CRSP). We obtain annual accounting data from Compustat, and the risk-free rate is downloaded from Kenneth French's website. We also collect the analyst coverage and forecast data from I/B/E/S and the intra-day stock trades and quotes data from the Trade and Quote (TAQ) database. We obtain media coverage data from the RavenPack News Analytics. Finally, we collect signed option volume data from the Chicago Board Options Exchange (CBOE) and the International Security Exchange (ISE).

Our sample only includes common stocks listed in the U.S. (share code equals 10 or 11). To avoid extremely illiquid stocks, we only include stocks with a closing price above five dollars at the end of each month. Following the option return predictability literature, we apply standard data filters to the option data. First, to mitigate the early-exercise concern, we eliminate any option whose underlying stock pays a dividend during the option's remaining life. Second, we remove all options that violate the no-arbitrage condition.[2] Third, we eliminate illiquid options that are not

[2] For example, no-arbitrage conditions for a call option price C is $S \geq C \geq max(0, S\text{-}Ke^{-rt})$, and no-arbitrage condition for a put option price P is $K \geq P \geq max(0, Ke^{-rt}\text{-}S)$ where S, K, T, and r are the underlying stock price, the option strike

traded during their remaining lives and have zero open interest at the beginning of the portfolio formation date. Fourth, to avoid bias related to the microstructure, we only retain options in which the bid quotes are positive and strictly smaller than the ask quotes, the midpoint of the bid and ask quotes is at least \$0.125, and the bid-ask spread is greater than the minimum tick size.[3] Fifth, we only include options with moneyness between 0.8 and 1.2.[4] Sixth, most of the options selected each month have the same maturity, and we drop options whose maturities differ from most options. From the remaining observations, at the end of each month and for each optionable stock, we obtain options that are closest to being at-the-money and have the shortest maturity among those with more than one month to expiration.

2.2. Variables

2.2.1 Delta-Hedged Option Returns

We use returns to daily-rebalanced delta-hedged option portfolios as our major dependent variables. Tian and Wu (2021) estimate that the delta-hedged strategy with daily rebalancing (monthly rebalancing) can remove about 90% (70%) of the variance of the option investment. As a result, we use daily rebalanced delta-hedged option returns for our analyses to avoid the influence of the underlying stock to the most extent. We measure the daily-rebalanced delta-hedged option returns following Bakshi and Kapadia (2003) and Cao and Han (2013). We first define the dollar gain of the daily-rebalanced delta-hedged option portfolio, which is the change in the value of a self-financing portfolio that consists of a long position in the option, hedged by a short position in the underlying stock. The delta-hedged option portfolio is not sensitive to small stock price movement, with the net investment earning the risk-free rate.

Specifically, consider a portfolio of a call option that is hedged N times discretely over a period $[t\,, t+\tau]$. The rebalancing times are t_n (where $t_0 = t$ and $t_N = \ t+\tau$). The dollar gain of the daily-rebalanced delta-hedged call option portfolio is:

$$\Pi_{t,t+\tau} = C_{t+\tau} - C_t - \sum\nolimits_{n=0}^{N-1} \Delta_{c,t_n}\left(S_{t_{n+1}} - S_{t_n}\right) - \sum\nolimits_{n=0}^{N-1} \frac{a_n r_{t_n}}{365}\left(C_{t_n} - \Delta_{c,t_n} S_{t_n}\right), \qquad (1)$$

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price, the option time to maturity, and the risk-free rate, respectively.

[3] Minimum tick size is \$0.05 when the option price is below \$3 and \$0.1 when the option price is higher than \$3.

[4] We pick short term (with time-to-maturity about 50 calendar days) options that are closest to being at-the-money. Our results are robust with regards to different moneyness and maturity. Results in different moneyness and maturity sample are shown in Table 9.

where Δ_{c,t_n} is the Black-Scholes delta of the call option on date t_n, $r_{t_n}$is the annualized risk-free rate on date t_n, and a_n is the number of calendar days between t_n and t_{n+1}. The dollar gain of the daily-rebalanced delta-hedged put option portfolio is defined similarly. $\Pi_{t,t+\tau}$ is the dollar gain of the delta-hedged option portfolio. Since the option price is homogeneous of degree one in the stock price and the strike price, $\Pi_{t,t+\tau}$ is proportional to the initial stock price. To make it comparable across stocks, we scale the dollar gain by the absolute value of the initial cost, i.e. $\Delta_{c,t}S_t - C_t$ for call options and $P_t - \Delta_{p,t}S_t$ for put options. Unless otherwise stated, delta-hedged option returns are equivalent to daily-rebalanced delta-hedged option returns hereafter.

Our final sample contains 344,323 observations for call options and 290,983 for put options. Over the entire 311-month sample period, our sample includes 7,258 unique firms. Panel A (B) of Table 1 reports the pooled summary for the delta-hedged option returns and option characteristics for the call (put) option sample. The moneyness of options in our sample is close to 1, and the maturity of most options is about 50 calendar days. The sign and magnitude of the daily-rebalanced delta-hedged option returns are consistent with recent option return literature (see, e.g., Bali, Beckmeyer, Moerke, and Weigert 2021 and Tian and Wu 2021).

[Insert Table 1]

2.2.2. Abnormal Trading Volume

Scholars use different measures of abnormal trading volume to proxy for investor attention in the literature. For example, Gervais et al. (2001) use binary variables to measure the abnormal trading volume, and Barber and Odean (2008) use the ratio of the trading volume on each trading day over the average trading volume over the past year alternatively. In our study, we use the *Standardized Unexpected Volume* (*SUV*) to measure the abnormal trading volume. *SUV* is first introduced by Garfinkel and Sokobin (2006) and later shown to be related to firms' real activities, such as investment expenditures and financing cash flows, by Israeli et al. (2021).

We choose the *SUV* as the measure of abnormal trading volume and the proxy for investor attention for the following reasons. First, as Israeli et al. (2021) suggested, *SUV* is a continuous measure shown to be closely related to investor attention. Second, and more importantly, the traditional binary measure or ratio measure is contaminated as a proxy for investor attention, especially in the equity option market. The low abnormal trading volume might contain information unrelated to investor attention but can influence the pricing of equity options. Akbas

(2016) shows that the abnormally low trading volume before a firm's earnings announcement signals subsequent negative earnings surprises because informed traders tend to leave the firm alone due to the short-sale constraints. He further documents that put options can alleviate the short-sale constraints and thus face higher demand. As a result, the cross-sectional variation of abnormal trading volume contain both information related to investor attention and informed trading. By controlling the level of contemporaneous returns, *SUV* reduces the informtiveness embedded in the stock trading volume and can be a better proxy for investor attention in the equity option market.

Following previous literature on the HVP, we compute the abnormal trading volume using periods of one week or less (Gervais et al. 2001, Kaniel et al. 2012, Akbas 2016, and Israeli et al. 2021). *SUV* is estimated as the standardized prediction error from a regression of trading volume on the absolute value of returns during the week before the end of each month (trading days [-6, -2] relative to the end of each month, hereafter, formation period). To avoid any potential bias related to the market microstructure, we skip one day between the formation period of *SUV* and the holding period of the portfolio.

To calculate *SUV*, we first estimate the following regression from trading days [-56, -7] relative to the end of each month (hereafter, reference period):

$$\log Vol_{i,k,t} = \alpha_{i,t,0} + \alpha_{i,t,1}|R_{i,k,t}|^{+} + \alpha_{i,2}|R_{i,k,t}|^{-} + \epsilon_{i,k,t} \ , \tag{2}$$

where $\log Vol_{i,k,t}$ is the natural logarithm of one plus the dollar trading volume for firm *i* at day *k* before the end of month *t*. $|R_{i,k}|^{+}$ equals the absolute value of the return of firm *i* at day *k* before the end of month *t* if the return is positive and 0 otherwise. $|R_{i,k,t}|^{-}$ equals the absolute value of the return of firm *i* at day *k* before the end of month *t* if the return is negative and 0 otherwise. We require at least 30 observations in the reference period. Next, we calculate the expected trading volume for each day during the formation period using the coefficients estimated from Equation (2):

$$E\left[\log Vol_{i,k,t}\right] = \hat{\alpha}_{i,t,0} + \hat{\alpha}_{i,t,1}|R_{i,t,k}|^{+} + \hat{\alpha}_{i,t,2}|R_{i,t,k}|^{-}. \tag{3}$$

The unexpected volume (UV) is defined as the difference between the observed trading volume and the expected trading volume:

$$UV_{i,k,t} = \log Vol_{i,k,t} - E\left[\log Vol_{i,k,t}\right] \ . \tag{4}$$

We sum the UV during the formation period and standardize it by the product of the standard deviation of residuals from Equation (5) and the square root of the number of trading days in the formation period.

$$SUV_{i,t} = \frac{\sum_{k=-6}^{-2} UV_{i,k,t}}{\sigma_\epsilon \sqrt{5}} \ . \tag{5}$$

2.2.3. Control Variables

We include control variables from three perspectives. First, since we hypothesize that the abnormal trading volume impacts delta-hedged option returns through the investor attention channel, we include six proxies for investor attention selected from Chen et al. (2021). ***ERet*** is the Extreme Return (Barber and Odean 2008), calculated as the ratio of stock returns at the end of each month to the average return over the previous 12 months. ***PRet*** is the Past Return (Aboody, Lehavy, and Trueman 2009), computed as the cumulative return over the previous 12 months. ***12mH*** is the Nearness to the 12-month high (George and Hwang 2004), defined as the ratio of a stock's price at the end of each month to its highest price over the past 12 months. ***MC*** is the Media Coverage (Chen, Goyal, Veeraraghavan, and Zolotoy 2019), defined as the number of news stories covering a firm. ***AC*** is the Analyst Coverage (Hirshleifer and Teoh 2003, Peng 2009, Hirshleifer, Hsu, and Li 2013), defined as the number of analysts following a firm. ***ASVI*** is the Abnormal Google Search Volume Index (Da, Engelberg, and Gao 2011), defined as the percentage change of Google Search Volume Index at the end of each month compared with that of last month. Besides the above investor attention proxies, we also include three dummy variables, $\boldsymbol{I_L}$, $\boldsymbol{I_W}$, and $\boldsymbol{I_{WL}}$, from Choy and Wei (2022) to proxy for investor attention.[5] Kumar, Ruenzi, and Ungeheuer (2017) show that these dummy variables can predict stock returns through the investor attention channel, and Choy and Wei (2022) extend their studies to the equity option market. Table 2 reports the correlation between *SUV* and the above proxies for investor attention in the call option sample, showing *SUV* generally has low correlations with those proxies. The correlation matrix in the put option sample is very similar to that in the call option sample and reported in Panel B of Table A1.

[Insert Table 2]

Second, we control several stock characteristics from previous option return predictability literature. ***IVOL*** is the Idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang 2006) estimated from the Fama-French 3-factor model. ***VRP*** is the difference between historical and implied

[5] See Choy and Wei (2022) for the construction in details.

volatility (Goyal and Saretto 2009), calculated as the difference between the realized volatility over the previous 12 months and the implied volatility over the last month. ***Amihud*** is the log-transformed Amihud illiquidity measure (Amihud 2002). ***AUTO*** is the Autocorrelation of stock returns (Jeon et al. 2019), calculated using daily returns over the past 132 days. We also include seven[6] stock characteristics from Zhan et al. (2022). ***DISP*** is the Analyst Dispersion (Diether, Malloy, and Scherbina 2002), defined as the standard deviation of the analyst forecast of earnings scaled by the average earnings forecast. ***CFV*** is the Cash Flow Variance (Haugen and Baker 1996), defined as the variance of the monthly ratio of cash flow to the market value of equity over the last 60 months. ***Cash*** is the Cash to Asset ratio (Palazzo 2012), calculated as the ratio of a firm's cash holdings to the value of the firm's total assets. ***Issue1Y*** is the One-year new equity issues (Pontiff and Woodgate 2008), defined as the growth in the number of shares between month *t*-18 and *t*-6. ***Lnprice*** is the log-transformed stock price at the end of each month (Eisdorfer et al. 2022). ***Profit*** is the firm's Profitability (Fama and French 2006), defined as the ratio of earnings to the book equity, in which earnings defined as income before extraordinary items. ***TEF*** is the Total External Financing (Bradshaw, Richardson, and Sloan 2006), defined as the net share issuance plus net debt issuance minus cash dividends, scaled by total assets.

Finally, we include three option characteristics. First, ***Option_spread*** is the bid-ask spread of an option, defined as the bid-ask spread of the option contract scaled by its midpoint quote (Christoffersen et al. 2018). Moreover, we also include option Greeks ***Gamma*** and ***Vega*** as control variables.

Panel C of Table 1 shows the summary statistics for control variables in the call option sample, including alternative measures for investor attention, stock characteristics, and option characteristics. Panel A of Table A1 shows the summary statistics of these variables in the put option sample.

3. Empirical Results

We present our main empirical results in this section. First, we examine the predictability of *SUV* on the delta-hedged option returns using the single portfolio sorting test. Second, we test whether the predictive power of *SUV* can survive when individually controlling several alternative investor

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[6] We do not include all the variables documented in Zhan et al. (2022) due to the consideration of sample coverage. However, our main results are still robust when we include the other variables in Zhan et al. (2022).

attention proxies using the dependent double portfolio sorting test. Finally, we implement the Fama-Macbeth regression to investigate the robustness of *SUV*'s predictability while including a comprehensive list of control variables.

3.1. Single Portfolio Sorting

We first apply the single portfolio sorting test to investigate the predictability of *SUV* on the delta-hedged option returns. Each month, we sort all options into quintile portfolios by *SUV* and calculate the average return for each portfolio. When averaging the return for each portfolio, we implement three weighting schemes, including assigning equal weight to every option (EW), weighting options by the market value of their underlying stocks (Stock-VW), and weighting options by the market value of options (Option-VW)[7]. Table 3 reports the mean return for each portfolio and the 5-minus-1 portfolio return spread between the highest and lowest *SUV* portfolio.[8] Panel A (B) shows that *SUV* significantly predicts delta-hedged option returns for both call options and put options, and the relationships are strictly monotonic. For example, the 5-minus-1 portfolio return spread is -0.48% (-0.34%) with a t-statistics of -8.41 (-7.03) for call (put) options when the weighting scheme is EW, and its magnitude is considerable, which is 204% (98%) in magnitude compared with the sample mean return. Moreover, our results are still significant when the weighting scheme shifts to Stock-VW or Option-VW. For example, the 5-minus-1 portfolio return spread in the call option sample is -0.48% (-0.34%) and statistically significant under the Stock-VW (Option-VW) weighting scheme. Results in the put option sample also hold under alternative weighting schemes.

[Insert Table 3]

3.2. Double Portfolio Sorting

Previous literature documents plenty of proxies for investor attention, and it is crucial to test whether *SUV* can provide incremental information to predict the delta-hedged option returns. In this section, we use the nonparametric test, the dependent double portfolio sorting, to examine the incremental predictive power of *SUV* by individually controlling each continuous investor attention proxy we list in section 2.2.3. Each month, we first sort options into quintile portfolios

[7] Market value of options is defined as the mid-price of the option contract times the open interest.
[8] We also report the 10-minus-1 portfolio return spread for robustness.

by one of the proxies of investor attention (Proxy hereafter). Then, within each Proxy portfolio, we further sort options into quintile portfolios by *SUV*. After this process, we obtain 25 Proxy-*SUV* portfolios. Finally, for each *SUV* quintile, we average returns across Proxy quintiles, resulting in 5 Proxy-average portfolios. We calculate the 5-minus-1 portfolio return spread between the highest and lowest *SUV* quintile. If the predictability of *SUV* is mainly driven by one of the investor attention proxies, then the return spread should be reduced significantly compared with the baseline results.

Panel A of Table 4 shows the dependent double portfolio sorting results. Our results indicate that none of the continuous investor attention proxies can subsume the predictability of *SUV* on the delta-hedged option returns in both call and put option samples. Specifically, the maximum decrease in return spread occurs when controlling the media coverage in the call option sample. However, the shrinkage is only 0.06% and accounts for less than 15% of the baseline results. In the put option sample, the return spread barely changes. The maximum decrease occurs when controlling the analyst coverage, but the magnitude of this reduction can be neglected. In Table A2, we also individually control various stock or option characteristics using the same method, and the predictability of *SUV* remains statistically and economically significant.

[Insert Table 4]

3.3 Fama-Macbeth Regression

Although double portfolio sorting does not rely on assumptions about the cross-sectional relations between variables, it has difficulty controlling multiple variables simultaneously. In this section, we use the Fama-Macbeth regression (Fama and MacBeth 1973) to further test the robustness of *SUV*'s predictability on the delta-hedged option returns. The dependent variable is the delta-hedged option return, and the independent variables are the variable of interest, *SUV*, and various control variables. All independent variables are winsorized at 1% level and standardized for each month so that their impacts on the dependent variable can be compared directly through the magnitude of their coefficients.

We conduct our analysis in three stages. First, we do the univariate Fama-Macbeth regression to confirm the predictability of *SUV*. Then, we include all the proxies of investor attention in Section 2.2.3 to show that *SUV* can provide incremental information not contained by previous attention measures. Finally, we further include several stock or option characteristics documented as significant option return predictors to demonstrate that our results are novel enough.

Panel B of Table 4 reports the results of the Fama-Macbeth regression. Column 1 (4) of Panel B shows that increase of one standard deviation in *SUV* is associated with a 0.170% (0.124%) decrease in the delta-hedged call (put) option return, mimicking the results of the single portfolio sorting test. After including alternative investor attention proxies, the coefficient of *SUV* decreases to -0.141 (-0.110) in the call (put) option sample with t-statistics of -6.90 (-6.51). Although the magnitude shrinks slightly, the coefficient remains economically and statistically significant. Moreover, the impact of *SUV* on the delta-hedged option returns is still significant after we add a comprehensive list of control variables (14 stock or option characteristics). Albeit the sample size is reduced, the coefficient of *SUV* is still a significant -0.124 (-0.099) for the call (put) options. Our regression results are also consistent with the findings of previous literature, and the magnitude of the coefficient of *SUV* is comparable with important option return determinants.

4. Potential Explanation of the Return Patterns

In this section, we rule out two channels that possibly drive our results and provide evidence for the hypothesized channel.

4.1. Informed Trading Channel

Although we treat *SUV* as a measure of investor attention, one may have concern that it influences the delta-hedged option returns through the informed trading channel. For example, positive private information can lead to both high trading volume in the underlying stocks and high end-user demand for call options, thus resulting in a negative relation between abnormal trading volume and future call option returns. Due to the put-call parity, it is natural that put option returns also decrease with the abnormal trading volume. In this section, we rule out this channel from several perspectives.

First, the abnormal trading volume in our analysis is measured by *SUV*, from which the informativeness of stock trading volume is removed to some extent by controlling the contemporaneous stock returns. Second, suppose *SUV* influences delta-hedged option returns through the informed trading channel. In that case, we should observe that only call options experience higher end-user demand with higher *SUV*, or the relationships between option demand pressure and *SUV* for call options and put options have opposite signs. However, Section 4.3 shows that when the underlying stock experiences higher abnormal trading volume, both call options and put options face higher demand pressure from option end-users, inconsistent with the informed trading channel. Finally, we investigate the relationship between SUV and the option implied measure of informed trading, $\Delta CVOL$-$\Delta PVOL$, proposed by An, Ang, Bali, and Cakici (2014). An et al. (2014) suggest that if there is good (bad) private information about a stock, the implied volatility of its call (put) options should increase in this period. As a result, if the informed trading story can explain our results, we should find that the $\Delta CVOL$ increases (decreases) with SUV, and $\Delta PVOL$ (increases) decreases with SUV in the call (put) option sample. In other words, the relation between SUV and $\Delta CVOL$-$\Delta PVOL$ should be increasing in the call option sample and decreasing in the put option sample. In contrast, as shown in Panel A of Table 5, we document no significant relationship between SUV and $\Delta CVOL$-$\Delta PVOL$ in both call and put option samples. In sum, the predictability of SUV can hardly come from the informed trading channel.

[Insert Table 5]

4.2. Risk Channel

In the literature about abnormal trading volume, some scholars treat the abnormally high trading volume as a signal of high risk. For example, Schneider (2009) argues that higher trading volume indicates lower information quality and higher uncertainty. Likewise, Banerjee and Kremer (2010) suggest that high trading volume manifests more diverged investor opinion to the future, thus leading to higher uncertainty and risk currently. From the option pricing perspective, Duan and Wei (2009) find that a higher amount of systematic risk leads to higher implied volatility, i.e., higher current option prices and lower future option returns. Therefore, it is possible that a higher SUV indicates a higher risk level and is associated with lower future option returns through the risk channel. In this section, we provide evidence to rule out the risk channel.

First, we investigate the relation between SUV and $\Delta CVOL + \Delta PVOL$, which is a risk measure implied from option information. Cao, Goyal, Xiao, and Zhan (2019) argue that the implied volatility changes contain information about the uncertainty shocks to the underlying stock and influence corporate bond returns. Higher implied volatility change indicates that the risk level of the underlying stock is increasing. If SUV truly influences delta-hedged option returns through the risk channel, we should observe a significantly positive relationship between SUV and $\Delta CVOL + \Delta PVOL$. However, as shown in Panel A of Table 5, the implied volatility change decreases with SUV, expressing decreasing risk of the underlying stock. Second, we adjust the raw option return spreads in Section 3.1 using a set of comprehensive common risk factors, including the Fama and French (2015) five factors, the momentum factor in Carhart (1997), the liquidity factor in Pástor and Stambaugh (2003), and the zero-beta S&P 500 straddle factor. In addition, we also apply a factor model that is more appropriate for explaining option returns proposed by Bali, Cao, Chabi-Yo, Song, and Zhan (2022). Panel B of Table 5 shows that controlling these common risk factor models can hardly explain the return patterns of our results. After adjusting by several combinations of common risk factors, the return spreads remain economically and statistically significant, and the magnitude barely changes, providing convincing evidence that *SUV* is unlikely to affect delta-hedged option returns through the risk channel.

4.3. Investor Attention Channel

4.3.1. Contemporaneous relationships between SUV and the Option Order Imbalance

After ruling out the informed trading channel and the risk channel, we provide evidence for our hypothesis that *SUV* impacts delta-hedged option returns through the attention channel in this section. We conjecture that the abnormally high trading volume attracts the attention of investors (especially retail investors) to the underlying stock. These attracted investors not only trade in the stock market but also make their bets in the equity option market. As a result, options written on stocks with high *SUV* experience higher demand pressure and are temporarily overpriced, thus having lower returns over the next month due to the correction of the mispricing.

Utilizing signed option trading volume data from two prominent exchanges for options, the Chicago Board Options Exchange (CBOE) and the International Stock Exchange (ISE), we can directly test whether the abnormal trading volume of the underlying stocks impacts the demand pressure of options, measured by the option order imbalance. Signed option trading volume data from CBOE and ISE are widely used in the option pricing literature. For example, Cao, Li, Zhan, and Zhou (2022) employ the CBOE dataset, Ge, Lin, and Pearson (2016), Christoffersen et al. (2018), Ramachandran and Tayal (2021) utilize the ISE dataset, and Golez, Goyenko, and Koijen (2022) take advantage of both of them. To expand our sample coverage, we merge the two datasets. Specifically, we sum up the trading volume from two exchanges for each option contract and then aggregate the contract-level data to the firm level by summing up trading volumes across different moneyness and maturity. We avoid options with deep moneyness and extraordinary time to maturity[9].

For each optionable stock, we aggregate the signed option trading volume data during the formation period of each month and calculate the option order imbalance. Since previous literature finds that trades opening new positions are more informative (Pan and Poteshman (2006), Ge et al. (2016)), we use the order imbalance based on the volume of trades opening new positions in our main analysis and that based on total trading volume as robustness checks. The option order imbalance for the firm *i* at month *t* is defined as:

$$OIB_{i,t}^{call} = \frac{Open\ Buy_{i,t}^{call} - Open\ Sell_{i,t}^{call}}{Open\ Buy_{i,t}^{call} + Open\ Sell_{i,t}^{call}} \tag{6}$$

$$OIB_{i,t}^{put} = \frac{Open\ Buy_{i,t}^{put} - Open\ Sell_{i,t}^{put}}{Open\ Buy_{i,t}^{put} + Open\ Sell_{i,t}^{put}}, \tag{7}$$

where, for call options, $Open\ Buy_{i,t}^{call}$ is the volume of trades initiated by buyers to open new long option positions for firm *i* during the formation period of month *t*. $Open\ Sell_{i,t}^{call}$ is the volume of trades initiated by sellers to open new short option positions for firm *i* during the formation period of month *t*. Variables for put options are defined similarly. In addition to order imbalance based on option trading volume, we also construct order imbalance based on the number of trades as robustness, as suggested by Barber and Odean (2008), to alleviate the issue of overweighting wealthier investors.

We use the single portfolio sorting test to investigate the contemporaneous relation between *SUV* and the option order imbalance, and Table 6 reports the results. The relationship between SUV and the option order imbalance is strictly monotonically positive. From the portfolio with the lowest *SUV* to the highest *SUV*, the option order imbalance moves from -0.24 (-0.28) to -0.01 (-0.13) for call (put) options, and the spread is 0.22 (0.15) with a t-statistics of 22.30 (14.38). The results indicate that options whose underlying stocks are experiencing abnormally high trading volume face significantly higher demand pressure from end-users during the formation period. We also report relationships between *SUV* and option order imbalance with alternative constructions in Table A3. Panel A of Table A3 reports the results using option order imbalance based on the number of trades as the target variable, and the patterns are very similar to those reported in Table 6. Panel B of Table A3 reports the results using option order imbalance calculated using the volume

[9] Options with deep moneyness are options with moneyness greater than 1.25 or less than 0.75. Options with extraordinary time to maturity are options whose time to maturity greater than 100 days or less than 5 days.

of trades both opening new positions and closing existing positions, and the relationship between SUV and the option order imbalance is still significant. For example, the difference of order imbalance between the highest and lowest *SUV* group is 0.11 (0.06) with a t-statistics of 14.22 (6.68) for call (put) options.

[Insert Table 6]

4.3.2. Decomposition of Option Order Imbalance

Different types of investors suffer from different levels of attention friction. Compared with professional investors, retail investors are thought to be less sophisticated and suffer from more attention friction. If retail investors generally have low attention levels toward the stock market, then the attention-grabbing events should have stronger effects on them. Therefore, we further decompose the option order imbalance by different clientele and provide evidence about the source of the option demand pressure. CBOE and ISE use the same criteria to group orders, so we can easily aggregate the two datasets. Specifically, by their size, orders are classified as small orders (less than 100 contracts), medium orders (100-199 contracts), or large orders (more than 200 contracts) based on their sizes. By their clientele, orders are also classified as from public customers or professional customers. We use small orders from public customers to approximate orders from retail investors. Medium and large orders from public customers and all orders from professional customers are defined as orders from professional investors (non-retail investors). Since orders from professional customers are identified by both exchanges only after 1st October 2009, our sample period of this analysis is from October 2009 to December 2021.

As shown in Table 6, the relationship between *SUV* and option order imbalance only appears among orders from retail investors. Among orders from retail investors, the increasing pattern from the lowest *SUV* group to the highest *SUV* group is strictly monotonic, and the difference between the highest *SUV* and lowest *SUV* group is even bigger, which is 0.24 (0.16) with a t-statistics of 24.59 (15.94) for call (put) options. In contrast, there are no significant relations between *SUV* and option order imbalance from professional investors for both call and put options. The option order imbalance from professional investors for each SUV portfolio is close to 0, and the OIB spread between the highest SUV and lowest SUV portfolio is also indistinguishable from 0, which is -0.01 (-0.05) with a t-statistics of -0.57 (-1.62) for call (put) options. By decomposing the option order imbalance by the order types, we provide evidence that the abnormal trading volume mainly attracts retail investors' attention. This argument still holds when using alternative constructions of option order imbalance, as shown in Table A3.

4.3.3. Lead-lag Relations between SUV and the Option Order Imbalance at Daily Basis

Previously, we examine the contemporaneous relationship between *SUV* and option order imbalance during the formation period, which inevitably introduce endogeneity issues and look-ahead biases. Here, we investigate their relationship on the daily basis to avoid endogeneity issues and provide clear evidence about whether and how investors react to the abnormal trading volume in the equity option market. Barber and Odean (2008) find that stocks experience higher order imbalance on the same day with higher abnormal trading volume, and we empirically find similar patterns in the equity option market.

During the formation period, instead of aggregating unexpected volume (UV) across the whole period, we test whether the daily-frequency unexpected volume has a significant relationship with the option order imbalance on the same day. The definition and construction of UV are provided in Section 2.2.2. Table 7 shows a very strong relationship between daily frequency UV and the option order imbalance on the same day. The difference of option order imbalance between the portfolio with the highest UV and the lowest UV is 0.21 (0.12), with a t-statistics of 33.03 (21.68) for call (put) options. In addition to the same-day relationship, we test whether UV can predict the option order imbalance over the next 5 days. We find that UV has significant predictive power on the option order imbalance for at least 5 days. Although the spreads between the highest and lowest UV group are decreasing with the time interval, the option order imbalance of the highest UV group is still higher than that of the lowest UV group by 0.08 (0.05) with a t-statistics of 13.19 (6.59) for call (put) options when the time interval equals 5 days. Similar to the contemporaneous relations, the predictive power of UV on option order imbalance is still concentrated among orders from retail investors, and the daily relationships between UV and the option order imbalance from non-retail orders are generally insignificant, if not negative. By investigating the lead-lag relationships between the abnormal trading volume and the option order imbalance, we show that retail investors react to the abnormal trading volume of the underlying stocks and buy more of their options in the equity option market.

[Insert Table 7]

The predictability of *SUV* on delta-hedged option returns can be rationalized by the demand-based option pricing model proposed by Gârleanu et al. (2009). Their model indicates that the demand helps explain the expensiveness of options because option market makers cannot perfectly hedge their inventories. As a result, option market makers will charge higher premiums for options with higher demand pressure, thus making these options overpriced temporarily and have lower future delta-hedged returns. Consistent with their model, we find that options with higher *SUV* of their underlying stocks face significantly higher demand pressure and lower delta-hedged option returns. Our story is clear at this stage: Abnormally high trading volume of the underlying stocks attracts the attention of retail investors and allures them to bet in the equity option markets. As a result, retail investors exert higher demand pressure on options of these stocks, quickly making them overpriced and having lower future delta-hedged returns.

4.4. Heterogeneity of the Impact of *SUV* on the Option Trading Activity

In this section, we use the independent double portfolio sorting strategy to investigate the heterogeneity of the impact of *SUV* on option trading activities. Since the prices of call options and put options are closely connected by the put-call parity and can affect each other, it is hard to separately investigate the heterogeneity of the predictability of *SUV* on the option pricing for call options and put options. Therefore, we switch our focus to option trading activities to avoid this issue. Specifically, we independently sort options based on *SUV* and a variable that may influence the effect of *SUV* and see whether the impact of *SUV* on option trading activities varies among different groups of stocks.

4.4.1. Short-Sale constraints

Investors face short-sale constraints in both the stock market and the equity option market. In the stock market, investors often cannot short-sell stocks due to regulatory needs or face high costs when short-selling stocks, and the equity option market serves as a good playground for them to bypass the short-sale constraints.[10] In the equity option market, investors need to meet the margin requirements if they want to open short option positions, so the margin requirement act as a kind of short-sale constraint. Choy and Wei (2022) argue that the margin requirement is one of the key

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[10] See, for example, Figlewski and Webb (1993), Ofek, Richardson, and Whitelaw (2004), and Chen, Chen, and Chou (2020) for empirical evidence.

drivers of their results. Short-sale constraints in both markets can possibly affect the impact of *SUV* on option trading activities. On the one hand, investors whose attention is attracted by the abnormal trading volume can purchase put options to overcome their short-sale constraints in the stock market, which will enhance the demand pressure faced by put options and have little impact on call options. If this channel is correct, the relationship between *SUV* and the demand pressure of put options should be stronger among stocks with higher short-sale constraints. On the other hand, if the margin requirement is an important consideration for the attracted investors, they will short relatively fewer options whose margin requirements are higher. We should observe that the demand pressure of both call options and put options are stronger, thus leading to stronger relationships between *SUV* and the option order imbalance in both option samples.

Following Ramachandran and Tayal (2021), we use the lending fee and utilization rate obtained from IHS Markit to proxy for the short-sale constraints in the stock market. The lending fee is the fee that would be paid by the short seller to borrow a stock, and the utilization rate is measured as shares lent out on loan scaled by the total lendable supply of shares. Panel A of Table 8 shows that the relationship between *SUV* and the put option order imbalance is significantly stronger among stocks with higher short-sale constraints. In contrast, we do not find a similar difference in the relation between *SUV* and call option order imbalance.

For the option margin requirement, following Choy and Wei (2022), we calculate the average CBOE margin requirement[11] for each option and scale it by the option price during the formation period of *SUV*. As reported in Table 8, we find no significant difference between the demand pressure spread of options with the highest and lowest margin requirements, demonstrating that the *SUV*-induced demand pressure faced by options is possibly not influenced by the margin requirement in our analysis. Intuitively, the potential gain of long option positions is unlimited, while the potential gain of short option positions is bounded. We conjecture that the lottery preference of investors might be the reason why they buy more options than sell. We further find that the investors do buy more options on stocks that are more lottery-alike when their attention is attracted by the abnormal trading volume. Our results indicate that when investors' attention is captured by stocks with abnormal trading volume and bet in the equity option market, short-sale

[11] The CBOE margin requirement is defined as the following: The margin requirement for shorting call options is $C + max[(20\% \cdot S - OTM), 10\% \cdot S,\ \$1]$ and that for shorting put options are $P + max[(20\% \cdot S - OTM), 10\% \cdot K,\ \$1]$, where C and P are the call and put option prices, S and K are the stock price and option strike price, and OTM indicates the dollar amount in which the option is out-of-the-money.

constraints in the stock market are important to their decisions, while option margin requirements may not be.

4.4.2. Attention Level

Israeli et al. (2021) find that their findings are concentrated among firms with lower levels of investor recognition, and we should find similar patterns if *SUV* influences option trading because it increases investor attention toward firms. We use a firm's size and price level as proxies for its investor attention level. Size has long been a proxy for a firm's visibility, and price level has been shown to influence option pricing through the investor attention channel by Eisdorfer et al. (2022). Panel B of Table 8 shows the results of the double portfolio sorting based on proxies of investor attention level and *SUV*, and the target variable is still the option order imbalance. We find that the relation between *SUV* and option OIB significantly differs between the highest and lowest attention groups. The option OIB spread is 0.11 (0.09) lower for call options and 0.12 (0.08) lower for put options if we use the firm size (stock price level) as the proxy for investor attention level.

[Insert Table 8]

5. Robustness Checks

5.1. Alternative Option Sample and Return Construction

In this section, we investigate the robustness of the predictability of *SUV* on daily-rebalanced delta-hedged option returns in option samples with different moneyness and maturity. In our main analysis, we consider options whose moneyness is closest to 1 within the range from 0.8 to 1.2 and whose maturity is 1.5 months. In this section, we consider several alternative option samples, including in-the-money (ITM) options with maturity of 1.5 months, out-of-the-money (OTM) options with maturity of 1.5 months, at-the-money (ATM) options with maturity of 2.5 months, and at-the-money (ATM) options with maturity of 3.5 months.

We define ITM options as call options whose moneyness is closest to 0.9 within the range from 0.8 to 1.0 and put options whose moneyness is closest to 1.1 within the range from 1.0 to 1.2. OTM options are defined as call options whose moneyness is closest to 1.1 within the range from 1.0 to 1.2 and put options whose moneyness is closest to 0.9 within the range from 0.8 to 1.0. Apart from different moneyness, we also consider different maturities. In our baseline results, at the end of month t, our sample includes options expiring in month *t+2*, meaning they have 1.5 months to expire. Here we include at-the-money (ATM) options expiring in *t+3* and *t+4*, respectively. This sample is equivalent to a sample that includes options with 2.5 months and 3.5 months to expire, respectively. We only include firm-month observations appearing in our main analysis and exclude option contracts used in the main analysis. Data filters are similar to those in Section 2.1.

Panel A of Table 9 reports the predictive power of *SUV* on the delta-hedged option returns in alternative option samples. The predictability of *SUV* remains significant in 7 samples, except for the sample including ATM put options with 3.5-month maturity. Among samples with significant results, the return spreads vary from -0.33% (-0.17%) to -0.54 (-0.41%) for call (put) options. The magnitudes of return spreads in OTM option samples are about two folds compared to those in ITM option samples and are also larger than those in ATM option samples. Since OTM options have higher embedded leverages, this finding is consistent with retail investors' preference to maximize their potential gains. It provides evidence that *SUV* influences option pricing because it attracts retail investor attention.

[Insert Table 9]

5.2. Alternative Measures of Abnormal Trading Volume

In our main analysis, we use the *SUV* computed during the formation period to measure stocks' abnormal trading volume. In this section, we implement alternative measures of the abnormal trading volume and test their predictability on delta-hedged option returns. We consider three different scenarios. First, we stick to the construction of *SUV*, but replace the *SUV* during the formation period with the unexpected volume (UV) on the date 2 days prior to the end of each month. In other words, we shorten the formation period from the range [-6, -2] to [-2], and the reference period changes to the range [-52, -3] correspondingly. Second, we use the binary variables to measure the abnormal trading volume following Gervais et al. (2001). We compare the average trading volume during the formation period and the daily volumes during the reference period. If a stock's average trading volume of the formation period in month *t* is among the highest (lowest) 10% of the daily volumes during the reference period, we consider the stock is experiencing abnormally high (low) trading volume, and a variable High (Low) will be 1 for that stock. Otherwise, the variable High (Low) will be 0. Third, we use the ratio of the average trading volume during the formation period over the average trading volume over the past one year as the measure of the abnormal trading volume following Barber and Odean (2008).

For continuous alternative measures, each month, we sort options into quintile portfolios based on the alternative measures and report the average return for each portfolio and the 5-minus-1 portfolio return spread. For binary measures, each month, we classify options into three groups, Low, Mid, and High, by the variable High and Low and report the average return for each portfolio and the return spread of High-Mid, High-Low, and Low-Mid. Panel A and Panel B of Table 10 show the portfolio sorting results based on continuous and binary alternative measures, respectively. Although the return spreads based on UV are smaller than those based on *SUV*, they are still statistically significant. The return spreads based on the ratio measure are also significant and comparable to those based on *SUV* in magnitude. Panel B proves the binary measures' predictability on the delta-hedged option returns and shows that the high abnormal trading volume group mainly contributes to the predictive power.

[Insert Table 10]

5.3. Split Trading Volume into Buyer or Seller-initiated

Stock trading volume can be split into buyer-initiated and seller-initiated trades. In this section, we explore whether *SUV*'s predictability on delta-hedged option returns depends on order types. This investigation can also lend support to rule out the hypothesis that *SUV* influences the delta-hedged option returns through the informed trading channel. If the informed trading channel is correct, when the underlying stock has positive (negative) private information, the *SUV* based on buyer-initiated (seller-initiated) trading volume and the demand pressure of call (put) options should increase, while those of put (call) options should not be influenced much. As a result, we should observe that *SUV* based on buyer-initiated (seller-initiated) trading volume has significant impacts on call options but less or no impact on put options. Using Trade and Quote (TAQ) data from 1996 to 2020, we implement the Lee and Ready (1991) algorithm to classify trades into buyer-initiated or seller-initiated. Then, we aggregate the trading volume of two types of trades daily and use the same method in Section 2.2.2 to calculate *SUV* based on buyer-initiated or seller-initiated trading volume (*SUV*_BUY and *SUV*_SELL).

In Panel A of Table 11, we document that *SUV*_BUY and *SUV*_SELL influence the delta-hedged option returns in the same direction and almost the same magnitude. Given the put-call parity concern, we show evidence from the option order imbalance perspective in Panel B of Table 11. Panel B of Table 11 documents that *SUV*_BUY and *SUV*_SELL not only influence delta-hedged option returns similarly but also impact option order imbalance similarly, contradicting the informed trading channel. These findings show that our results are robust to order types and provide more evidence that the informed trading channel does not drive our results.

[Insert Table 11]

6. Conclusion

This paper extends the literature about the *abnormal trading volume* and investigates its effect on equity options. Using *SUV* to measure the abnormal trading volume, we document significantly negative relations between *SUV* and the daily-rebalanced delta-hedged option returns for both call options and put options. Our results show that *SUV* provide incremental information for predicting the cross-section of option returns, and its predictability can survive after controlling a comprehensive list of control variables. We also show that our results are robust to alternative option samples, different measures of the abnormal trading volume, and different constructions of *SUV*.

We further provide evidence about the economic channel through which *SUV* influence equity options. We rule out the informed trading channel and the risk channel from various perspectives and argue that the investor attention channel is the most likely one. Utilizing signed option trading volume data, we find that options written on stocks with higher *SUV* face higher demand pressure from end-users, especially retail investors, contemporaneously. On the daily basis, we show that the abnormal stock trading volume is significantly positively associated with the intraday option order imbalance and can predict future option order imbalance for at least one week. These findings show that investors quickly react to the abnormal stock trading volume and make their bets in the equity option market, exerting higher demand pressure on corresponding options and making them overpriced.

Our study contributes to the literature in the following three ways. First, we extend the literature about *abnormal trading volume*. Previous studies about *abnormal trading volume* focus on the stock market. We first provide evidence that investors also trade equity options after observing the high abnormal trading volume. We document that the net buying pressure is significantly higher for options written on stocks with abnormal trading volume. Second, our paper contributes to the literature about the effect of investor attention on equity options. We investigate the trading and pricing of equity options when investors are attracted by the abnormal trading volume of their underlying stocks. We find that investors, especially retail investors, react to the attention shock to the underlying stock in the equity option market. We show that investors buy more options whose underlying stocks attract them, and this trend lasts for a few days. Third, our paper contributes to the rapidly growing literature about option return predictability. We document significant negative relations between the abnormal trading volume and the cross-section of delta-hedged option returns.

Table 1: Summary Statistics

This table reports the descriptive statistics of option returns, option characteristics, textual indicators, and equity characteristics. The sample period is from January 1996 to November 2021. Panel A (B) reports the pooled summary of delta-hedged call (put) option returns and the characteristics of call (put) options involved. A delta-hedged call (put) option portfolio involves buying one contract of an equity call (put) and a short position of Δ shares of the underlying stock, where Δ is the Black-Scholes call (put) option delta. The position is held for 1 month or until option maturity. Delta-hedged option return is defined as the total dollar gain of the delta-hedged option portfolio scaled by the absolute value of the cost of the delta-hedged option portfolio at its formation date. Moneyness is the ratio of option strike price to stock price. Days to maturity is the number of calendar days until the option expiration. Gamma is the Black-Scholes option gamma. Vega is the Black-Scholes option vega. Option bid-ask spread is the ratio of the difference between ask and bid quotes of option to the midpoint of the bid and ask quotes at the end of each month. Panel C reports the time-series average of cross-sectional statistics for *SUV* and control variables in the call option sample (winsorized each month at the 1% level). *SUV* is the standardized unexpected volume as in Garfinkel and Sokobin (2006) and Israeli, Kaniel, and Sridharan (2020). ERet is the ratio of returns at the end of each month to the average over previous 12 months as in Barber and Odean (2008). PRet is the cumulative return over previous 12 months as in Aboody, Lehavy, and Trueman (2009). 12mH is the ratio of a stock's price at the end of each month to its highest price over previous 12 months as in George and Hwang (2004). MC is the media coverage (Chen et al. 2019), defined as the number of news stories covering a firm. AC is the analyst coverage, defined as the number of analysts following the firm, following Hirshleifer and Teoh (2003), Peng (2009), and Hirshleifer, Hsu, and Li (2013). ASVI is the Abnormal Google Search Volume Index, defined as the percentage change of Google Search Volume Index at the end of each month compared with that of last month as in Da, Engelberg, and Gao (2011). I_L, I_W, and I_{WL} are dummy measures for investor attention from Choy and Wei (2018). IVOL is the idiosyncratic volatility computed as in Ang et al. (2006). VRP is the difference between realized volatility and implied volatility as in Goyal and Saretto (2009). Amihud is the natural logarithm of the illiquidity measure from Amihud (2002). AUTO is the first-order autocorrelation of underlying stock's return as in Jeon et al. (2020). DISP is the analyst earnings forecast dispersion, as in Diether, Malloy, and Scherbina (2002). CFV is the cash flow variance as in Haugen and Baker (1996). Cash is the cash-to-assets ratio as in Palazzo (2012). ISSUE_1Y represents 1-year new issues as in Pontiff and Woodgate (2008). LNPRICE is the log of the underlying stock price at the end of last month. PROFIT is the profitability as in Fama and French (2006). TEF is total external finance as in Bradshaw et al. (2006).

Panel A: Pooled Summary of Delta-Hedged Returns and Option Characteristics for Call Options							
Variable	Mean	Std Dev	10th Pctl	25th Pctl	Median	75th Pctl	90th Pctl
Daily-rebalanced return (%)	-0.24	5.72	-5.06	-2.50	-0.59	1.42	4.75
Buy & hold return (%)	-0.98	9.02	-8.55	-5.06	-2.20	1.21	7.57
Moneyness (%)	100.64	5.76	94.12	97.56	100.39	103.64	107.60
Days to Maturity	50	2	46	49	50	51	52
Gamma	0.11	0.07	0.04	0.06	0.09	0.14	0.20
Vega	5.45	6.85	1.18	2.05	3.60	6.41	10.63
Option bid-ask spread (%)	22.98	24.98	5.31	8.70	14.63	26.67	50.00

Panel B: Pooled Summary of Delta-Hedged Returns and Option Characteristics for Put Options							
Variable	Mean	Std Dev	10th Pctl	25th Pctl	Median	75th Pctl	90th Pctl
Daily-rebalanced return (%)	-0.35	4.80	-4.51	-2.38	-0.71	1.06	3.91
Buy & hold return (%)	-0.64	7.52	-7.00	-4.24	-1.79	1.23	6.57
Moneyness (%)	99.21	5.75	92.25	96.15	99.44	102.22	105.71
Days to Maturity	49.67	2.06	46.00	49.00	50.00	51.00	52.00
Gamma	0.10	0.07	0.03	0.05	0.09	0.13	0.19
Vega	5.70	7.25	1.26	2.13	3.68	6.58	11.05
Option bid-ask spread (%)	22.51	24.87	5.19	8.33	14.29	26.09	48.89

Panel C: *SUV* and Control Variables in the Call Option Sample (Time-Series Average of Cross-Sectional Statistics)							
Variable	Mean	Std Dev	10th Pctl	25th Pctl	Median	75th Pctl	90th Pctl
SUV	-0.11	1.79	-2.31	-1.36	-0.24	1.00	2.25
ERet	0.28	20.64	-9.33	-2.90	0.09	3.17	9.74
PRet (%)	26.85	65.88	-33.38	-12.36	12.84	46.44	97.83
12mH	0.74	0.18	0.48	0.63	0.78	0.89	0.95
MC	119.67	263.42	18.20	31.79	56.08	101.74	202.79
AC	10.37	7.19	2.74	4.96	8.73	14.32	20.77
ASVI	0.04	0.35	-0.26	-0.09	0.00	0.09	0.32

I_L	0.13	0.34	0.00	0.00	0.00	0.00	0.93
I_W	0.13	0.34	0.00	0.00	0.00	0.00	0.87
I_{WL}	0.10	0.30	0.00	0.00	0.00	0.00	0.50
IVOL	0.02	0.01	0.01	0.01	0.02	0.03	0.04
VRP	0.01	0.12	-0.11	-0.04	0.01	0.07	0.14
Amihud	-6.49	1.76	-8.82	-7.71	-6.47	-5.26	-4.21
AUTO	-0.01	0.10	-0.14	-0.08	-0.01	0.06	0.12
DISP (%)	18.82	51.11	0.94	1.91	4.62	12.87	36.19
CFV	-0.04	0.18	-0.04	-0.01	0.00	0.00	0.00
Cash	0.22	0.23	0.01	0.04	0.13	0.34	0.59
Issue1Y	-0.29	0.79	-0.98	-0.15	-0.02	0.01	0.04
Lnprice	3.27	0.77	2.20	2.70	3.30	3.83	4.27
Profit	0.14	0.40	-0.19	0.05	0.17	0.28	0.43
TEF	-0.06	0.20	-0.32	-0.09	-0.01	0.04	0.10

Table 2: Time-Series Average of Cross-Sectional Correlations

The table presents the cross-sectional Pearson correlations of *SUV* and several alternative investor attention proxies in the call option sample. The variables are described in Table 1 and are winsorized each month at the 1% level. We compute the cross-sectional correlations each month and report the time-series average of these correlations. The sample period is from January 1996 to November 2021.

	SUV	ERet	PRet	12mH	MC	AC	ASVI	I_L	I_W	I_{WL}
SUV	1	0.021	0.056	0.164	0.042	-0.023	0.119	0.006	0.137	0.079
ERet		1	0.007	0.048	0.001	0.003	0.008	-0.034	0.022	-0.001
PRet			1	0.333	-0.020	-0.087	0.003	0.033	-0.008	0.051
12mH				1	0.062	0.111	0.004	-0.216	0.013	-0.243
MC					1	0.390	0.010	-0.017	-0.023	-0.025
AC						1	-0.018	-0.044	-0.084	-0.139
ASVI							1	0.020	0.051	0.077
I_L								1	-0.154	-0.133
I_W									1	-0.133
I_{WL}										1

Table 3: Option Portfolios Sorted by *SUV*

This table reports the average monthly returns to the daily-rebalanced delta-hedged option portfolios sorted by *SUV*. At the end of each month, we rank all underlying stocks into quintiles by their *SUV* and hold the portfolios for one month. The detailed description of *SUV* and its construction are provided in Section 2.2.2. Portfolios are rebalanced on each trading day. This table reports the return to the daily-rebalanced delta-hedged option portfolio for each quintile and the high-low return spread (i.e., the difference between the returns of the top and bottom quintile portfolios). At the end of each month, we use three weighting schemes when computing the average return of a portfolio: equal weight (EW), weight by the market capitalization of the underlying stock (Stock-VW), and weight by the market value of option open interest (Option-VW). All returns are expressed in percentage. The sample period is from February 1996 to November 2021. To adjust for serial correlations, robust Newey and West (1987) t-statistics are reported in brackets. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Option Type	Weighting Scheme	1	2	3	4	5	5-1	10-1
Call Option	EW	-0.01 (-0.08)	-0.14 (-1.14)	-0.17 (-1.34)	-0.29 (-2.43)	-0.49 (-3.90)	-0.48*** (-8.41)	-0.59*** (-8.70)
	Stock-VW	0.04 (0.30)	-0.09 (-0.74)	-0.12 (-1.02)	-0.25 (-2.09)	-0.44 (-3.53)	-0.48*** (-9.01)	-0.59*** (-9.01)
	Option-VW	-0.16 (-1.21)	-0.21 (-1.79)	-0.32 (-2.52)	-0.45 (-3.90)	-0.50 (-3.12)	-0.34** (-2.42)	-0.62*** (-5.79)
Put Option	EW	-0.20 (-1.72)	-0.23 (-2.15)	-0.26 (-2.30)	-0.35 (-3.34)	-0.53 (-5.05)	-0.34*** (-7.03)	-0.43*** (-6.67)
	Stock-VW	-0.15 (-1.32)	-0.19 (-1.81)	-0.22 (-2.05)	-0.31 (-3.03)	-0.48 (-4.60)	-0.33*** (-7.65)	-0.43*** (-7.28)
	Option-VW	-0.38 (-3.63)	-0.36 (-3.50)	-0.41 (-3.34)	-0.55 (-5.26)	-0.75 (-6.38)	-0.37*** (-4.40)	-0.45*** (-3.75)

Table 4: Dependent Double Sorting and Fama-Macbeth Regression

In Panel A of this table, we investigate whether several investor attention proxies can individually explain *SUV*'s effect. We conduct the dependent sorting test by first sorting all options into quintiles based on one of the investor attention proxies, including extreme stock return (ERet), cumulative return over the past 12 months (PRet), ratio of current stock price to its 12-month high (12mH), media coverage (MC), analyst coverage (AC), abnormal Google Search Volume Index (ASVI). Then, we further sort the options into quintiles based on *SUV*. Finally, we average returns for each *SUV* quintile across the groups of investor attention proxies, yielding five proxy-adjusted quintile returns. We report the baseline results without any control variables in the first row and the after-adjustment results in the rows below. The weighting scheme is equally weighted. Panel B reports the Fama-Macbeth regression results of daily-rebalanced delta-hedged option returns on *SUV*. The detailed description of *SUV* and its construction are provided in Section 2.2.2. In addition to the variables included in Panel A, we add 3 dummy variables in Choy and Wei (2022) and 14 stock or option characteristics as control variables. Their description and construction are described in Section 2.2.3. The sample period is from February 1996 to December 2018. To adjust for serial correlations, robust Newey-West (1987) t-statistics are reported in brackets. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Dependent Double Portfolio Sorting by Investor Attention Proxies and *SUV*

	Call Options	Put Options
Baseline	-0.48***	-0.34***
	(-8.41)	(-7.03)
ERet	-0.48***	-0.34***
	(-9.58)	(-7.38)
PRet	-0.48***	-0.34***
	(-8.81)	(-7.10)
12mH	-0.49***	-0.36***
	(-9.74)	(-7.53)
MC	-0.42***	-0.39***
	(-6.29)	(-6.93)
AC	-0.47***	-0.33***
	(-9.23)	(-7.43)
ASVI	-0.52***	-0.39***
	(-9.15)	(-7.02)

Panel B: Fama-Macbeth Regressions						
	Call Options			Put Options		
	(1)	(2)	(3)	(4)	(5)	(6)
SUV	-0.170*** (-8.92)	-0.141*** (-6.90)	-0.124*** (-5.49)	-0.124*** (-7.54)	-0.110*** (-6.51)	-0.099*** (-6.76)
ERet		0.025 (1.62)	0.032* (1.78)		0.006 (0.44)	0.033** (1.99)
PRet		-0.084** (-2.26)	0.108*** (2.76)		-0.062** (-2.09)	0.094*** (2.69)
12mH		0.082 (1.64)	-0.304*** (-5.55)		0.061* (1.69)	-0.243*** (-6.08)
MC		-0.056*** (-5.61)	0.006 (0.51)		-0.050*** (-5.83)	-0.010 (-1.06)
AC		0.075*** (3.02)	0.100*** (4.52)		0.106*** (5.68)	0.125*** (6.54)
ASVI		-0.032 (-1.65)	-0.007 (-0.30)		-0.022 (-1.26)	-0.008 (-0.36)
I_L		-0.391*** (-7.62)	-0.009 (-0.13)		-0.323*** (-6.94)	0.004 (0.08)
I_W		-0.291*** (-5.66)	-0.016 (-0.27)		-0.174*** (-3.49)	0.102 (1.42)
I_{WL}		-0.920*** (-7.84)	-0.025 (-0.20)		-0.926*** (-10.57)	0.024 (0.18)
Stock or option Characteristics	No	No	Yes	No	No	Yes
Adj. R^2 (%)	0.234	2.894	10.739	0.242	3.351	11.679

Table 5: Potential Economic Channel for SUV

Panel A reports the relationships between SUV and informed trading and risk measure implied from option information. The informed trading measure is the difference between the innovation of implied volatility of call options and put options, $\Delta CVOL - \Delta PVOL$, following An et al. (2014). The risk measure is the sum of the innovation of implied volatility of call options and put options, $\Delta CVOL + \Delta PVOL$, suggested by Cao et al. (2019). At the end of each month, we sort options into quintile portfolios by the SUV of their underlying stocks. We report the average informed trading measure and risk measure for each portfolio as well as the 5-minus-1 spread. Panel B shows the alphas of the delta-hedged option return spread based on SUV with respect to various stock market or option market common risk factor models. FF5 are the Fama and French (2015) five factors, UMD is the Carhart 1997 momentum factor, PS is the Pástor and Stambaugh (2003) liquidity factor, CS is the zero-beta S&P 500 straddle factor in Coval and Shumway (2001), BCCSZ are the option return factors proposed by Bali et al. (2022). To adjust for serial correlations, robust Newey-West (1987) t-statistics are reported in brackets. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Relationships between SUV and Option Implied Informed Trading Measure and Risk Measure

		1	2	3	4	5	(5-1)
$\Delta CVOL - \Delta PVOL$	Call	-0.15 (-2.14)	-0.01 (-0.09)	-0.06 (-0.95)	-0.01 (-0.22)	-0.15 (-1.98)	-0.00 (-0.02)
	Put	-0.07 (-0.97)	0.07 (1.07)	0.02 (0.25)	0.03 (0.43)	-0.08 (-1.15)	-0.01 (-0.16)
$\Delta CVOL + \Delta PVOL$	Call	0.16 (0.28)	0.14 (0.26)	-0.15 (-0.31)	-0.71 (-1.40)	-1.45 (-2.51)	-1.61*** (-3.39)
	Put	0.32 (0.55)	0.39 (0.74)	0.11 (0.22)	-0.43 (-0.82)	-1.07 (-1.83)	-1.39*** (-2.80)

Panel B: Alphas of Different Factor Models

	Baseline	FF5	FF5+UMD+PS	FF5+UMD+CS	BCCSZ
Call	-0.48*** (-8.41)	-0.49*** (-8.24)	-0.49*** (-7.55)	-0.50*** (-7.77)	-0.48*** (-3.68)
Put	-0.34*** (-7.03)	-0.33*** (-6.92)	-0.33*** (-6.50)	-0.35*** (-6.27)	-0.39*** (-3.32)

Table 6: Relationship between *SUV* and Option Order Imbalance

Panel A (B) of this table reports the relationship between *SUV* and option order imbalance of call (put) options. Option order imbalance is defined as the difference between the option trading volume of buyer-initiated orders and seller-initiated orders, scaled by the total option trading volume. Option order imbalance is first aggregated across different moneyness and maturity and then aggregated across the formation period of *SUV*. Retail order imbalance is defined as the order imbalance calculated using only small orders (less than 100 contracts) from public customers. Non-retail order imbalance is defined as the order imbalance calculated using medium and large orders from public customers and all orders from professional customers. The sample is restricted to the option return sample, and the sample period is from October 2009 to December 2021. To adjust for serial correlations, robust Newey-West (1987) t-statistics are reported in brackets. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Relationship between *SUV* and Order Imbalance of Call Options						
	1	2	3	4	5	(5-1)
Total Order Imbalance	-0.24 (-16.96)	-0.21 (-12.81)	-0.17 (-11.30)	-0.12 (-7.32)	-0.01 (-0.88)	0.22*** (22.30)
Retail Order Imbalance	-0.25 (-17.24)	-0.22 (-13.26)	-0.17 (-11.24)	-0.12 (-7.32)	-0.01 (-0.88)	0.24*** (24.59)
Non-retail Order Imbalance	0.02 (0.70)	0.01 (0.46)	-0.01 (-0.24)	0.00 (0.16)	0.00 (0.24)	-0.01 (-0.57)
Panel B: Relationship between *SUV* and Order Imbalance of Put Options						
	1	2	3	4	5	(5-1)
Total Order Imbalance	-0.28 (-24.43)	-0.25 (-24.21)	-0.23 (-20.99)	-0.20 (-16.54)	-0.13 (-10.30)	0.15*** (14.38)
Retail Order Imbalance	-0.31 (-25.92)	-0.28 (-24.75)	-0.26 (-23.27)	-0.22 (-18.27)	-0.15 (-11.41)	0.16*** (15.94)
Non-retail Order Imbalance	0.06 (2.73)	0.07 (3.71)	0.04 (2.13)	0.04 (2.94)	0.01 (0.31)	-0.05 (-1.62)

Table 7: Daily Relationship between *SUV* and the Option Order Imbalance

This table reports the relationship between *SUV* and the option order imbalance on the same day and the predictive power of *SUV* on the option order imbalance for the next few days. During the formation period of the weekly *SUV*, we obtain the unexpected volume (UV) of stocks on each day. The detailed construction of UV is provided in Section 2.2.2. We implement the single portfolio soring test and report the OIB spread between the highest and lowest UV group in the table. Row "T = 0" represents the relation between UV and the option order imbalance on the same day, and row "T = 1" represents the relation between UV and next-one-day option order imbalance and so on. The sample is restricted to the option return sample, and the sample period is from October 2009 to December 2021. To adjust for serial correlations, robust Newey-West (1987) t-statistics are reported in brackets. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Call			Put		
	Total OIB	Retail OIB	Non-retail OIB	Total OIB	Retail OIB	Non-retail OIB
T = 0	0.21*** (33.03)	0.22*** (35.24)	-0.01 (-0.67)	0.12*** (21.68)	0.14*** (23.33)	-0.08*** (-4.10)
T = 1	0.15*** (23.77)	0.16*** (25.09)	-0.03 (-1.52)	0.08*** (12.87)	0.09*** (14.64)	-0.09*** (-3.81)
T = 2	0.12*** (19.49)	0.12*** (19.87)	-0.02 (-1.05)	0.07*** (9.52)	0.07*** (9.92)	-0.02 (-0.82)
T = 3	0.11*** (16.10)	0.11*** (16.86)	-0.04* (-1.75)	0.07*** (10.98)	0.07*** (11.36)	-0.05** (-2.07)
T = 4	0.10*** (14.78)	0.10*** (14.91)	-0.05** (-2.38)	0.05*** (7.18)	0.05*** (7.86)	-0.05** (-2.17)
T = 5	0.08*** (13.19)	0.08*** (12.89)	-0.01 (-0.25)	0.05*** (6.59)	0.05*** (6.91)	-0.02 (-0.61)

Table 8: Heterogeneity of the Impact of *SUV* on the Option Trading Activity

This table reports the results of independent double portfolio sorting tests based on *SUV* and variables (VAR hereafter) that potentially influence the impact of *SUV* on the option trading activity. We sort options into 3 VAR portfolios and 5 *SUV* portfolios simultaneously and report the option OIB spread based on *SUV* in each VAR portfolio and the difference of option OIB spread between the highest and lowest VAR portfolio. Panel A reports the results of independent double portfolio sorting tests based on *SUV* and proxies for short-sale constraints and lottery preference. Following Ramachandran and Tayal (2021), short-sale constraints in the stock market are proxied by the lending fee and the utilization rate. Lending_fee is defined as the fee that would be paid by the short seller to borrow a stock. Utilization_rate is measured as shares lent out on loan scaled by the total lendable supply of shares. Short-sale constraints in the equity option market is defined as the margin requirements of shorting options following Choy and Wei (2018). The calculation of margin requirements of shorting options is described in Section 4.4.1. The proxy for the lottery preference is MAX5, measured as the average of the 5 highest daily returns within the month. Panel B reports the results of independent double portfolio sorting tests based on *SUV* and proxies for the investor attention level. Investor attention level is proxied by Size and Lnprice. Size is the product of a stock's price and its outstanding shares. Lnprice is the natural logarithm of a stock's price level. The sample is restricted to the option return sample, and the sample period is from October 2009 to November 2021. To adjust for serial correlations, robust Newey-West (1987) t-statistics are reported in brackets. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Independent Double Sorting Based on *SUV* and Proxies for Short-Sale Constraints and Lottery Preference								
	Call				Put			
	Low	Mid	High	H-L	Low	Mid	High	H-L
Lending Fee	0.25***	0.23***	0.24***	-0.01	0.03	0.15***	0.17***	0.13***
	(4.95)	(18.43)	(16.99)	(-0.12)	(0.83)	(13.28)	(10.84)	(3.48)
Utilization Rate	0.22***	0.25***	0.24***	0.02	0.12***	0.16***	0.18***	0.06***
	(15.98)	(22.23)	(18.16)	(1.20)	(11.48)	(10.74)	(11.60)	(3.70)
Margin Requirement	0.23***	0.24***	0.24***	0.00	0.16***	0.18***	0.14***	-0.02
	(20.07)	(17.98)	(17.34)	(0.33)	(10.27)	(11.43)	(9.38)	(-1.05)
MAX5	0.20***	0.23***	0.25***	0.06***	0.11***	0.18***	0.20***	0.08***
	(15.69)	(14.05)	(20.15)	(3.43)	(9.44)	(12.64)	(11.41)	(3.86)
Panel B: Independent Double Sorting Based on *SUV* and Proxies for Investor Attention level								
	Low	Mid	High	H-L	Low	Mid	High	H-L
Size	0.29***	0.24***	0.18***	-0.11***	0.21***	0.19***	0.09***	-0.12***
	(19.03)	(19.47)	(13.66)	(-6.11)	(11.68)	(14.29)	(7.49)	(-5.40)
Lnprice	0.27***	0.26***	0.18***	-0.09***	0.19***	0.16***	0.11***	-0.08***
	(18.64)	(18.73)	(14.13)	(-4.63)	(10.08)	(10.09)	(9.59)	(-3.78)

Table 9: Predictability of *SUV* in Alternative Option Samples

This table examines the robustness of the predictability of *SUV* in different option samples. We replicate the portfolio sorts in Table 3 using options with different moneyness and maturities. ITM represents in-the-money option, and OTM represents out-of-the-money option. 2.5-month ATM (3.5-month ATM) are at-the-money options with 2.5-month (3.5-month) maturity. The weighting scheme is equal-weighted. All returns are expressed in percentage. The sample period is from February 1996 to November 2021. To adjust for serial correlations, robust Newey-West (1987) t-statistics are reported in brackets. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Alternative Samples - Call Options						
	Low	2	3	4	High	H-L
ITM	0.14	0.05	0.01	-0.03	-0.15	-0.29***
	(1.30)	(0.52)	(0.16)	(-0.30)	(-1.56)	(-6.68)
OTM	0.20	0.12	0.00	-0.13	-0.34	-0.54***
	(1.17)	(0.78)	(0.01)	(-0.80)	(-2.15)	(-7.04)
2.5-month ATM	0.05	-0.04	-0.07	-0.21	-0.33	-0.38***
	(0.32)	(-0.25)	(-0.54)	(-1.65)	(-2.26)	(-4.55)
3.5-month ATM	0.10	-0.07	-0.07	-0.15	-0.24	-0.33***
	(0.61)	(-0.44)	(-0.47)	(-1.09)	(-1.76)	(-3.94)

Panel B: Alternative Samples - Put Options						
	Low	2	3	4	High	H-L
ITM	-0.15	-0.16	-0.16	-0.23	-0.35	-0.20***
	(-2.48)	(-2.97)	(-2.65)	(-3.93)	(-5.66)	(-5.92)
OTM	-0.10	-0.13	-0.18	-0.28	-0.51	-0.41***
	(-0.52)	(-0.69)	(-0.98)	(-1.54)	(-2.73)	(-6.15)
2.5-month ATM	-0.17	-0.18	-0.17	-0.26	-0.33	-0.17**
	(-1.46)	(-1.86)	(-1.58)	(-2.26)	(-2.64)	(-2.48)
3.5-month ATM	-0.14	-0.11	-0.11	-0.20	-0.21	-0.07
	(-1.12)	(-0.98)	(-1.00)	(-1.74)	(-1.86)	(-0.89)

Table 10: Predictability of Alternative Measures of Abnormal Trading Volume on Delta-Hedged Option Returns

This table examines the robustness of the predictability of alternative measures of abnormal trading volume on delta-hedged option returns. Panel A reports the results for two continuous alternative measures, UV and Ratio. UV is the unexpected volume at the day 2 days prior to the end of each month, and detailed definition of UV is described in Section 5.2. Ratio is the ratio of average trading volume during the formation period in each month over the average trading volume over the past one year. Panel B reports the predictability of binary measures, High and Low, implemented in Gervais et al. (2001). The detailed descriptions and constructions of High and Low are provided in Section 5.2. We classify options into three portfolios, Low, Mid, and High, based on High and Low. We report the average return for each portfolio and the return spread of High-Mid, Low-Mid, and High-Low. The weighting scheme is equal weighted. The sample period is from February 1996 to November 2021. To adjust for serial correlations, robust Newey-West (1987) t-statistics are reported in brackets. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Predictability of Continuous Alternative Abnormal Trading Volume Measures

	Call						Put					
	1	2	3	4	5	(5-1)	1	2	3	4	5	(5-1)
Ratio	-0.15	-0.09	-0.08	-0.20	-0.58	-0.43***	-0.32	-0.19	-0.18	-0.30	-0.59	-0.27***
	(-1.04)	(-0.71)	(-0.70)	(-1.68)	(-4.42)	(-7.01)	(-2.76)	(-1.70)	(-1.65)	(-2.78)	(-5.54)	(-5.18)
UV	-0.16	-0.13	-0.16	-0.21	-0.45	-0.29***	-0.32	-0.22	-0.23	-0.29	-0.50	-0.18***
	(-1.16)	(-1.02)	(-1.24)	(-1.69)	(-3.61)	(-5.18)	(-2.84)	(-2.02)	(-2.16)	(-2.71)	(-4.72)	(-3.71)

Panel B: Predictability of Binary Alternative Abnormal Trading Volume Measures

	Call						Put					
	Low	Mid	High	H-M	L-M	H-L	Low	Mid	High	H-M	L-M	H-L
Binary	-0.09	-0.22	-0.61	-0.39***	0.13*	-0.52***	-0.26	-0.30	-0.64	-0.35***	0.04	-0.39***
	(-0.62)	(-1.74)	(-4.61)	(-6.40)	(1.67)	(-5.21)	(-2.04)	(-2.80)	(-5.74)	(-7.29)	(0.64)	(-4.46)

Table 11: Predictability of *SUV* by Different Order Types

This table reports the predictability of *SUV* calculated using buyer-initiated or seller-initiated volume. Orders are classified as buyer-initiated or seller-initiated using the Lee and Ready (1991) algorithm. We follow the same procedure as in Section 2.2.2 to calculate the *SUV* using volume from only buyer-initiated trades (seller-initiated trades), denoted as *SUV*_Buy (*SUV*_Sell). Panel A reports the results of single portfolio sorting with delta-hedged option returns as target variable and *SUV*_Buy (*SUV*_Sell) as sorting variable. Panel B reports the results of single portfolio sorting with option OIB during the formation period as target variable and *SUV*_Buy (*SUV*_Sell) as sorting variable. The sample period of Panel A is from February 1996 to November 2021, and the sample period of Panel B is from October 2009 to December 2021. To adjust for serial correlations, robust Newey-West (1987) t-statistics are reported in brackets. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Relationship between *SUV*_Buy (*SUV*_Sell) and Delta-hedged Option Returns							
		1	2	3	4	5	(5-1)
Call	*SUV*_Buy	0.03 (0.25)	-0.04 (-0.29)	-0.14 (-1.15)	-0.23 (-1.96)	-0.41 (-3.31)	-0.45*** (-8.04)
	*SUV*_Sell	0.04 (0.30)	-0.06 (-0.48)	-0.13 (-1.05)	-0.21 (-1.72)	-0.42 (-3.54)	-0.46*** (-8.65)
Put	*SUV*_Buy	-0.16 (-1.40)	-0.17 (-1.52)	-0.22 (-2.00)	-0.32 (-3.07)	-0.48 (-4.47)	-0.32*** (-6.88)
	*SUV*_Sell	-0.16 (-1.38)	-0.20 (-1.75)	-0.21 (-1.90)	-0.32 (-3.00)	-0.47 (-4.45)	-0.31*** (-5.97)
Panel B: Relationship between *SUV*_Buy (*SUV*_Sell) and Option OIB during the Formation Period							
		1	2	3	4	5	(5-1)
Call	*SUV*_Buy	-0.24 (-17.42)	-0.21 (-13.35)	-0.17 (-10.65)	-0.13 (-7.15)	-0.02 (-0.97)	0.23*** (22.58)
	*SUV*_Sell	-0.25 (-16.82)	-0.21 (-14.05)	-0.17 (-10.47)	-0.12 (-7.21)	-0.02 (-1.01)	0.23*** (22.79)
Put	*SUV*_Buy	-0.27 (-23.70)	-0.25 (-23.02)	-0.23 (-20.77)	-0.18 (-17.07)	-0.13 (-10.55)	0.14*** (13.27)
	*SUV*_Sell	-0.28 (-23.45)	-0.24 (-26.24)	-0.22 (-19.58)	-0.19 (-15.79)	-0.13 (-11.07)	0.15*** (13.73)

Table A1: Summary Statistics and Correlation in the Put Option Sample

Panel A reports the time-series average of cross-sectional statistics of the main variable and the control variables in the put option sample (winsorized each month at the 1% level). Definitions and constructions of variables can be found in Table 1. Panel B shows the cross-sectional Pearson correlations of *SUV* and several alternative investor attention proxies in the put option sample. All variables are winsorized each month at the 1% level. The sample period is from January 1996 to November 2021.

Panel A: *SUV* and Control Variables in the Call Option Sample (Time-Series Average of Cross-Sectional Statistics)

Variable	Mean	Std Dev	10th Pctl	25th Pctl	Median	75th Pctl	90th Pctl
SUV	-0.11	1.80	-2.32	-1.37	-0.24	1.01	2.27
ERet	0.24	20.77	-9.36	-2.89	0.07	3.14	9.68
PRet (%)	28.08	68.27	-33.46	-12.42	13.20	47.82	101.26
12mH	0.74	0.18	0.47	0.62	0.77	0.89	0.95
MC	127.42	285.52	19.30	33.50	58.99	107.60	214.31
AC	10.92	7.37	2.94	5.30	9.26	15.17	21.59
ASVI	0.04	0.34	-0.25	-0.09	0.00	0.09	0.32
I_L	0.14	0.35	0.00	0.00	0.00	0.00	0.94
I_W	0.13	0.34	0.00	0.00	0.00	0.00	0.87
I_{WL}	0.11	0.30	0.00	0.00	0.00	0.00	0.54
IVOL	0.02	0.01	0.01	0.01	0.02	0.03	0.04
VRP	0.01	0.12	-0.11	-0.04	0.01	0.07	0.14
Amihud	-6.68	1.73	-8.95	-7.89	-6.68	-5.47	-4.42
AUTO	-0.01	0.10	-0.14	-0.08	-0.01	0.06	0.12
DISP (%)	19.03	52.92	0.95	1.92	4.64	12.85	36.07
CFV	-0.04	0.18	-0.04	-0.01	0.00	0.00	0.00
Cash	0.22	0.23	0.01	0.04	0.13	0.34	0.60
Issue1Y	-0.32	0.86	-1.03	-0.20	-0.02	0.01	0.04
Lnprice	3.32	0.77	2.25	2.76	3.35	3.88	4.31
Profit	0.15	0.41	-0.19	0.05	0.17	0.29	0.44
TEF	-0.06	0.20	-0.32	-0.09	-0.01	0.04	0.10

Panel B: Correlation Matrix in the Put Option Sample										
	SUV	ERet	PRet	12mH	MC	AC	ASVI	I_L	I_W	I_{WL}
SUV	1	0.018	0.060	0.162	0.043	-0.023	0.123	0.012	0.134	0.082
ERet		1	0.006	0.046	0.001	0.003	0.008	-0.034	0.023	0.000
PRet			1	0.328	-0.021	-0.091	0.004	0.033	-0.006	0.054
12mH				1	0.065	0.122	0.004	-0.218	0.013	-0.244
MC					1	0.376	0.012	-0.022	-0.021	-0.025
AC						1	-0.018	-0.052	-0.081	-0.144
ASVI							1	0.023	0.050	0.081
I_L								1	-0.157	-0.138
I_W									1	-0.133
I_{WL}										1

Table A2: Dependent Double Sorting based on *SUV* and Stock or Option Characteristics

In this table, we investigate whether several stock or option characteristics can individually explain *SUV*'s effect. We conduct the dependent sorting test by first sorting all options into quintiles based on one of the characteristics, including IVOL, VRP, Amihud, AUTO, Option_Spread, Gamma, Vega, DISP, CFV, Cash, Issue_1Y, Lnprice, Profit, TEF. Then, we further sort the options into quintiles based on *SUV*. Finally, we average returns for each *SUV* quintile across the groups of each characteristic, yielding five characteristic-adjusted quintile returns. We report the baseline results without any control variables in the first row and the after-adjustment results in the rows below. The detailed definition and construction of stock or option characteristics are provided in Section 2.2.3. The weighting scheme is equally weighted. The sample is restricted to the option return sample, and the sample period is from January 1996 to November 2021. To adjust for serial correlations, robust Newey-West (1987) t-statistics are reported in brackets. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Dependent Double Portfolio Sorting by Stock or Option Characteristics and *SUV*

	Call Options	Put Options
Baseline	-0.48***	-0.34***
	(-8.41)	(-7.03)
IVOL	-0.35***	-0.25***
	(-6.93)	(-5.41)
VRP	-0.48***	-0.34***
	(-8.49)	(-7.08)
Amihud	-0.42***	-0.28***
	(-7.98)	(-6.38)
AUTO	-0.47***	-0.33***
	(-8.68)	(-6.97)
Option_Spread	-0.48***	-0.32***
	(-8.91)	(-6.81)
Gamma	-0.48***	-0.31***
	(-9.21)	(-6.61)
Vega	-0.51***	-0.34***
	(-10.26)	(-7.99)
DISP	-0.46***	-0.33***
	(-9.01)	(-7.82)
CFV	-0.45***	-0.33***
	(-7.81)	(-6.87)
Cash	-0.42***	-0.31***
	(-7.26)	(-6.76)
Issue_1Y	-0.45***	-0.32***
	(-8.04)	(-6.94)
Lnprice	-0.52***	-0.37***
	(-10.22)	(-8.47)
Profit	-0.46***	-0.34***
	(-8.58)	(-7.57)
TEF	-0.48***	-0.34***
	(-8.85)	(-7.29)

Table A3: Relationships between *SUV* and Option Order Imbalance with Alternative Constructions

Panel A of this table reports the relationship between *SUV* and the option order imbalance calculated using the number of trades for both call and put options. Trades in Panel A only include trades opening new option positions. Panel B of this table reports the relationship between *SUV* and the option order imbalance computed using all trading volumes, i.e., both the volume of trades opening new option positions and the volume of trades closing existing option positions. The sample is restricted to the option return sample, and the sample period is from October 2009 to December 2021. To adjust for serial correlations, robust Newey-West (1987) t-statistics are reported in brackets. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Relationship between *SUV* and the Option Order Imbalance based on the Number of Trades

		1	2	3	4	5	(5-1)
Call	Open Order Imbalance	-0.28 (-16.70)	-0.25 (-13.70)	-0.20 (-11.68)	-0.15 (-8.59)	-0.03 (-1.82)	0.24*** (26.20)
	Retail Open Order Imbalance	-0.29 (-17.05)	-0.26 (-13.95)	-0.21 (-11.83)	-0.16 (-8.69)	-0.04 (-1.90)	0.25*** (27.42)
	Non-retail Open Order Imbalance	0.04 (1.26)	0.02 (0.84)	0.00 (0.03)	0.00 (0.14)	-0.02 (-1.13)	-0.06** (-2.20)
Put	Open Order Imbalance	-0.29 (-23.64)	-0.26 (-24.44)	-0.24 (-21.30)	-0.20 (-16.74)	-0.13 (-9.79)	0.15*** (16.49)
	Retail Open Order Imbalance	-0.31 (-24.53)	-0.29 (-24.98)	-0.26 (-22.37)	-0.22 (-18.04)	-0.15 (-10.72)	0.17*** (18.14)
	Non-retail Open Order Imbalance	0.09 (4.16)	0.11 (5.14)	0.08 (3.85)	0.06 (3.52)	0.01 (0.56)	-0.08** (-2.24)

Panel B: Relationship between *SUV* and the Option Order Imbalance Calculated using Total Trading Volume

		1	2	3	4	5	(5-1)
Call	Order Imbalance	-0.21 (-21.87)	-0.19 (-20.06)	-0.16 (-18.28)	-0.14 (-15.85)	-0.09 (-10.09)	0.11*** (14.22)
	Retail Order Imbalance	-0.22 (-21.92)	-0.20 (-20.33)	-0.17 (-17.86)	-0.14 (-15.55)	-0.10 (-10.00)	0.12*** (15.76)
	Non-retail Order Imbalance	-0.01 (-0.59)	-0.03 (-1.45)	-0.04 (-2.55)	-0.03 (-1.90)	-0.05 (-3.72)	-0.04** (-2.12)
Put	Order Imbalance	-0.17 (-19.87)	-0.15 (-19.34)	-0.15 (-20.72)	-0.13 (-17.20)	-0.11 (-13.30)	0.06*** (6.68)
	Retail Order Imbalance	-0.18 (-20.66)	-0.17 (-19.72)	-0.16 (-19.92)	-0.15 (-17.49)	-0.12 (-14.65)	0.06*** (7.84)
	Non-retail Order Imbalance	0.03 (2.00)	0.04 (2.82)	0.02 (1.47)	0.01 (1.18)	-0.03 (-1.49)	-0.06** (-2.22)

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