Opinion Divergence and High-volume Anomaly: New Evidence from Equity Option Market

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[November 2021]

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Keywords: high-volume anomaly, delta-hedged options, opinion divergence, retail investors, short-sale constraints

JEL Classification: G11, G12, G14, G41

1. Introduction

Gervais, Kaniel, and Mingelgrin (2001) document that stocks with high abnormal trading volume have higher returns over the next month, known as the *high-volume return premium*. They attribute the *high-volume return premium* to the increase of stocks' visibility. When a stock experiences abnormally high trading volume, investors start to pay more attention to it. Attention increases the pool of the stock's potential investors, who have different views. Optimistic traders can easily take long positions in the stock market, while it is not easy for pessimistic traders to take short positions in the stock market. Most retail investors could only sell those stocks they currently own (Barber and Odean, 2008), and institutional investors often face tight short-sale constraints. Consequently, stocks with high abnormal trading volume may experience more buying pressure than selling pressure. Such asymmetry pushes up the price of these stocks, leading to the high return in the next month. To sum up, they interpret the *high-volume return premium* as a combination of visibility, divergent opinions, and the short-sale constraints.

Gervais, Kaniel, and Mingelgrin (2001) further predict that the *high-volume return premium* should be smaller among optionable stocks because the option market makes it easier for pessimistic investors to take short positions (Miller, 1977; Merton, 1987). Using the standardized unexpected volume (SUV), introduced by Garfinkel and Sokobin (2006) and Israeli, Kaniel, and Sridharan (2020), as a proxy for abnormal trading volume, we first confirm the existence of *high-volume return premium* in the optionable stock sample. Moreover, its magnitude is significantly smaller than that in the non-optionable stock sample. The difference is not explained by the stock characteristics, such as past trading volume, volatility, and market capitalization, documented as factors for option listing (Mayhew and Mihov, 2004). Moreover, we find that the order imbalance of stocks increases with SUV, indicating that stocks with higher abnormal trading volume experience stronger buying pressure in the two weeks after the SUV is constructed at the end of each month. The buying pressure from retail investors is stronger than that from institutions.

The stock market and the option market are closely connected, and information extracted from the option data can predict stock returns. We examine whether the effect of SUV on stock returns can be explained by the information contained in options' implied volatilities. Stocks with high abnormal trading volume may be riskier (Banerjee and Kremer, 2010; Schneider, 2009) or have positive cash flow news. These channels can also lead to higher stock returns over the next month. In the optionable stock sample, we rule out these channels by examining the relation between SUV and proxies for change of risk and cash flow news constructed using implied volatility information.

Gervais, Kaniel, and Mingelgrin (2001) argue that visibility shocks have a weaker impact on stocks with high visibility already. Optionable stocks are usually large and frequently exposed to the news media. Therefore, visibility has limited influence on the optionable stock sample, and the effect of SUV is likely driven by the opinion divergence.

Intuitively, if investors have different opinions towards the underlying stock, they can also go to the option market for trading. In the option market, we first test whether the high abnormal trading volume can predict future straddle returns. We document a significant negative relation between SUV and the cross-section of straddle returns, and this relation is robust to different return definitions and weighting schemes. Moreover, we observe that both call options and put options are more expensive, and their daily rebalanced delta-hedged returns tend to be lower over the next month when their underlying stocks experience higher abnormal trading volume (i.e., higher opinion divergence). Using signed option trading data from Chicago Board Options Exchange (CBOE) and International Security Exchange (ISE), we further confirm that both call options and put options written on stocks with higher SUV have significantly higher buying pressure. Similar to findings in the stock market, we find that the retail end-users' buying pressure is much stronger. We conclude that the opinion divergence among retail investors mainly drives the return patterns in the equity option market.

Previous studies document that the option market is important for investors with pessimistic views to circumvent short-sale constraints and express their negative opinions (for example, Easley, O'Hara, and Srinivas (1998), Pan and Poteshman (2006), Johnson and So (2012), and Chen, Chen, and Chou (2019) among others). As a result, it is not striking that investors with negative views buy more put options. However, it is interesting that we also find similar results on the call options since investors can directly buy stocks if they have positive views toward the firm. This finding is in line with the finding that embedded leverage plays an at least as important role as the short-sale constraint, as suggested by Black (1975), Chakravarty, Gulen, and Mayhew (2004), and Ge, Lin, and Pearson (2016). In addition, Han and Kumar (2013) show that retail investors have relatively higher lottery preferences, making the option market an ideal playground for high leverage and profit maximization.

Our study contributes to the literature in the following three ways. First, we have extended the literature about the *high-volume return premium*. Kaniel, Ozoguz, and Starks (2012) confirm the existence of *high-volume return premium* in the international stock markets and explain their findings through the stock visibility channel. Akbas (2016) finds that low abnormal trading volume before earnings announcement contains negative information and can predict future earnings surprises. Wang (2020) provides evidence that the *high-volume return premium* can predict macroeconomic fundamentals and explain the *high-volume return premium* from the risk perspective. Israeli, Kaniel, and Sridharan (2020) further apply the high-volume anomaly to corporate finance and document a positive relation between abnormal trading volume and firms' real economic activities.

The existing studies do not offer a conclusion for the *high-volume return premium*. There are two main arguments: visibility and risk. Gervais, Kaniel, and Mingelgrin (2001), Barber and Odean (2008), and Kaniel, Ozoguz, and Starks (2012) all attribute the effect of abnormal trading volume on stock returns to the visibility channel. On the other hand, Banerjee and Kremer (2010) view the abnormal trading volume as a signal of investor disagreement, as these stocks also have higher volatility. We attempt to understand the *high-volume return premium* and offer explanations by extending the *high-volume anomaly* to the equity option market. By focusing on the optionable stock sample, we avoid the visibility shock to some extent and find that abnormal trading volume influences stocks and options through the opinion divergence channel. Our results also show that risk measure or cash flow news measure constructed using option's implied volatilities cannot explain the effect of SUV in the optionable stock sample.

Second, our paper contributes to the opinion divergence literature. Empirical evidence on the effects of opinion divergence on stock returns is mixed (Atmaz and Basak, 2018). Some studies find that opinion divergence negatively predicts future stock returns. Diether, Malloy, and Scherbina (2002) find that stocks with higher analyst dispersion earn lower future returns. Using account-level data, Goetzmann and Massa (2005) construct an investor-based measure of opinion divergence and find that it is positively related to the contemporaneous returns and negatively related to future returns. Berkman et al. (2009) document that stocks with high opinion divergence earn significantly lower returns around earnings announcements. Yu (2011) provides evidence that market disagreement is negatively related to the ex-post expected market return. Doukas, Kim, and Pantzalis (2006) document evidence that stock returns are positively associated with opinion divergence and contradict the findings of Diether, Malloy, and Scherbina (2002). Avramov, Chordia, Jostova, and Philipov (2009) find that financial distress can help explain the negative cross-sectional relation between analyst dispersion and future stock returns. It also argues that the dispersion-return relation disappears if the dispersion measure is adjusted by credit risk. Garfinkel and Sokobin (2006) first construct the standardized unexpected volume (SUV) as a proxy for opinion divergence and conclude that opinion divergence is positively related to future stock returns. Our study shows that call and put options written on stocks with high SUV both face higher buying pressure, and the buying pressure from retail investors is stronger. This is direct evidence that high abnormal trading volume contains information about retail investors' opinion divergence.

Third, our paper contributes to the rapidly growing 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 et al. (2018) provide evidence that options' liquidity can predict future option returns. Zhan et al. (2021) document several stock characteristics that are important to predict future option returns. Ramachandran and Tayal (2021) show that put options writing on the overpriced stocks tend to have significantly lower returns over the next month. Jeon, Kan, and Li (2020) present findings that the return autocorrelation of underlying stocks can positively predict future option returns. We provide evidence that abnormal trading volume plays an important role in predicting option returns. Finally, we document robust negative relations between SUV and cross-section of option returns for straddle and delta-hedged option portfolios.

The remainder of this paper proceeds as follows. Section 2 describes the data and variables. Section 3 documents our empirical findings. Section 4 concludes the paper with suggestions for future research.

2. Data and Variables

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

2.1. Data and sample coverage

We obtain data from both equity and option markets. Our sample period is from January 1996 to December 2019. We collect individual stock options data from the Ivy DB database provided by OptionMetrics. The data sets 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). The risk-free rate is downloaded from Kenneth French's website, and we obtain annual accounting data from Compustat. We also collect the analyst coverage and forecast data from I/B/E/S and the intra-day stock quotes and trades data from Trade and Quote (TAQ) database. Finally, we obtain signed option volume data from the Chicago Board Options Exchange (CBOE) and International Security Exchange (ISE).

To avoid extremely illiquid stocks, we only include stocks with a closing price above five dollars at the end of the month. At the end of each month, if there are options writing on a stock, we include that stock in our optionable stock sample. Otherwise, the stock will be assigned to the non-optionable stock sample. We calculate several stock characteristics for both optionable stocks and non-optionable stocks. Panel A of Table 1 shows the summary statistics of stock characteristics of optionable stocks, and summary statistics of stock characteristics of non-optionable stocks are in Table A1. Optionable stocks are larger, more liquid (lower Amihud illiquidity measure and lower bid-ask spread), and have lower book-to-market ratio and higher market beta.

Following the option return predictability literature, we apply standard data filters on 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.[1] Third, we eliminate options that are not traded during their remaining lives and have zero open interest at the end of the month. 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.[2] Fifth, we only include options with moneyness between 0.8 and 1.2.[3] Sixth, most of the options selected each month have the same maturity. We drop options whose maturities are different from the majority of options. From the remaining observations, at the end of each month and for each optionable stock, we obtain a pair of options

[1] For example, no-arbitrage conditions for a call option price C is $S \geq C \geq \max(0, S-Ke^{-rt})$, and no-arbitrage condition for a put option price P is $K \geq P \geq \max(0, Ke^{-rt}-S)$ where S, K, T, and r are the underlying stock price, the option strike price, the option time to maturity, and the risk-free rate, respectively.
[2] \$0.05 when the option price is below \$3 and \$0.1 when the option price is higher than \$3
[3] 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 moneyness. Results in different moneyness sample are shown in Table A3.

that is closest to being at-the-money and have the shortest maturity among those with more than one month to expiration. Our final sample has 242,369 observations for straddle, 307,226 observations for call options, and 285,607 observations for put options.

[Insert Table 1 about here]

2.2. Option returns

We consider three types of option portfolios: straddle portfolio (i.e., a long position in both call and put options with the same underlying, strike price, and maturity), call option portfolio, and put option portfolio. To neutralize the impact of the dynamic of the underlying stock's price, we compute straddle returns using the zero-beta position proposed by Coval and Shumway (2001), daily rebalanced delta-hedged returns to call options, and put options.

We select a call option and a put option with maturity of 50 days and are closest to ATM, as in the main tests. Then, following Coval and Shumway (2001), we form zero-beta straddles by solving the equations below:

$$\begin{gathered} r_v = \theta r_c + (1-\theta) r_p \\ \theta\beta_c + (1-\theta)\beta_p = 0, \end{gathered} \tag{1}$$

where r_v is the straddle return, θ is the fraction of the straddle's value in call options, and β_c and β_p are the market betas of the call and put, respectively. β_c is calculated using:

$$\beta_c = \frac{S}{C}\Delta_c\beta_s, \tag{2}$$

where β_s is the rolling beta of stock, estimated using weekly returns over the past year. We hold this portfolio for one month and calculate zero-beta straddle returns.

The remaining unit of analyses in our study is about the daily rebalanced delta-hedged returns to call options and put options. We measure the delta-hedged call option return following Bakshi and Kapadia (2003) and Cao and Han (2013). We first define the daily rebalanced delta-hedged option gain, which is the change in the value of a self-financing portfolio that consists of a long call position, hedged by a short position in the underlying stock such that the portfolio is not sensitive to stock price movement, with the net investment earning risk-free rate. Specifically, consider a portfolio of a call option that is hedged discretely *N* times over a period $[t\ \ , t+\tau]$. The rebalancing times are t_n (where $t_0 = t$ and $t_N = t + \tau$). The daily rebalanced delta-hedged call option gain is:

$$\Pi_{t,t+\tau} = C_{t+\tau} - C_t - \sum_{n=0}^{N-1} \Delta_{c,t_n}\left(S_{t_{n+1}} - S_{t_n}\right) - \sum_{n=0}^{N-1} \frac{a_n r_{t_n}}{365}\left(C_{t_n} - \Delta_{c,t_n} S_{t_n}\right), \qquad (3)$$

where Δ_{c,t_n} is the call delta of the call option on the date t_n, r_{t_n} is the annualized risk-free rate on the date t_n, and a_n is the number of calendar days between t_n and t_{n+1}. The daily rebalanced delta-hedged put option gain is defined similarly. With a zero-net investment initial position, the delta-hedged option gain $\Pi_{t,t+\tau}$ is the excess dollar return of the delta-hedged option. 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 return by $\Delta_{c,t} S_t - C_t$ for call options and $P_t - \Delta_{p,t} S_t$ for puts.

Panel B to Panel D of Table 1 show the summary statistics of these option returns. The average monthly buy and hold zero-beta straddle returns are -10.97%, -0.70% for daily rebalanced delta-hedged call option returns, and -0.39% for daily rebalanced delta-hedged put option returns. The moneyness of options in our sample is close to 1, and the maturity of most options is about 50 calendar days.

2.3. SUV construction

Following Garfinkel and Sokobin (2006) and Israeli, Kaniel, and Sridharan (2020), we use the standardized unexpected volume (SUV) to measure the abnormal trading volume. Gervais, Kaniel, and Mingelgrin (2001) use the traditional binary measures of the abnormal trading volume. However, as Israeli, Kaniel, and Sridharan (2020) suggested, SUV is continuous and controls for the level of contemporaneous returns. As a result, we use SUV to measure the abnormal trading volume in our main analyses, and our main results remained when using the measure from Gervais, Kaniel, and Mingelgrin (2001). Following previous literature on the *high-volume return premium*, we compute the abnormal trading volume using periods of one week or less (Gervais, Kaniel, and Mingelgrin, 2001; Kaniel, Ozoguz, and Starks, 2012; Akbas, 2016; Israeli, Kaniel, and Sridharan, 2020). Standardized unexpected volume (SUV) is estimated as the standardized prediction error from a regression of trading volume on the absolute value of returns during week -1 (trading days [-6, -2]) prior to the end of the month. To avoid any potential bias related to market microstructure, we skip one day between the calculation period of the SUV and the holding period of the portfolio.

To calculate the SUV, we first estimate the following regression from trading days [-56, -7] prior to each end of the month:

$$\log Vol_{i,k} = \alpha_{i,0} + \alpha_{i,1}|R_{i,k}|^{+} + \alpha_{i,2}|R_{i,k}|^{-} + \epsilon_{i,k} \quad , \tag{4}$$

where $\log Vol_{i,k}$ is the natural logarithm of one plus the dollar trading volume for firm *i* at day *k* prior to the end of the month. $|R_{i,k}|^{+}$ equals to the absolute value of firm *i*'s return at day *k* if the return is positive and 0 otherwise. $|R_{i,k}|^{-}$ equals to the absolute value of firm *i*'s return at day *k* if the return is negative and 0 otherwise. Next, we calculate the expected trading volume during trading days [-6, -2] prior to the end of the month using the coefficients estimated from Equation (5):

$$E\left[\log Vol_{i,k}\right] = \hat{\alpha}_{i,0} + \hat{\alpha}_{i,1}|R_{i,k}|^{+} + \hat{\alpha}_{i,2}|R_{i,k}|^{-}. \tag{5}$$

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

$$UV_{i,k} = \log Vol_{i,k} - E\left[\log Vol_{i,k}\right] \quad . \tag{6}$$

We sum the UV during trading days [-6, -2] prior to the end of the month 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.

$$SUV_i = \frac{\sum_{k=-6}^{-2} UV_{i,k}}{\sigma_\epsilon \sqrt{5}} \quad . \tag{7}$$

Panel A of Table 1 shows the summary statistics of the SUV in the optionable stock sample. Table 2 reports the time-series average of the cross-sectional correlations of SUV with stock characteristics and other controlling variables. Again, the correlation coefficients are generally low.

[Insert Table 2 about here]

3. Empirical Results

In this section, we revisit the effect of the *high-volume return anomaly* on stock returns and document robust evidence of significant cross-sectional relation between future option returns and the standard unexpected volume (SUV). Our findings are distinct from existing determinants of option returns. In addition, we implement various option portfolio strategies and robustness checks to confirm the reliability of our findings.

3.1. Revisit high-volume anomaly and subsample analyses

Gervais, Kaniel, and Mingelgrin (2001) predict that the *high-volume return premium* should be smaller in the optionable stock sample because investors can go to the option market to take negative positions. We first investigate the effect of SUV on stock returns, and our evidence from regression and portfolio sorting confirms their prediction. In the full stock sample, we regress the stock excess return on SUV and the interaction term between SUV and OPTIONED, which is denoted whether the stock is optionable at each end of the month. Mayhew and Mihov (2004) state that exchanges are more likely to list options for stocks with higher trading volume, higher volatility, and larger market capitalization. We add the stocks' trading volume, volatility, market capitalization, and their interaction terms with SUV as controlling variables to control these stock characteristics. We also add market beta, book-to-market ratio, momentum, reversal, and idiosyncratic volatility into the regression as additional controls. Panel A of Table 3 shows the results from the Fama-Macbeth regression. In Column 1 of Table 3, when only the SUV is included in the regression, the coefficient on SUV is 0.259 with a t-statistics of 4.11, confirming that the *high-volume return premium* still exists when using SUV as the proxy for the abnormal trading volume. In Column 2 of Table 3, the coefficient on SUV is 0.346 and still significant (t-stat = 4.79) when OPTIONED and its interaction term with SUV are added to the regression. Meanwhile, the coefficient on the interaction term SUV×OPTIONED is -0.240 and significant (t-stat = -4.50). As a result, the effect of SUV on optionable stocks is less significant than its effect on non-optionable stocks. After adding VOLUME, VOLATILITY, SIZE, and their interaction terms with SUV, the magnitude of the coefficient on SUV×OPTIONED shrinks to -0.150 but is still negative and highly significant (t-stat = -3.24), meaning the effect of SUV is weaker in the optionable stock sample even after controlling the effects from trading volume, volatility, and size.

We further test the effect of SUV on the stock returns in the portfolio sorting setting. At each end of the month, we assign stocks into 5 groups based on their SUV and average stocks' excess return in each group, and the weighting scheme is equal-weighted. Panel B of Table 3 reports the results of portfolio sorting. Consistent with the results of Fama-Macbeth regression, the spread between the High-SUV and Low-SUV groups is 0.74% (t-stat = 4.20) in the full stock sample, confirming the existence of *high-volume return premium* when using SUV. The difference between spread return in the optionable stock sample and the non-optionable stock sample is obvious. The spread return is 0.33% (t-stat = 2.13) per month in the optionable stock sample, while it is 0.95% (t-stat = 4.67) per month in the non-optionable sample.

Investors with optimistic views can take positive positions and push up the stock prices. We conjecture that retail investors contribute more to this behavior. Using the TAQ data, we provide evidence related to this question. We obtain the intraday quotes and prices, and quantity of each trade from the TAQ datasets for a period from January 2006 to December 2019. Following Chordia, Subrahmanyam, and Anshuman (2001), we apply several standard filters to eliminate obvious data errors in the dataset. We use the Lee and Ready (1991) algorithm to classify each transaction as either buyer initiated or seller initiated. The Lee and Ready (1991) algorithm uses the fact that seller-initiated trades tend to execute at a price lower than buyer-initiated trades. Briefly, we implement the Lee and Ready (1991) algorithm as follows: If a trade is executed at a price above (below) the quote midpoint, we classify it as the buyer (seller) initiated trade; if a trade occurs exactly at the quote midpoint, we sign it by comparing the current transaction price with the previous transaction price (i.e., buyer initiated if the sign of the last non-zero price change is positive and vice-versa). We apply the tick test up to the past three price changes. If the past three price changes are all zero, then we do not use them in our analyses. Since the recording errors related to quotes and trades pointed by Lee and Ready (1991) are not observed in recent data (Chordia et al. 2005 among others), we do not impose any delays in our analyses.

We classify a trade as from retail investors if it is less than \$10,000 in size and from institutional investors if it is more than \$10,000. The buying pressure is measured as order imbalance (OIB), defined as the difference between buy orders and sell orders divided by the sum of buy orders and sell orders on a given day. A positive OIB indicates that buy orders are more than sell orders. The buy and sell orders are measured in terms of dollars traded. Panel C of Table 3 shows the results of the OIB of stocks. On average, retail investors are net buyers of optionable stocks, while institutional investors are net sellers. From the Low-SUV group to the High-SUV group, the buying pressure is increasing not only from retail investors but also institutional investors. However, the differential buying pressure from retail investors is more than that from institutional investors. The differential OIB is 0.88% for retail investors, and the differential OIB is 0.67% for institutional investors. The difference between these two is 0.21% with a t-statistics of 1.99, meaning that retail investors are more sensitive or respond more to the abnormal trading volume. To sum up, although both important, the *high-volume return premium* can be attributed more to retail investors.

[Insert Table 3 about here]

3.2. Alternative explanations to patterns on stock returns

The stock market and the option market are closely connected, and researchers have shown that options are not redundant (Buraschi and Jackwerth, 2001; Covel and Shumway, 2001). In this section, we confirm that the effect of *high-volume return premium* in the optionable stock sample cannot be explained by risk measure and cash flow news measure based on options' implied volatility.

Recent studies show that not only can firm attributes predict future option returns (Zhan et al. 2021), but also information extracted from the option market can predict future stock returns. For example, Bali and Hovakimian (2009) find that the difference between the implied volatility of at-the-money (ATM) call options and ATM put options can predict future stock returns. Xing, Zhang, and Zhao (2010) document that the difference between the implied volatility of out-of-the-money (OTM) put options and ATM call options is negatively related to future stock returns. An et al. (2014) find that the innovation of the implied volatility of ATM call options has predictive power on stock returns, and the innovation of the implied volatility of ATM put options can also predict future stock returns after controlling the effect from call options. Cao et al. (2021) find that corporate bonds with large increases in implied volatility over the past month underperform those with large decreases in implied volatility. They consider the implied volatility changes containing information about uncertainty shocks to the firm.

In our study, we use the sum of the innovation of the implied volatility of ATM call options and ATM put options as a proxy for change of risk (Cao et al. 2021). In addition to this, we use the difference between the innovation of the implied volatility of ATM call options and ATM put options as a proxy for change of cash-flow news (An et al. 2014).

$$\Delta CVOL = CVOL_t - CVOL_{t-1} \quad , \tag{8}$$

$$\Delta PVOL = PVOL_t - PVOL_{t-1} \quad , \tag{9}$$

where $CVOL_t$ is the implied volatility of ATM call options at time *t*, and $PVOL_t$ is the implied volatility of ATM put options at time *t*. Higher $(\Delta CVOL + \Delta PVOL)$ represents that the risk level of the underlying stock increases during the current month, and the stock return should be higher because investors demand a higher risk premium. Higher $(\Delta CVOL - \Delta PVOL)$ means that the underlying stock is experiencing better cash flow news in the current month, so the stock return should also be higher over the next month because of the better fundamentals.

Table 4 shows the results of this part of the analyses. Neither the proxy for change of risk nor the proxy for cash flow news can explain the effect of SUV in the optionable stock sample. The $(\Delta CVOL + \Delta PVOL)$ measure monotonically decreases from low-SUV group to high-SUV group, and the spread is significant (-0.77% with a t-statistics of -4.37). As a result, if the SUV predicts the stock return through the risk channel, it should forecast future stock return negatively, not positively that we find. Moreover, there is no significant relation between SUV and the $(\Delta CVOL - \Delta PVOL)$ measure, so SUV can hardly influence the stock return through this channel.

[Insert Table 4 about here]

3.3. The effect of SUV on returns to zero-beta straddle

In the option market, we first investigate the relation between SUV and the return to zero-beta straddle. At the end of each month, we sort all underlying stocks into 5 quintiles based on SUV and then compare the portfolios of zero-beta straddle on the stocks belonging to the top quintile versus the bottom quintile. To make the analyses robust to portfolio weighting, we use three weighting schemes in computing the average return of the zero-beta straddles: equal weight (EW), weight by the market capitalization of the underlying stock (Stock-VW), and weight by the market value of option open interest at the beginning of the holding period (Option-VW). We also test the effect of SUV on straddle returns defined in Goyal and Saretto (2009) and delta-neutral straddle returns as in Gao, Xing, and Zhang (2018), and find qualitatively similar results.[4]

Panel A of Table 5 reports the average return to zero-beta straddle for the 5 quintile portfolios sorted by the SUV and the difference between the top and the bottom quintile portfolios. The relation between SUV and the return to zero-beta straddles over the next month is economically and statistically significant. For the EW scheme, the (5-1) spread portfolio of zero-beta straddle has a monthly return of -1.67% with a t-statistics of -2.71. For the Stock-VW (Option-VW) case the spread return is –1.42% (-3.44%), with a t-statistics of -3.17 (-4.32). The returns of (10-1) spread portfolios express the same pattern.

[4] Results are shown in Table A2.

After controlling several proxies for opinion divergence and option return determinants, we further confirm the relation in the Fama-Macbeth regression. Proxies for opinion divergence include idiosyncratic volatility (IVOL, Boehme, Danielsen, Sorescu, 2006), the bid-ask spread of the underlying stock (SSPREAD, Handa, Schwartz, and Tiwari, 2003), and analyst dispersion (DISP, Diether, Malloy, and Scherbina, 2002). For option return determinants, we include the variance risk premium (VRP), the natural logarithm of the Amihud illiquidity measure (LOGAMIHUD, Amihud, 2002), the bid-ask spread of the option (OSPREAD, Christoffersen et al., 2018), return autocorrelation of the underlying stocks (AUTO, Jeon, Kan, and Li, 2020), and stock characteristics documented in Zhan et al. (2021).

To perform the Fama-Macbeth regression analyses, we run the following cross-section regression every month:

$$R_{i,t+1} = \alpha_{0,t} + \alpha_{1,t} SUV_{i,t} + \sum_k^K \lambda_{k,t} X_{i,t}^k + \epsilon_{i,t} \quad , \tag{10}$$

where $R_{i,t+1}$ is the return to zero-beta straddle portfolio on stock *i* formed at time *t* and is held to *t*+1. $SUV_{i,t}$ is the standardized unexpected volume of stock *i* at time *t*. $X_{i,t}^k$ are controlling variables such as proxies for opinion divergence and option return determinants that we have mentioned, including IVOL, BASPREAD, DISP, VRP, LOGAMIHUD, OSPREAD, AUTO, and stock characteristics in Zhan et al. (2021). We estimate Equation (11) every month in our sample and report the time-series average of the coefficients. We also report the t-statistics based on Newey-West (1987) in the brackets to adjust for serial correlation. Panel B of Table 5 shows these results.

Column 1 of Panel B of Table 5 shows the results of the univariate regression. The coefficient on SUV is -0.261 with a t-statistics of -3.27. The significantly negative coefficient implies that stocks with higher abnormal trading volume tend to have significantly lower returns to the zero-beta straddle written on them. In Column 2 of Panel B of Table 5, we add some well-known proxies for opinion divergence, variance risk premium, and the natural logarithm of Amihud illiquidity measure to the regression. The loading on the SUV even increases in absolute value from -0.261 to -0.398 and is still significant (t-stat = -5.19). We further include other option return determinants as additional controls in Column 3 of Panel B of Table 5. The coefficient on the SUV is -0.545 and still statistically significant (t-stat = -6.81). Our results on straddle returns are robust to different return definitions, and robustness checks can be found in Table A2.

[Insert Table 5 about here]

3.4. Delta-hedged option returns

Based on previous results from portfolio sorting and Fama-Macbeth regression of zero-beta straddle return, we demonstrate that SUV has significant predictive power in the option market. We conjecture that retail investors will go to the option market to buy call options or put options after observing the high abnormal trading volume of the underlying stocks. Options writing on stocks with high abnormal trading volume should face higher demand pressure. According to demand-based option pricing theory (Bollen and Whaley, 2004; Garleanu, Pedersen, and Poteshman, 2009), these options should be more expensive and have lower returns over the next month. We rerun the Fama-Macbeth regression analyses on call options and put options separately to test this hypothesis.

Table 6 documents the results of call options and put options. Column 1 and Column 4 of Table 6 show the results of univariate regression of call options and put options, respectively. The loading on SUV is -0.082 with a t-statistics of -4.57 for call options, and the loading is -0.104 with a t-statistics of -7.82 for put options. After adding proxies for opinion divergence and other controlling variables, the effect of SUV on both call options and put options is still significant, as shown in Column 2, 3, 5, and 6. These results are consistent with our hypothesis that options written on stocks with high abnormal trading volume tend to be overpriced. After observing high abnormal trading volume, investors will form different ideas toward the specific stock and may go to the option market to express their opinions. Investors with optimistic views will buy call options, and those with pessimistic views will buy put options. The buying pressure from investors pushes up current prices of options and thus makes these options have lower returns over the next month. In Section 3.5, we provide direct evidence that both call options and put options face higher buying pressure if their underlying stocks are experiencing higher abnormal trading volume.

[Insert Table 6 about here]

At first glance, it seems striking that we document similar effects of SUV on call options and put options. The short-sale constraint is important to explain the relationship between abnormal trading volume and future stock returns documented in Gervais, Kaniel, and Mingelgrin (2001). Ramachandran and Tayal (2020) document that put options written on overpriced stocks with tighter short-sale constraints will have lower returns over the next month because investors choose put options to bypass the short-sale constraints and drive up the demand for these put options. Since the option market can help investors circumvent the constraint, the natural intuition is that the effect of SUV on put options should be more significant because put options should experience higher demand pressure from end-users. However, studies also show that embedded leverage of options plays an important role in explaining option trading (Black (1975), Chakravarty, Gulen, and Mayhew (2004)), and Ge, Lin, and Pearson (2016) further emphasize that the embedded leverage of options is at least as important as bypassing short-sale constraints. Also, as documented in Han and Kumar (2013), retail investors have higher lottery preferences and have higher incentives to gamble. After observing the abnormal trading volume in the stock market, retail investors with positive views will trade options to take advantage of the high leverage provided by options. In general, it is natural that we find that SUV have significant prediction power on both delta-hedged call option and put option returns.

3.5. Option order imbalance

We have mentioned that both call options and put options written on stocks with high abnormal trading volume face buying pressure, which pushes up their current prices and make them have lower returns over the next month. In this section, using the ISE data, we empirically show that this is the case.

The dataset from Chicago Board Options Exchange (CBOE) and International Security Exchange (ISE) contains signed option volume information, and thus we can compute the option order imbalance based on this dataset. These two datasets cover about 70% of records in OptionMetrics. Many researchers have done several analyses and drawn insightful conclusions using ISE data.[5]

In CBOE and ISE data, contracts are classified as small, medium, and large based on the contract size. We consider that small orders are mainly from small investors, and medium and large orders are from large investors. Contracts in the signed option volume data are divided into four

[5] See, for example, Ge, Lin, and Pearson (2016), Muravyev (2016), Christoffersen et al. (2018); Chen, Joslin, and Ni (2019); Ramachandran and Tayal (2020).

categories: contracts that are bought to open new positions (open buy), contracts that are sold to open new positions (open sell), contracts that are bought to close existing positions (close buy), and contracts that are sold to close existing positions (close sell). Pan and Pteshman (2006) and Ge, Lin, and Pearson (2016) state that transactions are executed to open new positions contain more information, so we only include contracts that are traded to open new positions in our analyses. For each stock and each trading day, we aggregate option contracts that are traded to open new positions for small orders and large orders separately and compute the signed option trading volume as follows:

$$Signed\ \ Option\ \ Trading\ \ Volume_{it} = \frac{Open\ \ Buy_{i,t} - Open\ \ Sell_{i,t}}{Shares\ \ Outstanding_{i,t}} \quad , \tag{11}$$

where $Open\ \ Buy_{it}$ ($Open\ \ Sell_{it}$) is the total option trading volume of newly initiated long (short) position by public customers to open new positions one week prior to the end of the month, which is the formation period of SUV. We only include ATM options with days to maturity between 15 days and 150 days.

We assume that investors will quickly trade options after they observe the abnormal trading volume. At each end of the month, we sort signed option trading volume based on the SUV of its underlying stock and compute the High – Low (H-L) spread. Panel A of Table 7 shows the results. For both call and put options, the net demand from end-users is negative in the lowest SUV quintile and positive in the highest quintile, and the (H-L) is highly significant. This finding is consistent with our conjecture that the net demand of options is significantly higher when the underlying stock is experiencing abnormal trading volume. For call options, the net demand from end-users of small orders increases monotonically from the low-SUV group to the high-SUV group, and the difference is 1.27% with a t-statistics of 10.44. There is no significant pattern between the net demand of options of large orders and SUV. For put options, the results are very similar to those of call options. The net demand from end-users of small orders increases monotonically with a spread of 0.39% (t-stat = 5.34) between the low-SUV and high-SUV groups. Our empirical results demonstrate that options face significantly more buying pressure if their underlying stocks experience higher abnormal trading volume. Moreover, similar to the results of stock OIB, the buying pressure is mainly from small orders (i.e., retail investors). The (H-L) spread for net demand of options of large investors is not statistically significant for both call and put options. We find similar results when using different definitions of demand pressure of options (signed option volume scaled by stock trading volume and the order imbalance). The (H-L) spread of large orders is either statistically insignificant or smaller than small orders.

[Insert Table 7 about here]

3.6. Alternative explanation to patterns on option returns

3.6.1. Risk or other anomalies

One may concern that SUV captures known risk factors that determine option returns, for example: variance risk premium (Goyal and Saretto, 2009), liquidity risk (Amihud, 2002; Christoffersen et al., 2018), or well-known option anomalies such as stock return autocorrelation (Jeon, Kan, and Li, 2020), and stock characteristics documented in Zhan et al. (2021). This concern is reasonable because trading volume is indeed associated with many variables. For example, the denominator of the Amihud illiquidity measure is trading volume. Also, high trading volume is often accompanied by extreme returns, so controlling the lottery preference measure is also important. Wang (1994) shows that if the main motive for trading is speculation, the trading volume should induce negative autocorrelation. Jeon, Kan, and Li (2020) document that stock autocorrelation and option returns are positively related, so it is necessary to control the stock autocorrelation. We control all these variables in the Fama-Macbeth regression in Table 5 and Table 6. The coefficients on SUV are all statistically significant after controlling for these variables, so that we can exclude this explanation.

3.6.2. Informed trading

Options are great tools for informed traders to take advantage of their private information. Abnormal trading volume is also related to informed traders and contains information about firms' earnings. Akbas (2016) finds that the low abnormal trading volume before firms' earnings announcements contains negative information and can negatively predict future earnings surprises. Therefore, it is possible that abnormal trading volume influences option prices through the informed trading channel. We conduct two tests to exclude this explanation. First, the relation between net buying pressure and SUV in Table 7 can help exclude the informed trading channel. Akbas (2016) conjecture that if informed traders know negative news about the firm, they will avoid trading its stock. This leads to the low abnormal trading volume before earnings announcements. Intuitively, they can go to the option market and buy put options to leverage their private information. If this is the case, we should observe that the buying pressure should be higher for options of stocks with low abnormal trading volume. The empirical results contradict this hypothesis, and we find that the net buying pressure of put options increases with SUV. Second, we remove all observations whose underlying stocks with earnings announcements during the period [-6, -2] trading days following each end of the month in our sample. The sample of call options now has 277,765 observations, and that of put options has 258,700 observations. We rerun the Fama-Macbeth regression in Table 6 and find that all our results hold in the subsample. Third, if the informed trading channel drives the effect of SUV, we should observe that the SUV only affects call options or put options, or the sign on SUV in the regression should be opposite, according to the informed trading model presented by An et al. 2014. However, in Table 6, we show that the effect of SUV on call options and put options are similar and have the same signs. These three tests help us exclude the informed trading channel confidently.

[Insert Table 8 about here]

4. Conclusion

This paper extends the literature about the high-volume anomaly and investigates the effect of the *high-volume anomaly* in the option market. Using SUV as a proxy for the abnormal trading volume, we confirm the prediction that the effect of *high-volume return premium* is weaker in the optionable stock sample. By focusing on the optionable stock sample to avoid visibility shocks, we attribute the remaining effect of the high-volume anomaly in the optionable stock sample to retail investors' opinion divergence. Empirically, we use the OIB of stocks to show that retail investors mainly drive the *high-volume return premium*.

In the equity option market, we document a significant and robust negative relation between SUV and the return to zero-beta straddle portfolios in both portfolio sorting and the Fama-Macbeth regression setting. After controlling proxies for opinion divergence and common option return determinants, the relation between SUV and zero-beta straddle return is still statistically significant.

We also investigate the relation between SUV and returns to daily rebalanced delta-hedged option portfolios. We find that both call options and put options are more expensive and have lower returns over the next month. These findings are consistent with the hypothesis that investors trade both stocks and options after observing the high abnormal trading volume. According to the demand-based option pricing theory, options should be more expensive if they face higher demand pressure.

Our study contributes to the literature in the following three ways. First, we have extended the literature about the *high-volume return premium*. Previous studies about *high-volume return premium* focus on the stock market. We first provide evidence that investors trade both stocks and options after observing the high abnormal trading volume. We document that the net buying pressure is significantly higher for options of stocks with abnormal trading volume. Second, our paper contributes to the opinion divergence literature. We investigate the opinion divergence in the equity option market. We find that the high abnormal trading volume contains information about retail investors' opinion divergence. The high-volume anomaly influences both stocks and options through the opinion divergence channel. Third, our paper contributes to the rapidly growing literature about option return predictability. We document significant relation between the high-volume anomaly and cross-section of returns to zero-beta straddle and delta-hedged option portfolios.

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Table 1: Summary Statistics

This table reports the descriptive statistics of stock characteristics in the optionable stock sample and option returns used in the analyses. The sample period is from January 1996 to December 2019. Panel A reports the time-series average of cross-sectional statistics of stock characteristics (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). BETA is stock's CAPM beta estimated using daily stock returns of the previous month. SIZE is the natural logarithm of the stock's market capitalization. BM is the natural logarithm of stock's book-to-market ratio. MOM is the cumulative return of the stock during the 11-month period covering months t-11 to t-1. REV is the stock's return of month t. VRP is the variance risk premium, defined as the natural logarithm of the ratio of historical volatility to the implied volatility of the underlying stock. IVOL is the annualized idiosyncratic return volatility as in Ang, Hodrick, Xing, and Zhang (2006). LOGAMIHUD is the natural logarithm of the illiquidity measure from Amihud (2002). DISP is the analyst earnings forecast dispersion, as in Diether, Malloy, and Scherbina (2002). BASPREAD is the stock's bid-ask spread. AUTO is the first-order autocorrelation of underlying stock's return as in Jeon, Kan, and Li (2020). Panel B to Panel D report the pooled summary of returns to zero-beta straddle, daily rebalanced delta-hedged call options, and daily rebalanced delta-hedged put options. A zero-beta straddle position involves buying call options and put options in some given weights that are calculated based on the delta of call options and put options. A delta-hedged option position involves buying one contract of an option and a short position of Δ shares of the underlying stock, where Δ is the Black-Scholes option delta. The position is rebalanced every day. Moneyness is the ratio of option strike price to stock price. Days to maturity is the number of calendar days until the option expiration. Vega is the Black-Scholes option vega scaled by the stock price. The 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 A: Stock characteristics of optionable stocks (time-series average of cross-sectional statistics)

Variables	**Mean**	**Std**	**P25**	**Median**	**P75**
SUV	-0.12	1.75	-1.34	-0.23	0.98
BETA	1.15	1.32	0.35	1.03	1.84
SIZE	7.43	1.49	6.35	7.30	8.38
BM	-0.79	0.95	-1.35	-0.77	-0.28
MOM (%)	17.07	46.84	-10.76	9.16	33.21
REV (%)	1.34	11.04	-5.02	0.78	6.88
VRP	-0.02	0.23	-0.13	0.00	0.11
IVOL	0.34	0.20	0.20	0.29	0.42
LOGAMIHUD	-6.32	1.84	-7.61	-6.31	-5.04
DISP	0.16	0.43	0.02	0.04	0.11
BASPREAD (%)	0.52%	0.56%	0.18%	0.36%	0.67%
AUTO (%)	-0.01	0.10	-0.08	-0.01	0.06

Panel B: Pooled summary of returns to zero-beta straddle strategy and option characteristics

Variables	**Mean**	**Std**	**P25**	**Median**	**P75**
Straddle return until monthend (%)	-10.97	42.82	-36.26	-22.86	0.67
Moneyness = K/S	1.00	0.06	0.97	1.00	1.03
Days to maturity	50	2	49	50	51
Quoted option bid-ask spread (%)	17.88	15.79	8.21	13.20	21.56

Panel C: Pooled summary of returns to delta-hedged call options and option characteristics

Variables	**Mean**	**Std**	**P25**	**Median**	**P75**
Delta-hedged call optionreturn until monthend (%)	-0.70	4.77	-2.55	-0.85	0.82
Moneyness = K/S	1.00	0.05	0.97	1.00	1.02
Days to maturity	50	2	49	50	51
Vega (%)	0.14	0.01	0.14	0.14	0.15
Quoted option bid-ask spread (%)	0.17	0.21	0.08	0.13	0.19

Panel D: Pooled summary of returns to delta-hedged put options and option characteristics

Variables	**Mean**	**Std**	**P25**	**Median**	**P75**
Delta-hedged put option return until monthend (%)	-0.39	4.28	-2.23	-0.70	0.89
Moneyness = K/S	1.00	0.04	0.98	1.00	1.03
Days to maturity	50	2	49	50	51
Vega (%)	0.14	0.01	0.14	0.14	0.15
Quoted option bid-ask spread (%)	0.16	0.20	0.08	0.13	0.18

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

Table 2 presents the cross-sectional Pearson correlations of stock characteristics including SUV. 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 December 2020.

	SUV	BETA	SIZE	BM	MOM	REV	VRP	IVOL	LOGAMIHUD	DISP	BASPREAD	AUTO
SUV	1	-0.04	0.02	0.01	0.05	0.23	0.02	0.14	0.02	-0.01	-0.03	0.00
BETA		1	-0.05	-0.05	0.02	-0.01	0.04	0.21	0.03	0.05	-0.01	0.14
SIZE			1	-0.14	0.10	0.04	0.11	-0.38	-0.91	-0.16	-0.34	0.00
BM				1	-0.02	0.01	-0.08	-0.11	0.15	0.08	0.10	-0.04
MOM					1	-0.01	0.08	0.01	0.04	-0.08	-0.08	0.00
REV						1	0.13	0.07	0.04	-0.01	-0.03	0.01
VRP							1	0.08	-0.11	0.00	-0.11	-0.02
IVOL								1	0.34	0.17	0.15	0.09
LOGAMIHUD									1	0.14	0.39	-0.02
DISP										1	0.09	0.04
BASPREAD											1	-0.02
AUTO												1

Table 3: The Effect of SUV in Optionable and Non-optionable Stock Sample

Panel A of this table reports the average coefficients from the monthly Fama-MacBeth regressions with the stock excess return over the next month as the dependent variable in the optionable stock sample. SUV is the standardized unexpected volume. OPTIONED equals 1 if the stock is in the optionable stock sample, otherwise 0. AVGVOL is the average stock trading volume of the past 250 trading days. STD is the standard deviation of log returns of the past 250 trading days. SIZE is the natural logarithm of the stock's market capitalization at the end of each month. Panel B reports the average monthly return of stock excess return sorted on SUV in full stock, optionable stock, and non-optionable stock sample, respectively. We form quintile portfolios and report the (H - L) spread return, which is the average difference between the return of the top and bottom quintile portfolios. All returns in Panel B are expressed in percent. Panel C reports the average order imbalance (OIB) sorted on SUV for the period one week following each end of the month (inclusive). OIB is defined as the average daily OIB during the period, and daily OIB is defined as buy orders less sell orders divided by the sum of buy orders and sell orders. Small (Large) OIB is measured using trades that are less (greater) than $10,000. The buy and sell orders are measured in terms of the size of trades. OIB is multiplied by 100. The sample period of Panel A and Panel B is January 1996 to December 2019. The sample period of Panel C is January 2006 to December 2019. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Fama-Macbeth regression with excess stock return as dependent variable

	(1)	(2)	(3)
SUV	0.259***	0.346***	0.305***
	(4.11)	(4.79)	(5.49)
OPTIONED		0.151	0.336***
		(1.32)	(4.52)
SUV×OPTIONED		-0.240***	-0.150***
		(-4.50)	(-3.24)
AVGVOL			0.037
			(0.96)
SUV×AVGVOL			0.014
			(0.49)
STD			-0.220*
			(-1.70)
SUV×STD			0.003
			(0.10)
SIZE			-0.276***
			(-4.43)
SUV×SIZE			-0.131***
			(-4.48)
BETA			-0.018
			(-0.36)
BM			0.053
			(0.76)
MOM			0.250***
			(2.83)
RET			-0.298***
			(-4.69)
IVOL			-0.157***
			(-3.52)
ADJ R^2 (%)	0.384	1.025	6.400

Panel B: Excess stock return sorted on SUV

	Low SUV	**2**	**3**	**4**	**High SUV**	**H - L**
Full	0.29	0.55	0.67	0.81	1.03	0.74***
	(0.85)	(1.79)	(2.37)	(2.94)	(3.38)	(4.20)
Optionable	0.50	0.72	0.78	0.76	0.84	0.33**
	(1.33)	(2.02)	(2.40)	(2.36)	(2.56)	(2.13)
Non-optionable	0.06	0.43	0.58	0.81	1.00	0.95***
	(0.18)	(1.55)	(2.33)	(3.18)	(3.35)	(4.67)

Panel C: Stock OIB sorted on SUV [0, +4] days following the monthend

	Low SUV	**2**	**3**	**4**	**High SUV**	**H-L**
Small Order imbalance	-0.29	0.00	0.24	0.41	0.59	0.88***
	(-1.58)	(0.01)	(1.09)	(1.72)	(2.38)	(7.01)
Large Order imbalance	-0.96	-0.43	-0.32	-0.15	-0.30	0.67***
	(-2.95)	(-1.26)	(-0.93)	(-0.41)	(-0.83)	(4.64)
						0.21**
						(1.99)

Table 4: Potential Channels in the Optionable Stock Sample

This table reports the results of proxies for change of risk level and cash flow news sorted on SUV. The sorting results of stock excess returns are also reported as a comparison. Change of risk level proxy is the sum of the innovation of the implied volatility of call options and the implied volatility of put options, (ΔCVOL+ΔPVOL). Cash flow news proxy is the difference between the innovation of the implied volatility of call options and the implied volatility of put options, (ΔCVOL-ΔPVOL). We form optionable stocks into quintile portfolios and report their average change of risk level proxy and cash flow news proxy. H-L is the difference between the top and bottom portfolios. The sample period is January 1996 to December 2019. All figures in this table are represented in percentage. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Low-SUV	**2**	**3**	**4**	**High-SUV**	**H - L**
ΔCVOL+ΔPVOL	0.21	0.17	0.06	-0.26	-0.56	-0.77***
	(0.76)	(0.70)	(0.24)	(-1.11)	(-2.20)	(-4.37)
ΔCVOL-ΔPVOL	-0.03	-0.04	0.03	-0.02	-0.06	-0.02
	(-0.44)	(-0.62)	(0.57)	(-0.32)	(-0.81)	(-0.29)
Excess stock return	0.56	0.77	0.80	0.81	0.87	0.31**
	(1.47)	(2.14)	(2.42)	(2.47)	(2.64)	(2.04)

Table 5: The Effect of SUV on Zero-beta Straddle Returns

Panel A of this table reports the average monthly returns of zero-beta straddle sorted on SUV. At each end of the month, we rank all underlying stocks into quintiles by their SUV. For each stock, we long call option and put option in a weight calculated by their deltas to form the zero-beta straddle portfolio. The position is held for one month without daily rebalancing. We use three weighting schemes when computing the average return of a portfolio of zero-beta straddle on stocks: 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) at the beginning of the period. This panel reports the return for each quintile option portfolio and the (P5 - P1) spread return (i.e., the difference between the returns of the top and bottom quintile portfolios). We also form decile portfolios when sorting by SUV. The (P10 - P1) spread return is the average difference between the returns of the top and bottom decile portfolios of the zero-beta straddle. All returns in this panel are expressed in percentage. Panel B reports the results of Fama-Macbeth regression with returns to zero-beta straddle portfolios as dependent variables. SUV is the standardized unexpected volume. OSPERAD is the option's bid-ask spread ratio. CHTZ VARIABLES are stock characteristics documented in Zhan et al. (2021) except for analyst dispersion. Other controlling variables are defined in Table 1. All independent variables are winsorized each month at the 1% level. The sample period is from January 1996 to December 2019. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Zero-beta straddle returns sorted on SUV

	Low SUV	**2**	**3**	**4**	**High SUV**	**P5-P1**	**P10-P1**
EW	-12.88	-12.95	-13.87	-13.69	-14.09	-1.21***	-1.67***
	(-17.35)	(-15.26)	(-17.69)	(-16.98)	(-16.35)	(-2.71)	(-2.78)
Stock-VW	-12.16	-12.27	-13.27	-13.15	-13.58	-1.42***	-1.95***
	(-15.76)	(-13.81)	(-16.45)	(-15.78)	(-15.48)	(-3.17)	(-3.21)
Option-VW	-8.82	-7.37	-9.52	-10.58	-12.27	-3.44***	-3.80***
	(-8.49)	(-4.45)	(-9.01)	(-9.17)	(-11.94)	(-4.32)	(-3.38)

Panel B: Fama-Macbeth regression with zero-beta straddle returns as dependent variable

	(1)	**(2)**	**(3)**
SUV	-0.261***	-0.398***	-0.545***
	(-3.27)	(-5.19)	(-6.81)
IVOL		-0.411	1.718*
		(-0.60)	(1.66)
BASPREAD		-4.708***	-2.460
		(-3.75)	(-1.29)
DISP		-0.223*	-0.051
		(-1.67)	(-0.22)
VRP		13.016***	13.060***
		(12.56)	(11.25)
LOGAMIHUD		-2.173***	-1.596***
		(-17.19)	(-9.70)
OSPREAD			0.160***
			(5.02)
AUTO			6.696***
			(4.94)
CHTZ VARIABLES	NO	NO	YES
ADJ R^2 (%)	0.178	2.586	3.685

Table 6: The Effect of SUV on Delta-Hedged Option Returns

This table reports the results of Fama-Macbeth regression with returns to daily rebalanced delta-hedged option portfolios as dependent variables. SUV is the standardized unexpected volume. OSPERAD is the option's bid-ask spread ratio. CHTZ VARIABLES are stock characteristics documented in Zhan et al. (2021) except for analyst dispersion. Other controlling variables are defined in Table 1. Column1 to Column 3 are results for Call options, and Column 4 to Column 6 are results for Put options. All independent variables are winsorized each month at the 1% level. The sample period is from January 1996 to December 2019. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Calls			**Puts**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
SUV	-0.082***	-0.054***	-0.075***	-0.104***	-0.073***	-0.080***
	(-4.57)	(-2.76)	(-4.42)	(-7.82)	(-4.89)	(-6.42)
IVOL		-0.386***	-0.292***		-0.293***	-0.226***
		(-10.68)	(-10.52)		(-9.55)	(-9.90)
DISP		-0.049**	0.051**		-0.044**	0.021
		(-2.13)	(2.56)		(-2.24)	(1.17)
BASPREAD		-0.033**	-0.002		-0.059***	-0.053***
		(-2.16)	(-0.15)		(-4.68)	(-3.63)
HV - IV		0.891***	0.773***		0.681***	0.636***
		(16.80)	(13.99)		(17.44)	(14.09)
LOGAMIHUD		-0.061*	0.152***		-0.042	0.108***
		(-1.82)	(4.74)		(-1.49)	(3.63)
OSPREAD			-0.093***			-0.070***
			(-3.34)			(-3.59)
AUTO			0.055***			0.051***
			(3.24)			(3.65)
CHTZ VARIABLES	NO	NO	YES	NO	NO	YES
ADJ. R^2	0.228	7.636	10.430	0.248	6.527	8.868

Table 7: Net Buying Pressure Sorted on SUV

This table reports the signed option trading volume sorted on SUV. Panel A and Panel B report the signed option trading volume for the period one week prior to the end of the month ([-6, -2] days prior to the end of the month) for call options and put options, respectively. Signed option trading volume is defined as the difference between open buy orders and open sell orders divided by the shares outstanding of the underlying stock. Small Orders is the signed option trading volume from small customers, and Large Orders is measured using trades from medium and large customers. The sample period is May 2005 to November 2018. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Net buying pressure for call options for [-6, -2] days prior to the monthend

	Low SUV	**2**	**3**	**4**	**High SUV**	**H-L**	**Sacled by volume**	**OIB**
Small Orders	-0.32	-0.17	0.01	0.18	0.95	1.27***	1.75***	0.23***
	(-5.16)	(-3.36)	(0.16)	(2.81)	(8.80)	(10.44)	(5.92)	(22.49)
Large Orders	0.50	0.09	0.24	0.42	0.54	0.04	0.22	0.09***
	(1.21)	(0.72)	(1.47)	(1.88)	(2.59)	(0.09)	(0.26)	(5.32)

Panel B: Net buying pressure for put options for [-6, -2] days prior to the monthend

	Low SUV	**2**	**3**	**4**	**High SUV**	**H-L**	**Sacled by volume**	**OIB**
Small Orders	-0.25	-0.21	-0.17	-0.06	0.14	0.39***	1.43***	0.17***
	(-6.96)	(-6.86)	(-4.46)	(-1.25)	(1.74)	(5.34)	(6.94)	(22.42)
Large Orders	-0.02	0.12	0.34	-0.94	0.01	0.03	1.65	0.12***
	(-0.12)	(0.84)	(2.05)	(-1.01)	(0.04)	(0.10)	(1.05)	(6.76)

Table 8: The Effect of SUV on Delta-hedged Option Returns Using the Subsample without Earnings Announcement

This table reports the results of Fama-Macbeth regression similar to Table 5 using the subsample excluding observations with firms' earnings announcements during trading days [0, 4] following each end of the month (inclusive). SUV is the standardized unexpected volume. OSPERAD is the option's bid-ask spread ratio. CHTZ VARIABLES are stock characteristics documented in Zhan et al. (2021) except for analyst dispersion. Other controlling variables are defined in Table 1. Column1 to Column 3 are results for Call options, and Column 4 to Column 6 are results for Put options. All independent variables are winsorized each month at the 1% level. The sample period is from January 1996 to December 2019. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Calls			**Puts**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
SUV	-0.085***	-0.040*	-0.050***	-0.104***	-0.056***	-0.058***
	(-4.48)	(-1.95)	(-2.74)	(-7.50)	(-3.74)	(-4.17)
IVOL		-0.387***	-0.288***		-0.289***	-0.222***
		(-10.29)	(-9.62)		(-8.98)	(-8.61)
DISP		-0.053**	0.049**		-0.049***	0.018
		(-2.18)	(2.34)		(-2.62)	(0.96)
BASPREAD		-0.036**	-0.001		-0.068***	-0.059***
		(-2.18)	(-0.03)		(-4.69)	(-3.54)
VRP		0.905***	0.792***		0.686***	0.646***
		(17.03)	(14.24)		(18.10)	(14.59)
LOGAMIHUD		-0.051	0.174***		-0.028	0.126***
		(-1.50)	(4.92)		(-1.01)	(4.02)
OSPREAD			-0.103***			-0.080***
			(-3.57)			(-4.03)
AUTO			0.054***			0.051***
			(3.21)			(3.33)
CHTZ VARIABLES	NO	NO	YES	NO	NO	YES
ADJ. R2	0.250	7.722	10.689	0.254	6.418	8.993

Appendix Tables

Table A1: Summary Statistics of Non-optionable Stocks

This table reports the time-series average of cross-sectional statistics of stock characteristics in the non-optionable stock sample (winsorized each month at the 1% level). The sample period is from January 1996 to December 2019. Stock characteristics are defined in Table 1.

	Mean	**Std**	**P25**	**Median**	**P75**
SUV	-0.04	1.64	-1.11	-0.04	1.00
BETA	0.68	1.31	-0.05	0.51	1.27
SIZE	5.50	1.44	4.52	5.36	6.30
BM	-0.44	0.97	-0.94	-0.40	0.03
MOM (%)	17.01	43.48	-6.00	9.27	28.55
REV (%)	1.55	10.56	-3.71	0.68	5.60
IVOL	0.33	0.23	0.16	0.27	0.43
LOGAMIHUD	-3.44	2.24	-4.85	-3.45	-1.91
DISP	0.20	0.47	0.02	0.05	0.15
BASPREAD (%)	1.20	1.32	0.38	0.75	1.47
AUTO (%)	-0.06	0.15	-0.16	-0.05	0.05

Table A2: Robustness Checks of Results of Straddle Returns

This table reports several robustness checks of results of straddle returns. Column 1 reports the regression results whose dependent variable is the return to zero-beta straddle portfolios held to maturity instead of one month. Column 2 reports the regression results whose dependent variable is simple straddle return defined in Goyal and Saretto (2009). Column 3 reports the regression results whose dependent variable is the delta-neutral straddle return defined in Gao, Xing, and Zhang (2018). Controlling variables are the same as those in Table 5. All independent variables are winsorized each month at the 1% level. The sample period is from January 1996 to December 2019. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	**(2)**	**(3)**
SUV	-0.608***	-0.323***	-1.058***
	(-3.21)	(-5.18)	(-6.13)
IVOL	-2.087	1.134	3.286*
	(-0.97)	(1.22)	(1.68)
BASPREAD	-4.259	1.706	-12.077***
	(-1.23)	(1.05)	(-3.14)
DISP	-0.235	-0.065	-0.155
	(-0.41)	(-0.32)	(-0.36)
VRP	17.003***	11.947***	13.769***
	(8.86)	(11.93)	(4.79)
LOGAMIHUD	-1.706***	-0.844***	-3.575***
	(-4.98)	(-5.98)	(-9.55)
OPTION_SPREAD	0.095	-0.329***	1.293***
	(1.43)	(-13.90)	(10.28)
AUTO	10.299***	3.955***	12.346***
	(3.77)	(3.41)	(4.70)
CHTZ VARIABLES	YES	YES	YES
ADJ R^2 (%)	2.702	5.877	3.493

Table A3: Option Portfolio Returns for Other Moneyness Sample

Table 5 only shows the effect of SUV on at-the-money (ATM) option returns. Different moneyness option samples are used in this table: In-the-money (ITM) options and out-of-the-money (OTM) options. ITM options are options whose moneyness is closest to 0.8 for call options and 1.2 for put options. OTM options are options whose moneyness are closest to 1.2 for call and 0.8 for put. The average moneyness of ITM call options is 0.85, and of OTM call options is 1.14. The average moneyness of ITM put options is 1.15, and of OTM put options is 0.86. This table reports the average monthly returns of delta-hedged options sorted on SUV in other moneyness samples. The sample period is from January. 1996 to December 2019. To adjust for serial correlation, robust Newey-West (1987) t-statistics are reported in brackets. The symbols *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Low SUV	**2**	**3**	**4**	**High SUV**	**H-L**
OTM Call	-0.73	-1.02	-0.84	-0.98	-1.10	-0.37^{***}
	(-3.67)	(-6.00)	(-4.28)	(-5.79)	(-5.71)	(-3.51)
OTM Put	-0.96	-0.81	-0.93	-0.95	-1.29	-0.33^{***}
	(-3.33)	(-2.73)	(-3.30)	(-3.21)	(-4.62)	(-2.92)
ITM Call	0.06	0.03	0.05	0.03	-0.04	-0.11^{***}
	-0.87	-0.49	-0.78	-0.39	(-0.61)	(-2.98)
ITM Put	-0.23	-0.27	-0.28	-0.29	-0.37	-0.14^{***}
	(-5.11)	(-6.49)	(-6.14)	(-6.42)	(-8.24)	(-5.37)