Overreaction to Volatility Shock and Option Returns

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Abstract

I show that overreaction to the volatility shock generates a demand pressure for stock options with high volatility shock, making such options overpriced. Empirically, I find that straddles written on high variance change stocks underperform those on low variance change stocks by 5.30% per month. Volatility uncertainty and other risk factors can't explain my results. Further decomposition result shows that the idiosyncratic component of the variance change is the driving force for this return predictability. Variance risk premium regressions corroborating with earnings announcement test confirm investors overreact to the idiosyncratic component of the variance change, which generates the demand pressure. Dealers charge higher premiums and bid-ask spreads as compensations for the increased market making risk caused by the demand pressure.

Keywords: Volatility shock, Straddle returns, Overreaction, Demand pressure

JEL: G11, G12, G13, G14, G41

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1 Introduction

Investors are not rational and do not behave like Bayesian statisticians when it comes to incorporating new information into asset prices. A large body of stock market studies have shown that stock market investors underreact to information over short horizons (e.g. Jegadeesh and Titman (1993), Chan, Jegadeesh, and Lakonishok (1996), and Rouwenhorst (1998)) and overreact to information over long horizon (e.g. De Bondt and Thaler (1985), Chopra, Lakonishok, and Ritter (1992), and Lakonishok, Shleifer, and Vishny (1994)) in forming return expectations. Relying on cognitive biases or slow information diffusion assumptions, some behavioral models can successfully reconcile these short-term underreaction and long-term overreation.(e.g. Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999)). But, less is explored about agents perception of risk. Given agents perception of risk also play a critical role in asset pricing models, understanding investors expectation of volatility when incorporating new information is of equal importance. Two notable exceptions are Stein (1989) and Poteshman (2001), who both document the long-term implied volatility of index options overreact to the changes in short-term volatility along the implied volatility term structure.[1] What's less investigated is whether this overreaction can be translated into the cross sectional returns of stock options.[2] In this paper, I study whether investors overreaction to volatility shock at firm level and its implication on the cross-sectional option returns.

Following the same spirits of Stein (1989) and Poteshman (2001), I use variance change of underlying stock as a proxy for the volatility shock. Derivative textbooks emphasize the fact that options provide a mechanism for investors to trade on bliefs about volatility, and

[1] Giglio and Kelly (2018) reject internal consistency conditions in all term structures that they study, including equity options, currency options, credit default swaps, commodity futures, variance swaps, and inflation swaps.

[2] The answer to this question is nontrivial. Bollen and Whaley (2004) show that most trading in S&P 500 index options involves puts, whereas most trading in stock options involvas calls. They attribute this fact to the hedging demand of institutional investors, who purchase index puts as portfolio insurance against market declines. Lakonishok, Lee, Pearson, and Poteshman (2007) document that hedging motivated trading accounts for only a small fraction of trading in stock options and a majority of non-market maker stock option trading involves naked positions. Lemmon and Ni (2014) show that there is a significant difference between the clientele for index options and for individual stock options. Compared to index options trading, which is largely dominated by sophisticated institution investors, stock options trading is mainly driven by unsophisticated individual investors.

straddle is one of the leading volatility trading strategies (e.g. Section 9.3 in Hull (2003) and Section 3.4 in McDonald (2003)). Thus, I focus on the returns of zero-delta straddles on individual stocks. A zero-delta straddle is a combination of approximately equal positions in a call and a put with the same maturity and strike price, which is constructed to have an overall delta of zero. Thus, the return of a zero-delta straddle is invariant to the movements of the underlying stock price and it is a pure bet on the direction of volatility.

A first natural test would be to compare the returns to straddle positions with high variance change and low variance change. Therefore, at the end of each month during the period from 1996 to 2020, I sort straddles into deciles based on the variance change of their underlying stocks and form equal or value weighted straddle portfolios in each decile. I close out the straddles after 1 month and compute the 1-month holding period returns. Then, I compute the time-series averages of the monthly excess returns for each decile portfolio. I find a strong negative relation between the variance change and future one-month holding period straddle returns. The long-straddle, a position that bets on the direction of variance, has an average monthly excess return of -4.89% for the decile 10 (the highest variance change portfolio) and a return of 0.41% for the decile 1 (the lowest variance change portfolio) in equal weighted scheme. The equal weighted 10-1 strategy generates a monthly return spread of -5.30% with a t-statistic of -9.05. The results are similar for value weighted straddle portfolios.[3]

Then, I examine whether straddle returns to my 10-1 portfolio are related to option risk factors documented in the literature. After controlling for a comprehensive set of up to 10 option factors used in Horenstein, Vasquez, and Xiao (2020) and Heston, Jones, Khorram, Li, and Mo (2022), the risk adjusted alphas of my portfolio strategy remain statistically significant and the magnitudes are about the same as the raw return. Even using all the 10 factors in factor adjustment, the alpha is -4.88% with a t-statistic -6.22 in equal weight scheme and it is -5.50% with a t-statistic -5.66 in value weight scheme. Therefore, my result is not driven by its loadings on the existing option risk factors.

Next, I test whether this pattern can be explained by the correlation of variance change

[3]From a profitable trading strategy point of view, these numbers translate into a motnly sharpe ratio of 0.51 for equal weighted portfolio and 0.47 for value weighted portfolio, which is higher than the most profitable individual option momentum strategy in Table 8 of Heston, Jones, Khorram, Li, and Mo (2022).

with option and stock characteristics. I try to include a comprehensive set of control variables such as the difference between implied and historical volatility, idiosyncratic volatility, slope of the implied volatility term structure, stock price, individual option momentum, option greeks and others (see, e.g. Goyal and Saretto (2009), Cao and Han (2013), Vasquez (2017), Boulatov, Eisdorfer, Goyal, and Zhdanov (2022), Cao, Han, Zhan, and Tong (2021), and Heston, Jones, Khorram, Li, and Mo (2022)). Bivariate sort results confirm the negative relationship between variance change and straddle returns. While the magnitude of 10-1 returns are reduced compared to the univariate sort results, I still find significant 10-1 return differences in the range of -5.40% to -3.45% for independent sort and -5.68% to -3.75% for dependent sort. I further confirm the negative relationship between variance change and straddle returns via Fama and MacBeth (1973) regressions by controlling multiple characteristics at the same time.

Previous work has documented that transaction costs in option markets are high (e.g. Figlewski (1989) and Ofek, Richardson, and Whitelaw (2004)). A recent paper by Muravyev and Pearson (2020) show, even liquidity-taking strategies face costs that are much less than those implied by end-of-day quoted spreads. All my previous results are based on transactions at the midpoint of bid and ask quotes, which is at zero effective spread. A natural concern is that my result may be a manifestion of the transaction costs. To address this concern, I use alternative transaction prices by altering the ratios of effective spread to quoted spread and study the profitability of the trading strategy based on the variance change.[4] My strategy is still profitable for effective spreads up to 25%. Alternatively, I consider a low transaction cost sub-sample whose option bid-ask spreads are all lower than 10%. My strategy is profitable even for 100% effective spreads to quoted spreads. Thus, my results are robust to transaction costs.

In further robustness checks, I show my findings hold across different time periods (first half v.s second half period), both January and non-January months, both low and high sentiment periods, both market booms and busts, both recession and expansion periods, both low and high aggregate volatility period. And my results are invariant to using conditional

[4]From a profitable trading strategy point of view, the long side is chosen to have the higher average return. Thus, I long the decile 1 (low variance change) portfolio and short decile 10 (high variance change) portfolio in this transaction cost exercise.

betas in calculating factor adjustment alphas. My results are also robust to controlling the uncertainty about stock volatility as in Baltussen, Van Bekkum, and Van Der Grient (2018), Ruan (2020), and Cao, Vasquez, Xiao, and Zhan (2022). They are also invariant to controlling risk-neutral jump as in Yan (2011). My findings are also robust to using the holding to maturity return and longer maturity options.

To further understand the relation between variance change and straddle returns, I decompose the variance change into two components: systematic variance change and idiosyncratic variance change. I find that the negative relation between variance change and straddle returns can be attributed to the idiosyncratic variance change component. This result is confirmed both in the portfolio sorting and Fama and MacBeth (1973) regression results. Utilizing the decomposition results, I show increases in idiosyncratic variance leading to a higher variance risk premium.[5] This result holds both in panel regressions with time fixed effect and Fama and MacBeth (1973) regressions. This is the direct evidence of overreaction to idiosyncratic variance change at the firm level.

To corroborate the overreaction interpretation for the option return predictability, I leverage on the earnings announcement event test proposed by Engelberg, McLean, and Pontiff (2018). First, I divide the sample into two subsamples: no earnings sample and earnings sample based on whether the underlying stocks will make an earnings announcement during the portfolio holding period. Then, I do the univariate portfolio sorting for these two subsamples separately. Consistent with stronger anomaly return predictability on announcement days in Engelberg, McLean, and Pontiff (2018), the equal weighted 10 - 1 straddle portfolio excess return spread is -4% statistically lower for options with earnings announcement during the holding period. I also confirm these results in Fama and MacBeth (1973) regressions. This reflects the option mispricing, which is caused by overreaction to idiosyncratic variance change, is corrected upon the arrival of earnings announcemnt news.

Finally, I interpret my return predictability results to be consistent with the demand-based option pricing (e.g. Bollen and Whaley (2004), and Garleanu, Pedersen, and Poteshman (2009)). This interpretation is corroborated by two additional results. First, I examine how the end-user demand for options varies with idiosyncratic variance change. Follow-

[5]The variance premium is defined as the implied variance minus the actual realized variance

ing Cao and Han (2013), Cao, Han, Zhan, and Tong (2021), and Ramachandran and Tayal (2021), I use relative open interest (relative open value), measured as open interest scaled by the number of shares outstanding (open option value scaled by market cap), as a proxy for option demand. The idiosyncratic variance change is positively related to option demand. Thus, investors overreaction to volatility shock can generate a positive demand pressure. Second, dealers respond to such high investor demand. They will charge a higher option price and bid-ask spread for taking on the risk of market making.

Related literature

This paper contributes to several aspects of the literature. First, my paper contributes to the nascent and rapidly growing literature on cross sectional stock option return predictability. Goyal and Saretto (2009) show that straddles or delta hedged calls on stocks with low volatility deviation earn high returns, where the volatility deviation is defined as the log difference between the implied-volatility and the past one-year historical volatility . Cao and Han (2013) document that delta-hedged equity option returns decrease monotonically with an increase in the idiosyncratic volatility of the underlying stock, which is consistent with market imperfections and constrained financial intermediaries. Bali and Murray (2013) find a negative relation between risk-neutral stock skewness and the returns of skewness assets constructed from options and the underlying stock. An, Ang, Bali, and Cakici (2014) document that stocks with high past returns tend to experience increases in implied-volatility. Boyer and Vorkink (2014) document total skewness exhibits a strong negative relationship with average option returns. Byun and Kim (2016) show that call options written on the most lottery-like stocks underperform otherwise similar call options written on least lottery-like stocks. Muravyev (2016) documents that option market order-flow imbalance significantly predicts daily option returns. Vasquez (2017) shows that the slope of the implied volatility term structure is positively related to straddle returns. Christoffersen, Goyenko, Jacobs, and Karoui (2018) find more illiquid options tend to have higher daily delta-hedged option returns. Ruan (2020) and Cao, Vasquez, Xiao, and Zhan (2022) both document a negative relationship between volatility uncertainty and delta-hedged option returns. Cao, Han, Zhan, and Tong (2021) show that 10 stock characteristics (e.g., stock price,[6] profit margin, distress risk and so on) can predict the cross-section of delta-hedged option returns. Ramachandran and Tayal (2021) document a monotonically negative relationship between short-sale constraints and delta-hedged returns of put options on overpriced stocks. Heston, Jones, Khorram, Li, and Mo (2022) documents options with high historical returns continue to significantly outperform options with low historical returns at individual, industry, and factor level, which they term as option momentum. My paper contributes to this literature by uncovering a new option return predictor, which is theoretically motivated by the overreaction to volatility shock hypothesis. My return predictability results are robust to controlling for these effects and distinct from known patterns in the literature.

Second, my paper is also related to a number of studies documenting behavioral biases induced mispricing in options market. Stein (1989) shows a tendency for long maturity options on the S&P 100 Index to overreact to changes in short-term volatility, which rejects the rational expectation theory. Poteshman (2001) documents both underreact and overreact to daily changes in instantaneous variance and these two can be reconciled by the cognitive biases proposed by Barberis, Shleifer, and Vishny (1998). While some of my results are qualitatively similar, my analysis differs in my focus on the cross section of individual equity options and this is the first paper documenting investor overreaction to volatility shock in a large cross-section and its implication for option returns. Goyal and Saretto (2009) also suspect the return predictability of volatility deviation coming from overreaction. But they conjecture that the overreaction to current stock returns leads to misestimation of future volatility, which is consistent with Barberis and Huang (2008) behavioral model that people display both loss aversion and mental accounting. My paper is a direct test of the overreaction to volatility shock, which is different to Goyal and Saretto (2009)'s past return channel.[7] My overreaction results also complement the underreaction result of option mo-

[6] Boulatov, Eisdorfer, Goyal, and Zhdanov (2022) also document that delta-hedged options on low-priced stocks underperform those on high-priced stocks and interpret their results to be consistent with demand pressure on low-priced stocks induced by inattention to underlying stock prices.

[7] Goyal and Saretto (2009)'s result can also be reconciled with Atmaz (2022), who presents a model of stock return extrapolation in the presence of stochastic volatility. In the model, investors expect future returns to be higher (lower) but also less (more) volatile following positive (negative) stock returns. This biased volatility expectation introduces a new channel through which past returns and investor sentiment affect derivative prices. Again, the behavioral effects source from stock return not volatility itself. Moreover, my results remain

mentum documented by Heston, Jones, Khorram, Li, and Mo (2022).[8] There are also other evidence of behavioral effects in options. Focusing on index option prices, Han (2008) documents that sentiment can affect index option prices. Focusing on the effect of investors skewnees or lottery preferences, Boyer and Vorkink (2014) and Byun and Kim (2016) find evidence that investors' skewness preference drives up the demand for lottery-like options and make those options overpriced. Eisdorfer, Sadka, and Zhdanov (2022) and Boulatov, Eisdorfer, Goyal, and Zhdanov (2022) both document investor inattention can lead to option mispricing.[9] [10]

Third, my paper is also related to a number of studies investigating agents' beliefs. Growing survey evidence suggests that the expectations of households, firm managers, financial analysts, and professional forecasters show systematic predictability of forecast errors, which reject the rational expectations hypothesis.[11] Most of them focuses on the mean (first moment) and less is explored about the volatility (second moment). The existing literature on volatility expectation formation documents positive aggregate variance risk premium,[12]

unchanged when controlling their volatility deviation measure.

[8]Although they admit that underreaction and time-varying risk premia are impossible distinguish, they find week evidence of time-varying betas and no evidence that risk premia and betas interact in the way necessary to produce the momentum effect. Thus, I interpret their results to be more consistent with underreaction explanation.

[9]Eisdorfer, Sadka, and Zhdanov (2022) document that short-term options achieve significantly lower returns during months with 4 versus 5 weeks between expiration dates. Their interpretation of this seasonality result is due to investor inattention to exact expiration date. Boulatov, Eisdorfer, Goyal, and Zhdanov (2022) show that inattention to the underlying stock prices generates a demand pressure for options written on low-priced stocks, resulting in overpricing in such options.

[10]Another line of literature utilizes firm earnings announcement event to study how investors react to news or form expectations of uncertainty. Mahani and Poteshman (2008) find unsophisticated investors enter option positions that load up on growth stocks relative to value stocks in the days leading up to earnings announcement. They interpret this as evidence that unsophisticated option investors overreact to past news and mistakenly believe that mispriced stocks will move even further away from fundamentals at impending scheduled news releases. Gao, Xing, and Zhang (2018) document significantly positive straddle returns around earnings announcements, in sharp contract to the significantly negative returns over the whole sample. They interpret this as evidence of underestimation of uncertainty before earnings announcements.

[11]Such predictability has been documented for inflation and other macro forecasts (Coibion and Gorodnichenko (2012, 2015) and Fuhrer (2018)), the aggregate stock market (Bacchetta, Mertens, and Van Wincoop (2009), Amromin and Sharpe (2014), Greenwood and Shleifer (2014) and Adam, Marcet, and Beutel (2017)), the cross section of stock returns (La Porta (1996) Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999) and Bordalo, Gennaioli, Porta, and Shleifer (2019)), credit spreads (Greenwood and Hanson (2013) and Bordalo, Gennaioli, and Shleifer (2018)), short-term interest rate (Cieslak (2018)), and corporate earnings (De Bondt and Thaler (1985), Ben-David, Graham, and Harvey (2013), Gennaioli, Ma, and Shleifer (2016) and Bouchaud, Krueger, Landier, and Thesmar (2019))

[12]The variance premium is defined as the difference between risk-neutral (Q) minus physical (P) expectation

which means investors are willing to pay a lot to hedge fluctuations in stock market volatility (e.g. Coval and Shumway (2001) and Bakshi and Kapadia (2003)). A puzzling phenomenon is the "low premium response" documented in Bekaert and Hoerova (2014) and Cheng (2019), which refers to the fact that, when several ex-ante measures of risk have risen, the estimated variance premium from index options or VIX futures tends to fall or stay flat before rising later. Investors seem to underreact to volatility shock in aggregate. Cheng (2019) document that the "low premium response" is associated with falling hedging demand. By assuming agents' expectations of volatility are sticky and extrapolative, Lochstoer and Muir (2022) show that agents' slow-moving beliefs about stock market volatility can lead to initial underreaction to volatility shocks followed by delayed overreaction. They confirm the slow moving expectations about volatility in survey data using Graham and Harvey CFO survey (as well as the Shiller survey). Different from their conclusion of initial underreaction to volatility shock in time series regression, my paper decomposes the total volatility shock into two components and shows investors overreact to the idiosyncratic component in the cross-section, which can lead to option mispricing.

Finally, my paper is related to studies of demand-based option pricing. The seminal work by Black and Scholes (1973) and Merton (1973) lays the foundation of using no-arbitrage theory to price derivative prices independently of investor demand.[13] Recent studies depart fundamentally from the no-arbitrage framework by admitting that in imperfect markets, option market makers can't perfectly hedge their inventories, and, therefore, option demand can impact option prices. Bollen and Whaley (2004) document that daily changes in the implied volatility of an option series are significantly related to net buying pressure. Garleanu, Pedersen, and Poteshman (2009) theoretically model demand-pressure effects and empirically show that the expensiveness of individual options depends on net option demand. Boyer and Vorkink (2014) document that skewness preference is an important source of demand in option markets and intermediaries are compensated with large premiums when accommodating investor demand for lottery-like options. Byun and Kim (2016) identify lottery-like feature of the underlying stocks as an additional source of demand in option

of variance, where the risk neutral expectation is inferred from derivatives written on the underlying.

[13] There is a large literature developing various parametric implementations of the no-arbitrage theory to price options and see Bates (2003) for a comprehensive literature review.

markets. Ramachandran and Tayal (2021) shows that investors demand for put option on overpriced stocks increase with difficulty in short-selling. But the relation between investors behavioral bias and option demand is less explored.[14] My paper contributes to this literature by showing investors' biased expectation about volatility can drive the option demand and contribute to the option mispricing.

The rest of the paper is organized as follows. Section 2 describes the data sources and sample construction as well as the definitions of the key variables. Section 3 presents the main results of the paper by studying the relation between variance change and zero-delta straddle returns in univariate sort, bivariate sort, and Fama and MacBeth (1973) regressions. Various robustness checks are also presented in this section. Section 4 provides the overreaction to idiosyncratic variance change as a potential explanation. Section 5 concludes.

2 Data and Variables

This section introduces the data and variables used in the empirical study. First, I explain the filters that are applied to the option data and present summary statistics of my final sample. Next, I describe the procedure for calculating the straddle returns. Then, I present how to construct the firm level volatility shock measure. Finally, I detail other controls used in this paper.

2.1 Data and sample coverage

The data used in this study is obtained from several public sources. The option data is obtained from Ivy DB OptionMetrics which provides a comprehensive coverage of U.S. equity options from 1996 to 2020. For a given stock, the data set includes the detailed information of options across different maturities and strike prices written on it. The option information include implied volatility, daily closing bid and ask quotes, trading volume, option open interest and greeks computed by OptionMetrics based on standard market conventions. I

[14] Boulatov, Eisdorfer, Goyal, and Zhdanov (2022) is a notable exception and they identify investor inattention to the underlying stock prices as a source of demand pressure, which contributes to the overpricing of options on low-priced stocks.

obtain stock market data from the Center for Research on Security Prices (CRSP) and annual accounting data from Compustat. The short-interest data is also from Compustat. The quarterly institutional investor holding data is from Thomson Reuters (13F) database. The analyst coverage and forecast data are from I/B/E/S.

I use data of U.S.-listed options that are written on common stocks (CRSP share codes 10 and 11) trading on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotation (NASDAQ). All of them are American type options. To deal with options written on illiquid stocks, I exclude stocks with a closing price at the end of the previous month less than $5.

To minimize the impact of recording errors and illiquidity of the options, I apply a series of data filters on the options data following the standard in the literature (e.g. Goyal and Saretto (2009) and Cao and Han (2013)). First, I eliminate options whose prices violate arbitrage bounds.[15] Second, to avoid the microstructure biases, I drop observations with zero open interest and exclude observations when the ask price is lower than the bid price, or the bid price is zero, or the bid-ask spread is lower than the minimum tick size (equal to $0.05 for option trading below $3 and $0.1 in any other cases). Third, to deal with the early exercise premium, I exclude options whose underlying stocks pay dividends during the remaining life of the options. Fourth, I keep options with moneyness between 0.8 and 1.2, where the moneyness is defined as the ratio of strike price to stock price. Then, I select a pair of options (one call and one put) that are closed to being at-the-money (moneyness closest to 1) with the same strike price and have the shortest maturity among those with more than one month to expiration (around 50 calendar days). Finally, from the series remain, I only retain stocks with both call and put options available after the filtering process.[16]

My final sample contains 242,226 option-month observations for both call and put op-

[15]Specifically, I remove call options that are outside the range $[max(S - Ke^{-rT}, 0), S]$ and put options that are outside the range $[max(Ke^{-rT} - S, 0), Ke^{-rT}]$, where S is the spot price of the underlying stock, K is the strike price of the option, T is the time to maturity, and r is the risk-free rate.

[16]The options are matched to stocks in CRSP by using the WRDS link table. In rare cases, there will be a option matching to more than one stocks, i.e. one unique *optionid* to multiple *permnos*. To deal with this issue, I require the stock prices recorded in OptionMetrics and CRSP are the same when rounding at the third decimals. Alternatively, I can drop these duplicates, which have little effects on the results. All the filters mentioned above are standard in the literature, which are also adopted in Ramachandran and Tayal (2021), Cao, Han, Zhan, and Tong (2021), and Heston, Jones, Khorram, Li, and Mo (2022). However, removing any of these filters will not change the conclusion of the paper.

tions on individual stocks. Panel A and B of Table 1 show the characteristics summary results for the call and put options. The options chosen have an average maturity of 50 calendar days, with average moneyness close to 1.[17] The average option bid-ask spread is 17%, with a standard deviation of 17%. The average delta of call is 0.53 and it is -0.47 for put option, echoing the at-the-money property of these options. They are comparable to the numbers in Cao, Han, Zhan, and Tong (2021), Eisdorfer, Sadka, and Zhdanov (2022), and Heston, Jones, Khorram, Li, and Mo (2022). These short-term options are most actively traded, have a relatively smaller bid-ask spread, and thus their pricing information is more reliable. I will utilize this set of options throughout this study.

Insert Table 1 here.

2.2 Straddle returns

Since my interest is in studying returns on options based only on their volatility characteristics, I need to neutralize the impact of movements in the underlying stocks as much as possible. I accomplish this goal by forming zero delta straddles following Heston, Jones, Khorram, Li, and Mo (2022). For each pair of call and put with the same underlying, strike price, and maturity, I buy $-\Delta_P$ shares of call and Δ_C shares of put options,[18] where Δ_P and Δ_C are call and put option deltas. I construct the straddle at the end of last trading day of month t and hold the straddle for one month. Then I close the option positions at the end of month $t+1$. Thus, the one month holding period return is

$$Straddle\ ret = \frac{-\Delta_P(C_{t+1} - C_t) + \Delta_C(P_{t+1} - P_t)}{-\Delta_P C_t + \Delta_C P_t} \tag{1}$$

where C_t and C_{t+1} (P_t and P_{t+1}) are the bid-ask midpoint of the call (put) at the end of month t and $t+1$, and Δ_C (Δ_P) are deltas of the underlying call (put) options. Alternatively, I can

[17] The maturity is calculated as the number of calendar days between expiration date (*exdate*) and the last trading day of month t. In fact, stock option expiration dates were Saturdays prior to 2015, which are not trading days. If I adjust the expiration date to the prior trading day, the average maturity should be around 49.

[18] Alternatively, I can construct plain vanilla straddles of one call and one put following Goyal and Saretto (2009) and the results are almost the same. These results are omitted for brevity.

calculate the holding to maturity returns, which will be explored in Section 3.5.5. For the rest of my analysis, if not specified, the straddle returns refer to the one month holding period straddle returns.

Panel C of Table 1 presents the summary statistics for the one month holding period straddle returns. Given that my sample has 298 months, the 242,226 straddle returns with positive open interest translates to 813 straddles per month on average. Straddle returns are negative on average (-1.69%), volatile (51.24% standard deviation), and have positive skewness as indicated by the low median.

2.3 Volatility shock

In this section, I detail the construction of my main measure to proxy for the volatility shock. For each stock i at the end of each month t, I calculate its total variance Var_{it} based on its daily return ret_{id} on trading day d within month t

$$Var_{i,t} = \frac{1}{N}\sum_{d=1}^{N}(ret_{i,d} - \frac{1}{N}\sum_{d=1}^{N} ret_{i,d})^2 \tag{2}$$

where N is the total number of non-missing $ret_{i,d}$ within month t.

Further, I decompose the total variance into the idiosyncratic component and systematic component. To do that, I run a time series regression of daily returns relative to a return factor model within month t in the following form

$$r_{i,d} - rf_d = \alpha + \boldsymbol{\beta_t'}\boldsymbol{F_t} + \varepsilon_{i,d} \tag{3}$$

where $\boldsymbol{\beta_t'}$ is a vector of factor loadings and $\boldsymbol{F_t}$ is a vector of factors.[19] Following Ang, Hodrick, Xing, and Zhang (2006) and Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2016), the first return factor model that I consider is the market model (CAPM) specifying that $\boldsymbol{F_t}$ is the excess return of the CRSP value-weighted market portfolio over risk free rate. The second model specifies $\boldsymbol{F_t}$ as the 3×1 vector of Fama and French (1993) factors. Then, the

[19]Following Ang, Hodrick, Xing, and Zhang (2006), I require at least 17 daily observations available in calculating the volatility.

idiosyncratic variance is defined as

$$IVar_{i,t} = \frac{1}{N}\sum_{d=1}^{N}(\varepsilon_{i,d} - \frac{1}{N}\sum_{d=1}^{N}\varepsilon_{i,d})^2 \tag{4}$$

and the systematic variance can be obtained by

$$SVar_{i,t} = Var_{i,t} - IVar_{i,t} \tag{5}$$

Barberis, Shleifer, and Vishny (1998) propose a behavioral model which reconciles short-horizon underreaction and long-horizon overreaction by positing a representative investor who is subject to two well-established cognitive biases conservatism and the representativeness heuristic. An investor who displays representativeness heuristic finds patterns in data too readily, and as a result, tends to overreact to periods of mostly similar information. Thus, investors tend to overreact to information that is preceded by a large quantity of similar information. Precisely, investor misreaction to information is increasing in the quantity of previous similar information. Poteshman (2001) construct a measure using the change in instantaneous variances over the previous trade days to capture the increasing misreaction effect.[20]

Thus, I use the sum of the change in variance $\Delta Var_{i,t}$ in the previous two months as a proxy for volatility shock, which can potentially capture the increasing overreaction effect in the spirit of Barberis, Shleifer, and Vishny (1998) and Poteshman (2001)

$$\begin{aligned} \Delta Var_{i,t} &= \underbrace{Var_{i,t} - Var_{i,t-1}}_{\text{change from month } t-1 \text{ to } t} + \underbrace{Var_{i,t-1} - Var_{i,t-2}}_{\text{change from month } t-2 \text{ to } t-1} \\ &= Var_{i,t} - Var_{i,t-2} \end{aligned} \tag{6}$$

Similarly, the systematic component of the variance change is

$$\Delta SVar_{i,t} = SVar_{i,t} - SVar_{i,t-2} \tag{7}$$

[20]See equations (15) and (16) in Poteshman (2001) for more details.

and the idiosyncratic component of the variance change is

$$\Delta IVar_{i,t} = IVar_{i,t} - IVar_{it-2} \tag{8}$$

Having defined the main variables used throughout this paper, the next subsection turns to the control variables.

2.4 Control Variables

Existing studies (e.g. Goyal and Saretto (2009), Cao and Han (2013), Vasquez (2017), Cao, Han, Zhan, and Tong (2021), and Heston, Jones, Khorram, Li, and Mo (2022)) have identified multiple stock and option characteristics that can affect option returns. I broadly classify them into two categories:

1. Volatility related measure

   - $IV - HV$: volatility deviation measure as in Goyal and Saretto (2009), calculated as the log difference between the implied volatility (IV) and historical volatility (HV). IV is computed by taking the average of the at-the-money call and put implied volatilities. HV is calculated as the standard deviation of realized daily stock returns over the past 12 months. Both are annualized.
   - $Ivol$: idiosyncratic volatility as in Cao and Han (2013), computed as the standard deviation of the regression residual of individual stock returns on the Fama and French (1993) three factors using daily data in the previous month, with the requirement at least 17 observations available in calculating the $Ivol$.
   - $Slope$: slope of the implied volatility term structure, as in Vasquez (2017), is defined as the difference between the long-term and the short-term implied volatility. The short-term implied volatility is defined as the average of the short-term at-the-money put- and call-implied volatility. The long-term implied volatility is the average implied volatility of the at-the-money put and call options that have the longest time to maturity available. To construct this measure, I require the short-term and long-term options have the same strike prices.

- *Smile*: slope of the implied volatility curve, as in Heston, Jones, Khorram, Li, and Mo (2022), computed as the difference between the implied volatility of a call with delta of 0.3 and the implied volatility of a put with delta of -0.3.
- *VoV*: volatility of the implied volatility, as in Baltussen, Van Bekkum, and Van Der Grient (2018), is defined as standard deviation of the daily implied volatility (IV) scaled by the time series average of the daily IV within month t. The IV is defined as the average IV of the call option and put option that are closet to being at the money.
- *Optionmom*: individual option momentum based on zero-delta straddle, as in Heston, Jones, Khorram, Li, and Mo (2022), is calculated as the simple average of monthly straddle returns over the past 12 months, skipping the most recent month.

2. Stock characteristics uncovered in Cao, Han, Zhan, and Tong (2021), including cash flow variance (CFV) in Haugen and Baker (1996), cash-to-assets ratio (CH) in Palazzo (2012), analyst earnings forecast dispersion ($DISP$) as in Diether, Malloy, and Scherbina (2002), one-year new issues ($ISSUE_{1y}$) in Pontiff and Woodgate (2008), five-year new issues $ISSUE_{5y}$ in Daniel and Titman (2006), profit margin (PM) in Soliman (2008), log of stock price ($log(P)$) Blume and Husic (1973), profitability ($PROFIT$) in Fama and French (2006), total external financing (TEF) in Bradshaw, Richardson, and Sloan (2006), and z-score in Dichev (1998).[21]

On top of those variables documented in the option return literature, I also control some of the option and stock characteristics that are commonly used in the literature:[22]

- VoI, volume to open interest ratio, is calculated as the ratio of option trading volume to open interest.

[21] See Section 1.3 in Cao, Han, Zhan, and Tong (2021) for the detailed constructions of those stock characteristics

[22] In fact, there are no direct option characteristics for straddles. Since a straddle is a combination of calls and puts, I calculate the option characteristics for straddles as the weighted average of the call and put, when controlling those characteristics. The weights are the number of shares in constructing the zero-delta straddles. Alternatively, I can calculate them as the simple average of the call and put option characteristics. It barely changes my results.

- *BidAsk*, the option bid-ask spread, as in Cao and Han (2013), is the ratio of bid-ask spread of option quotes over the mid point of bid and ask quotes.

- *Gamma*, option gamma, is the second derivative of option price to stock price.

- *Vega*, option vega, is the first derivative of option price to implied volatility.

- *Size*: natural logarithm of market capitalization (in million dollar), as in Fama and French (1993), where market capitalizaion is calculated as stock price times shares outstanding.

- *Bm*: book to market ratio, as in Fama and French (1993) and Davis, Fama, and French (2000), where the book equity is measured as stockholders book equity, plus balance sheet deferred taxes and investment tax credit if available, minus the book value of preferred stock. Stockholders' equity is the value reported by Compustat, if it is available. If not, we measure stock holders equity as the book value of common equity plus the par value of preferred stock, or book value of assets minus total liabilities. Depending on availability, I use redemption, liquidating, or par value for the book value of preferred stock.

- *Mom*: 12 month stock momentum skipping the most recent month, as in Jegadeesh and Titman (1993), is based on prior 11-month returns from month $t-11$ to $t-1$ at the end of month t skipping the most recent month.

- *Reversal*, the return in month t, as in Jegadeesh (1990). I require that a stock must have a valid price at the end of month $t-1$ and a valid return for month t.

- *LTreversal*, long-term reversal, as in De Bondt and Thaler (1985), is constructed based on the prior returns from month $t-59$ to $t-12$.

- *Maxret*, maximum daily return, as in Bali, Cakici, and Whitelaw (2011), is defined as the maximal daily return in month t, requiring a minimum of 15 daily returns.

- *Skewness*, the third moment of the daily returns over the past one year

- *Kurtosis*, the fourth of the daily returns over the past one year

- *Amihud*, amihud illiquidity, as in Amihud (2002), is calculated as the ratio of absolute daily stock return to daily dollar trading volume, averaged over the prior six months, requiring a minimum of 50 daily observations.

3 Empirical Results

In this section, I first present robust cross-sectional negative relation between variance change and straddle returns in univariate portfolio sort. By performing bivariate portfolio analysis and Fama and MacBeth (1973) regression, I show that my findings are distinct from known determinants of option returns documented in the literature. In further robustness checks, I show that my results are robust to different sub-periods, using conditional betas in calculating the factor adjust alphas, controlling for the volatility uncertainty, controlling for the jump risk, using hold to maturity straddle returns, and using longer maturity options.

3.1 Straddle portfolio returns

In this subsection, I use univariate portfolio sorting method to investigate the relationship between variance change and option returns. The variance change is defined in equation (6). Following Heston, Jones, Khorram, Li, and Mo (2022), I focus on zero-delta straddle returns as defined in equation (1). At the end of each month, I form decile straddle portfolios based on the variance change for all optional stocks and hold these straddle portfolios for 1 month without daily rebalancing. Decile 10 portfolio contains straddles with high variance change and decile 1 portfolio contains straddles with low variance change. The average returns within a decile are calculated using equal or value weight scheme. The value weight scheme uses the initial total investment at the beginning of the holding period to assign portfolio weight. Then I can calculate the time series average straddle excess returns for each decile and the difference between decile 10 and decile 1.

Insert Table 2 here.

Table 2 reports the average straddle return for each decile portfolio and the return spread between the top and bottom decile portfolios. To adjust serial correlations, I use Newey and

West (1987) standard errors with 12 lags in calculating t-statistics. There is a striking negative relationship between variance change and straddle portfolio returns. For the equal weight result, the decile 1 portfolio excess return is 0.41% and the decile 10 portfolio excess return is -4.89%. The 10-1 spread is -5.30% with a t-statistic of -9.05. For the value weight result, the decile 1 portfolio excess return is -0.04% and the decile 10 portfolio excess return is -6.05%. The 10-1 spread is -6.01% with a t-statistic of -8.13.

Insert Figure 1 here.

Figure 1 plots the time series of the equal weight 10-1 straddle returns. About 72% of the monthly straddle returns are negative. The maximum 10-1 straddle return is 32% and the minimum is -39%. Over the sample, most of the negative returns are above -20%. I also present the QQ-plot of the equal weight 10-1 straddle returns in Figure 2. The distribution of straddle returns is negatively skewed and fat-tailed. The skewness of the distribution is -0.19, and kurtosis is 1.19, which are consistent with the findings in Broadie, Chernov, and Johannes (2009) and Vasquez (2017) that the long-short straddle returns display non-normality. Then, one may concern that some extreme outliers can drive my results and the large t-statistics in Table 2 should be interpreted with caution. To deal with this non-normality, I also report the 95% bootstrap confidence intervals for the mean of the 10-1 straddle excess returns in Table 2. I perform bootstrap with replacement 50000 times to generate 50000 bootstrap samples. For each sample, I calculate the mean of 10-1 straddle excess returns and this leaves me with 50000 bootstrapped means. I extract the 2.5th and 97.5th percentile to form the 95% bootstrap confidence interval. The 95% bootstrap confidence interval for equal weight 10-1 excess return is [-6.48%, -4.11%] and it is [-7.45%, -4.56%] for value weight, which confirms that my results are not driven by some extreme outliers.

Insert Figure 2 here.

Another concern is that the statistically significant negative spread of 10-1 can be a manifestation of loadings on other factors that are already documented in the literature. To address the concern that some risk factors are driving my results, I need to calculate the risk-adjusted return spread relative to some option factors. Following Horenstein, Vasquez, and Xiao (2020) and Heston, Jones, Khorram, Li, and Mo (2022), I use up to 10 factors in this factor adjustment exercise.[23] These factors include decile sort long-short straddle returns based on the log difference between implied and historical volatility ($IV - HV$), firm size ($Size$), idiosyncratic volatility ($Ivol$), implied volatility term spread ($Slope$), and the slope of the implied volatility smirk ($Smile$), along with two factors constructed by shorting SPX straddles (SPX) and equally weighted short equity straddles return ($EW - Straddle$). Addition to these 7 factors, I also include three momentum factors based on option returns: $Individual\ Option\ Momentum$, $Option\ Industry\ Momentum$, and $Option\ Factor\ Momentum$ as constructed in Heston, Jones, Khorram, Li, and Mo (2022). The replication results using my sample are presented in Table A1 and they are largely consistent with the results in Heston, Jones, Khorram, Li, and Mo (2022).

The factor adjustment results are also reported in Table 2. Specifically, when controlling $IV - HV$ (1-Factor), the $10 - 1$ equal weight spread is -5.00% with a t-statistic -7.14. When controlling $IV - HV$, $Size$, and $Ivol$ together (3-Factor), the $10 - 1$ equal weight spread is -4.86% with a t-statistic -6.57. Augmenting the factors with $Slope$, $Smile$, SPX and $EW - Straddle$ (7-Factor), the $10 - 1$ equal weight spread is -4.77% with a t-statistic -5.30. Even when I include all the factors (10-Factor), the $10 - 1$ equal weight spread is -4.88% with a t-statistic -6.22, which is comparable to the excess return without factor adjustment. The value weight results show very a similar pattern in terms of the economic magnitude and statistical significance. For example, the value weight 10-factor alpha of the spread is -5.50 with a t-statistic -5.66. Combining together, my results are invariant to the factor adjustment procedure.[24]

In summary, using univariate portfolio sorts, Table 2 shows that there is a robust cross-sectional negative relation between variance change and straddle returns. The return predictability result is new in the literature and robust to different weighting schemes and factor adjustments with up to 10 factors.[25]

[23]The factor structure of option returns is relatively under-explored and there is no consensus on the factor space. Following Heston, Jones, Khorram, Li, and Mo (2022), I try to include as many factors as possible in this exercise to show the robustness of my result.

[24]I also consider factor model with conditional betas in the robustness check and these results are presented in Section 3.5.2.

[25]In untabulated results, I also control the common factors used in the cross-sectional stock returns, such as Fama and French (1993) three-Factor, Fama and French (2015) five-Factor and their augmented model with

3.2 Bivariate-sorted portfolios

To account for potential correlation of the variance change with other characteristics, I examine portfolio returns in a bivariate-sorted portfolio framework. The control variables include log difference between the implied volatility and historical volatility ($IV - HV$), idiosyncratic volatility ($Ivol$), slope of the implied volatility term structure ($Slope$), volatility of the implied volatility (VoV), individual option momentum ($Optionmom$), log of stock price ($Log(p)$), volume to open interest ratio (VoI), option bid-ask spread ($BidAsk$), option gamma ($Gamma$) and option vega ($Vega$), market cap ($Size$), book to market ratio (Bm), past one month stock return ($Reversal$), paste 12 month stock return skipping the most recent month (Mom), maximum daily return of the past one month ($Maxret$), long term reversal ($LTreversal$), third moment of past one year daily stock returns ($Skewness$), fourth moment of past one year daily stock returns ($Kurtosis$), and stock illiquidity ($Amihud$), which are defined in Section 2.4.[26]

I try two different sorting procedures: dependent sorting and independent sorting. Each month, I first sort all optional stocks into quintiles based on one of the control variables listed above and the stocks are further sort into deciles within each quintile (dependent sorting) or independently (independent sorting) based on the variance change. This procedure produces 50 characteristic/variance change portfolios. For each variance change decile, I average returns across the characteristic quintiles, which leaves me with ten variance change decile returns. Then, I can compute the return difference between decile ten (highest variance change) and decile 1 (lowest variance change). This bivariate sorting process controls for correlation between the underlying stock variance change and various characteristics. For example, if the effect of the variance change on zero-delta straddle returns is primarily driven by variance change's correlation with *Size*, then returns to long-short portfolios in this analysis should be close to zero because I first sort the portfolios on *Size*.

Insert Table 3 here.

Carhart (1997) momentum factor. The results are almost the same.

[26] I choose those variables for several reasons: some are shown to have strong return predictability in the literature (e.g. $IV - HV$, $Ivol$, $Slope$ and et al); some are commonly used in the stock literature (e.g. $Size$, Bm, $Maxret$ and et al); some are related to the characteristics of the option contract (e.g. VoI, $BidAsk$ and et al). In untabulated robustness check, I consider all the variables defined in Section 2.4 in the double sorting procedure and the results still hold. They are omitted for brevity.

Table 3 reports the excess returns of the decile 1, decile 10 and 10-1 portfolios both in dependent sorting and independent sorting. The excess returns reported in Table 3 are generally comparable to those in Table 2, ranging from -3.45% per month for *Ivol* control to -5.40% per month for *Gamma* control in dependent sorting and from -3.75% for *Ivol* control per month to -5.73% for price control per month in independent sorting. And the t-statistics are all significant at the conventional level. In Table A2, I sort the stocks into quintiles instead of deciles in the second sort and do the same bivariate-sorted portfolio procedure. Though a bit weaker because of less extreme groups used, the results are consistent with the results in Table 3. For example, the 5-1 spreads range from -3.03% to -4.11% with all the t-statistics less than -5 in dependent sorting.

Taken together, I conclude that the negative relationship between variance change and straddle returns is robust to controlling other characteristics in bivariate-sorted portfolios.

3.3 Fama-MacBeth regressions

To further show the robustness of my results, I perform a multivariate regression analysis by running Fama and MacBeth (1973) regressions. An advantage of this approach is that it allows me to calculate the marginal influence of the variance change on future straddle returns while controlling multiple variables at the same time. Specifically, the regression specification is

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t}\Delta Var_{i,t} + \phi_t' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t+1} \tag{9}$$

where $R_{i,t+1}$ is the straddle return multiplied by 100 of stock i, $\Delta Var_{i,t}$ is stock i's variance change defined in equation (6) at the end of month t, and $\boldsymbol{Z}_{i,t}$ is a vector of control characteristics. To compare the economic significance between my variance change measure and other predictors documented in the literature, all explanatory variables are assigned to deciles ranging from zero to one based on the last non-missing available observations for each month t, which follows the procedure of Lee, Sun, Wang, and Zhang (2019) and Ramachandran and Tayal (2021). Each month, I run these regressions and report the time-series average of γ and ϕ coefficients and their t-statistics with 12 lags Newey and West (1987) adjustment.

Insert Table 4 here.

The estimation results are presented in Table 4. I include the existing return predictors documented in the literature such as $IV - HV$ in Goyal and Saretto (2009), *Ivol* in Cao and Han (2013), *Slope* in Vasquez (2017), amihud illiquidity in Christoffersen, Goyenko, Jacobs, and Karoui (2018), 10 characteristics uncovered in Cao, Han, Zhan, and Tong (2021), and individual option momentum (*Optionmom*) in Heston, Jones, Khorram, Li, and Mo (2022). Other option and stock characteristics are also included as controls. The option characteristics include measures of option liquidity such the ratio of option volume to open interest (*VOI*), and option bid-ask spread (*BidAsk*), and also option greeks such as *Gamma* and *Vega* that can potentially reflect difference in the riskiness of options and, therefore, affect straddle returns. The stock characteristics include logarithm of market capitalization (*Size*), book-to-market ratio (*BM*), past 1 month return (*Reversal*), past 12 months return skipping the most recent month (*Mom*), long term reversal (*LTreversal*), max daily return in the past month (*Maxret*), stock return skewness (*Skewness*), and kurtosis (*Kurtosis*).

All these regressions include both stock and option characteristics as controls and their coefficients are omitted for brevity.[27] The coefficients reported in Table 4 for other return predictors are consistent with the existing studies. Consistent with the findings of Goyal and Saretto (2009), $IV - HV$ is negatively related to straddle returns. And *Ivol* has a significantly negative coefficient, which confirms the finding in Cao and Han (2013). Meanwhile, $Log(p)$ is statistically positive as in Cao, Han, Zhan, and Tong (2021) and Eisdorfer, Sadka, and Zhdanov (2022). The *Slope* and *Optionmom* are both positive and significant, which are consistent with the findings in Vasquez (2017) and Heston, Jones, Khorram, Li, and Mo (2022).

Turning to the variable of interest, the coefficients γ_1 of variance change are statistically negative in all the regression specifications. For example, without controlling any existing option return predictors, the coefficient of γ_1 in column (1) is -4.62 with a t-statistic -9.97, indicating that the average monthly return spread of straddles in the 10 and 1 deciles is

[27] The coefficients of those controls are largely consistent with the existing studies. For example, stocks with large size, high past return, high option bid-ask spread, high skewness, and high kurtosis tend to have lower straddle returns.

-4.26%.

To further distinguish my variance change effect from the existing option return predictors, I control an existing predictor each time in columns (2) to (16). When controlling the volatility deviation ($IVHV$) in column (2), the magnitude of γ_1 coefficient reduces slightly and the corresponding t-statistic remains less than -6. Columns (3) to (16) show that the magnitude and significance of the coefficient γ_1 remains virtually the same when comparing with other option return predictors. And these numbers are comparable to the univariate sorting in Section 3.1 and bivariate sorting result in Section 3.2. Even when all the controls are added in the same regression in column (17), the coefficient of variance change is -2.73 with a large t-statistic -5.28. The result in column (17) shows that the negative effect of variance change on straddle returns is different and far beyond what the existing predictors capture.[28]

In summary, my results are robust to controlling existing predictors documented in the literature, option characteristics, and stock characteristics in Fama and MacBeth (1973) regressions.[29]

3.4 Accounting for transaction cost

The results so far rely on calculating zero-delta straddle returns from midpoint bid-ask quotes. The actual trading prices might be different and, therefore affects the robustness of my result. Existing literature shows that transaction costs in option markets are high (e.g. Figlewski (1989), George and Longstaff (1993) and Ofek, Richardson, and Whitelaw (2004)). Recently, Muravyev and Pearson (2020) show that the option traders can time their executions and take liquidity at lower costs than conventionally thought. They conclude that the after-cost profitability of option trading strategies should be reconsidered with execution timing.

To formally take the transaction cost into consideration, I consider several scenarios that differ from midpoint bid-ask quotes. Specifically, I consider trading at different values of

[28] The result in column (17) should be interpreted with caution as requiring all the controls available reduces the number of observations significantly.

[29] In untabulated results, I also run the specifications without option and stock characteristics and the results are almost the same.

the effective bid-ask spread (ESPR) measured in percentage of the quoted bid-ask spread (QSPR). For example, if the bid price of an option is \$3 and the ask price is \$4, then, assuming $\frac{ESPR}{QSPR} = x\%$, the option is bought at $(3+4)/2 + x\% \times (4-3)$ and sold at $(3+4)/2 - x\% \times (4-3)$.[30] I consider scenarios of $x\% = 0\%, 10\%, 20.3\%, 25\%$.

Insert Table 5 here.

Table 5 reports these results. Panel A presents the result for the whole sample and the first row $\frac{ESPR}{QSPR} = 0\%$ is the same as the excess return result in Table 2 except the sign is flipped.[31] As expected, returns to the short (decile 10) portfolio increase and become less negative, as $x\%$ increases, while returns to the long (decile 1) decrease. The mean excess returns of the 1-10 portfolio remain highly statistically significant for the value weight with the values of $x\%$ up to 25%. The value weight 1-10 portfolio excess return is 2.47% with a t-statistic of 3.32. While for equal weight strategy, the 1-10 portfolio excess return is 0.71% with a t-statistic of 1.16, which is not statistically significant. I also consider a scenario of $\frac{ESPR}{QSPR} = 20.3\%$, which Muravyev and Pearson (2020) and Heston, Jones, Khorram, Li, and Mo (2022) term as "Algo" traders' scenario. In this case, the equal and value weight 1-10 excess returns are all economically large and statistically significant. Thus, my strategy would be highly profitable if one could achieve the trading cost as the "Algo" traders in Muravyev and Pearson (2020).

Alternatively, one can consider only trading straddles that have relatively low bid-ask spreads as suggested by Heston, Jones, Khorram, Li, and Mo (2022). In the same spirit of Heston, Jones, Khorram, Li, and Mo (2022), I consider strategies that avoid trading options with bid-ask spread above 10% of option midpoints, as these options are clearly the costliest to trade. Meanwhile, this strategy can be easily implemented in real time ex-ante. These results are shown in Panel B of Table 5. In this low trading cost sample, the 1-10 portfolio returns are all above 5% with large t-statistics in both equal and value weight schemes even when paying for 25% of QSPR. For example, assuming $\frac{ESPR}{QSPR} = 25\%$, the equal weight 1-10

[30]For example, if $x = 10$, the option is bought at \$3.6 and sold at \$3.4

[31]From a trading strategy point of view, one need to make sure the long side is with higher average returns. Thus, I long the decile 1 (low variance change) options and short decile 10 (high variance change) options

spread is 5.09% with a t-statistic 5.39 and it is 5.61% with a t-statistic 5.05 for value weight.[32]

In summary, my findings on option return predictability can survive transaction costs, despite their large impact on the profits of my option strategies.

3.5 Robustness check

In this subsection, I conduct a battery of tests to further show the robustness of my results. These robustness checks include subperiod analyses, using conditional betas in calculating the factor adjust alphas, controlling for uncertainty about stock volatility, controlling for jump risk, using the holding to maturity straddle returns, and using longer maturity options.

3.5.1 Subperiod result

In Table 6, I conduct a variety of subperiod analyses to show the robustness of the results. This is done by partitioning the time series of straddle returns into different groups based on certain variables.

Insert Table 6 here.

I first partition the full sample into two periods (1996-2008 v.s. 2009-2020). The 10-1 spread remains economically large and statistically significant in both periods, although the result is weaker in the recent period. Furthermore, the results are robust during both January and non-January months, while the results for January sample seem to be larger.

To see whether my result is robust to the market conditions, I partition the full sample into low and high sentiment period based on the sentiment index from Baker and Wurgler (2006).[33] The low and high sentiment is divided based on the median of the sentiment index. The results are significant in both period and comparable to each other. Moreover, I can divide the full sample into low and high market return period based on the median of the

[32] In untabulated tables, the 1-10 spread is statistically significant even with x% up to 100%, which means paying the full bid-ask spread.

[33] The sentiment index data is obtained from Jeffrey Wurgler's website http://people.stern.nyu.edu/jwurgler/.

$S\&P500$ index return. My results are significant in both periods and seem to be stronger in high market return periods.

Then, I check whether my results are robust to the business cycles.[34] I achieve this task by dividing the full sample into NBER recession and expansion and the results are robust, though the results for recession period are a bit weaker due to less observations. Finally, I check whether my results are robust to the aggregate volatility level using the VIX index.[35] I divide the sample into low and high VIX sample based on the median of the VIX index. My results are significant in both low and high VIX periods.

To conclude, the negative relationship between variance change and future straddle returns is robust in different subperiods.

3.5.2 Conditional betas

In Table 2, I use linear factor models with constant β loadings in calculating the alphas. A drawback of this implementation is that it neglects the time-varying property of the β loadings. The decile 10 options with high variance change may be those straddles expose more to risk factors and this will induces time variation in the 10-1 factor loadings. Combining with the time-varying factors, it is possible that the interaction of betas and factors could explain my result.

To formally rule out this possibility, I estimate the following factor-model regression with conditional betas:

$$R_{10-1,t} = \alpha_{10-1} + \Theta_{10-1,t-1} + (\beta_{0,10-1} + \beta_{1,10-1}\Theta_{10-1,t-1})O_t + \varepsilon_{10-1,t} \tag{10}$$

where $R_{10-1,t}$, is the 10-1 portfolio straddle returns, Θ's are either portfolio implied volatility (IV), greeks ($Delta$, $Gamma$, and $Vega$), or aggregate implied volatility measured by VIX, and O_t are the option factors used in Table 2.

Table A3 presents the results for factor-model regressions with conditional betas. The row labeled with IV in column Θ means that I assume the beta loadings are correlated with

[34]The business cycle dates are from https://www.nber.org/research/business-cycle-dating.

[35]The VIX index is obtained from CBOE's website https://www.cboe.com/tradable_products/vix/vix_historical_data/

portfolio implied volatility. This is implemented in Equation (10) by setting Θ as the 10-1 portfolio implied volatility. All the results are similar to those in Table 2.

Thus, my results can't be explained by the dynamic beta loadings with respect to portfolio implied volatility, greeks, and aggregated implied volatility.

3.5.3 Controlling for uncertainty about stock volatility

In this subsection, I show that my results are robust to controlling for uncertainty about stock volatility. An enormous body of work has shown that volatility in asset returns is time varying (e.g. Engle (1982) and Bollerslev (1986)) and stochastic volatility models of Heston (1993) type have better performance in contrast to models with constant volatility. Meanwhile, investors' uncertainties about future stock volatility create a "model risk" as in Figlewski (1998) and Green and Figlewski (1999). This "model risk" will create sizable risk exposure for option writers and risk-averse option sellers can increase the volatility input, which can increase the mean return and reduce the fraction of losing trades. Thus, when the uncertainty about the underlying stock volatility increases, option sellers charge a higher option premium to compensate for this "model risk", resulting in a lower expected return for buyers. This could explain my findings if the variance change is correlated with the uncertainty about stock volatility. Meanwhile, Ruan (2020) and Cao, Vasquez, Xiao, and Zhan (2022) define uncertainty about stock volatility as volatility of volatility in Baltussen, Van Bekkum, and Van Der Grient (2018) and they both document a negative relationship between option returns and volatility of implied volatility (VoV). Thus, a careful comparison is needed in this subsection.

The significant 10-1 biavariate portfolio sorting result based on VoV partially mitigates this concern.[36] To formally rule out this possibility in a regression framework. I run the same Fama-MacBeth regressions as in Table 4 with volatility of implied volatility (VoV) as an additional control. Table A4 presents the result. The coefficients of VoV are all significantly negative, which confirms the findings in Ruan (2020) and Cao, Han, Zhan, and Tong (2021). It is also consistent with Green and Figlewski (1999)'s argument that option writers charge

[36] The equal weight 10-1 excess return is -4.19% with a t-statistic -6.95 in dependent sort and it is -4.82% with a t-statistic -7.83.

a higher option premium when facing the volatility uncertainty risk. More importantly, the coefficients for the ΔVar are almost the same as the coefficients reported in Table 4, and are all statistically significant at the 1% level.

Thus, I conclude that the predictive power of variance change for future straddle returns is independent and unexplained by the effect of stock volatility uncertainty.

3.5.4 Controlling for jump risk

Green and Figlewski (1999) suggest that option dealers charge a premium for the jump risk when they write options. Another strand of literature examines the effects of jumps to option pricing. Articles such as Duffie, Pan, and Singleton (2000), Pan (2002), and Broadie, Chernov, and Johannes (2009) show that the empirical patterns of option prices can be better explained by incorporating jumps in the option pricing models. A natural concern is that options experiencing large variance changes are caused by the large price movements. Thus, these large variance movements may be manifestations of the jump risk. In this subsection, I examine whether my results could be explained by the correlations between jump risk and variance change.

Following equation (9) in Yan (2011), I use the slope of implied volatility smile to proxy for risk-neutral jump. Table A5 shows the results for controlling jump risk in Fama and MacBeth (1973) regressions. Clearly, the presence of risk-neutral jump risk proxies does not change the sign and statistical significance of the coefficients for variance change. They are almost the same as those in Table 4. Thus, my results are not driven by risk-neutral jump risk.

3.5.5 Holding to maturity straddle returns

In this subsection, I check whether my results hold for using holding to maturity straddle returns. The return predictability results up to now are all based on one month holding period straddle returns, which requires to sell the options at the end of next month. The other way to calculate the straddle returns is to hold the straddles until maturity and this involves exercising the options on expiration date. The holding to maturity straddle returns are calculated as

$$Straddle\ ret^{HTM} = \frac{-\Delta_P(max(\frac{S_T}{\frac{cfacpr_T}{cfacpr_t}} - K_t, 0) - C_t) + \Delta_C(max(K_t - \frac{S_T}{\frac{cfacpr_T}{cfacpr_t}}, 0) - P_t)}{-\Delta_P C_t + \Delta_C P_t} \quad (11)$$

where K_t is the strike price, $cfacpr_t$ is the cumulative factor to adjust price at the end of month t, $cfacpr_T$ is the cumulative factor to adjust price at expiration date, and S_T is the stock price at expiration date.

Table A6 presents the results based on holding to maturity straddle returns (about 50 calendar days). The patterns in general are similar to the corresponding results in Table 2 with larger magnitudes due to longer holding period. For example, the equal weight 10-1 excess return is -6.69% with a t-statistic -8.15 and it is -8.13% with a t-statistic -7.23 for value weight 10 -1 spread. Thus, my results are robust to using holding to maturity straddle returns.[37]

3.5.6 Evidence from longer maturity options

My results so far are based on zero-delta straddles constructed from at the money short maturity options (about 50 calendars to maturity), which expire on the third Friday of month $t + 2$. The primary reason for this choice is because these options are most actively traded and have the highest liquidity. In this subsection, I also explore whether the negative relationship between variance change and zero-delta straddle returns holds for using longer maturity options.

To explore these, I consider options maturity date in month $t + 3$ (about 80 calendar days to maturity) and $t + 4$ (about 110 calendar days to maturity) and do the same portfolio sorting procedure as in Table 2 except straddles are constructed from longer maturity options. The results still hold for longer maturity options, though the magnitudes tend to be weaker compared to short-term options. For example, the value-weight excess returns for 10-1 spread is -3.47% with a t-statistic -4.28 with expiration date in month $t + 3$. The value-weight excess returns for 10-1 spread is -3.07% with a t-statistic -3.65 with expiration date in

[37] In untabulated results, I also re-run Table 3 and 4 using the holding to maturity returns and the results are similar.

month $t+4$.[38]

4 Potential Explanations

After establishing a robust negative relation between variance change and zero-delta straddle returns, I conduct additional analyses to understand the underlying mechanisms. First, I conduct a decomposition exercise of the total variance change and show its idiosyncratic component is the driving force of the return predictability. Then, I show investors overreact to this idiosyncratic component in variance risk premium regressions. The overreaction results are confirmed both in panel regressions with time fixed effect and Fama and MacBeth (1973) regressions. To collaborate the overreaction interpretation, I leverage on the earnings announcement test proposed by Engelberg, McLean, and Pontiff (2018). I find that the return predictability result is stronger among the sample with earnings announcement, which further confirms the overreaction interpretation. Finally, I show investors overreaction to volatility shock generates a demand pressure on option prices, which is responsible for the overpricing of high variance change options. Dealers respond to this demand pressure by charging higher option premium and option bid-ask spread.

4.1 Which component drives the return predictability? A decomposition approach

In this subsection, by combining equations (5) to (8), I decompose the total variance change into systematic and idiosyncratic components as follows:

$$\Delta Var_{it} = \underbrace{\Delta SVar_{it}}_{\text{systematic component}} + \underbrace{\Delta IVar_{it}}_{\text{idiosyncratic component}} \tag{12}$$

where the idiosyncratic component is defined relative to the market model by setting $\boldsymbol{F_t}$ in equation (3) as the excess return of the CRSP value-weighted market portfolio over risk free

[38] For options maturity beyond month $t+4$, the results also hold but with smaller spreads and t-statistics due to less observations available. And those results are omitted for brevity.

rate.[39] Then, I do the portfolio sorting procedure using these two components separately as in Table 2.

Insert Table 7 here.

These portfolio sorting results are presented in Table 7, where Panel A shows the results for the systematic component and Panel B shows the results for the idiosyncratic component. The 10-1 spreads are all close to zero and insignificant for the systematic component in Panel A of Table 7. For example, the equal weight 10-1 spread excess returns is -0.32% with a t-statistic -0.42 in Panel A. In sharp contrast to the results in Panel A, the 10-1 spread results in Panel B are all economically large and statistically significant. Most importantly, the numbers are comparable to the numbers in Table 2. For example, the 10-1 equal weight excess returns is -5.46% with a t-statistic -9.13 in Panel B of Table 7, while it is is -5.30% with a t-statistic -9.05 in Table 2. Thus, idiosyncratic component drives the portfolio sorting result in Table 2.

I also run Fama-MacBeth regressions to formally check which component drives the return predictability result. I replace the total variance change by these two components in the same regression as in Equation (9)

$$R_{i,t+1} = \gamma_{0,t} + \gamma^{S}_{1,t}\Delta SVar_{i,t} + \gamma^{I}_{1,t}\Delta IVar_{i,t} + \phi'_t \boldsymbol{Z}_{i,t} + \varepsilon_{i,t+1} \tag{13}$$

where $\Delta SVar_{i,t}$ and $\Delta IVar_{i,t}$ are the systematic and idiosyncratic components of the total variance change.

Insert Table 8 here.

The variables of interest are $\gamma^{S}_{1,t}$ and $\gamma^{I}_{1,t}$, and the estimation results are presented in Table 8. The coefficients of the idiosyncratic component $\gamma^{I}_{1,t}$ in all regressions are significantly negative and they are comparable to the numbers in Table 4, while coefficients of the systematic component $\gamma^{S}_{1,t}$ are positive and barely significant. For example, without controlling

[39] All the following results will go through if I define idiosyncratic component relative to Fama and French (1993) model.

other option return predictors in column (1) of Table 8, the coefficient of $\Delta IVar$ is -5.04 with a t-statistic -10.6, while it is 0.74 with a t-statistic 1.46 for $\Delta SVar_{i,t}$. Even when adding all the option return predictors in column (17), the coefficient of $\Delta IVar$ is -3.45 with a t-statistic -6.59, while it is 1.11 with a t-statistic 2.32 for $\Delta SVar_{i,t}$.

In summary, both Table 7 and 8 deliver the same message: the idiosyncratic component dominates the systematic component and the idiosyncratic component of the total variance change is responsible for the return predictability.

4.2 Overreaction to volatility change

In this subsection, I further explore the source of the return predictability by investigating whether these two components can predict variance risk premium. The zero-delta straddle is a strategy which trades the volatility and its profitability is related to the realized variance risk premiums as documented in Vasquez (2017). The negative relationship between variance change and future straddle returns could be due to the fact that investors overreact to volatility shock and are paying a higher variance premiums for options written on stocks with the high variance changes. Following Lochstoer and Muir (2022), I define firm i's variance risk premiums as

$$VRP_{i,t} = IV_{i,t}^2 - RV_{i,t+1} \tag{14}$$

where $IV_{i,t}^2$ is the square of implied volatility at the end of month t and $RV_{i,t+1}$ is the actual realized variance over month $t+1$.

To formally test whether variance change can predict the variance risk premium, I perform the following Fama and MacBeth (1973) regression:

$$IV_{i,t}^2 - RV_{i,t+1} = a + \beta_1 \Delta SVar_{i,t} + \beta_2 \Delta IVar_{i,t} + \boldsymbol{\gamma} \mathbf{X_{i,t}} + \varepsilon_{i,t+1} \tag{15}$$

and panel regression with month fixed effect:

$$IV_{i,t}^2 - RV_{i,t+1} = a + \beta_1 \Delta SVar_{i,t} + \beta_2 \Delta IVar_{i,t} + \boldsymbol{\gamma} \mathbf{X_{i,t}} + \tau_t + \epsilon_{i,t+1} \tag{16}$$

where $\Delta SVar_{i,t}$ and $\Delta IVar_{i,t}$ are defined in Equation (12) relative to CAPM, $\mathbf{X_{i,t}}$ is the control vector and τ_t is for the month fixed effect. The controls include volatility measures related option anomalies such as log difference between the implied volatility and historical volatility ($IVHV$), idiosyncratic volatility ($Ivol$), implied volatility term structure ($Slope$), stock price ($Log(p)$) and volatility of implied volatility (VoV) as defined in Section 2.4.[40] The coefficients of interest are β_1 and β_2. Before performing these two regressions, each month, I winsorize all the independent variables at 1% and 99% levels to deal with the extreme values.[41]

Insert Table 9 here.

Table 9 presents the regression results. Panel A shows the seven Fama-MacBeth regression results with Newey and West (1987) adjustment up to 12 lags. In the first regression, the coefficient of $\Delta SVar$ is -0.05 with a t-statistic -1.22, while the coefficient of $\Delta IVar$ is 0.05 with a t-statistic 4.87. In columns (2)-(6), I add one control at a time. The coefficients associated with $\Delta IVar$ range from 0.03 to 0.05 and are all statistically significant at the 1% level.[42] For $\Delta SVar$, the coefficients are generally negative but not robustly significant. Finally, when I add all the controls in column (7), the coefficient of $\Delta IVar$ is 0.03 with a t-statistic 2.48, while it is -0.06 with a t-statistic -1.64 for $\Delta SVar$. Thus, the Fama-MacBeth regressions show a robust positive relationship between $\Delta IVar$ with future realized variance premium, which is the evidence that investors overreact to idiosyncratic component of variance change in forming the volatility expectation.

Panel B of Table 9 shows the results using panel regression with month fixed effect. The month fixed effect serves the purpose to remove any aggregate movements in firm level

[40] Shue and Townsend (2021) document that investors have non-proportional thinking in financial markets and higher nominal share price is associated with lower volatility. Meanwhile, Boulatov, Eisdorfer, Goyal, and Zhdanov (2022) and Cao, Han, Zhan, and Tong (2021) both document that delta-hedged options on low-priced stocks underperform high-price stocks. Thus, I include $Log(p)$ as a control, though it is not a literal volatility measure.

[41] My result is robust to the winsorization with different levels or without winsorization and those results are omitted for brevity.

[42] The positive coefficients of $IVHV$, $IVOL$, and VOV are consistent with the fact that they are negatively related to future straddle returns as documented in Goyal and Saretto (2009), Cao and Han (2013), Ruan (2020) and Cao, Vasquez, Xiao, and Zhan (2022). And the negative coefficient of $Slope$ and $Log(p)$ are consistent with the fact that they are positively related to future straddle or delta-hedged option returns as documented in Vasquez (2017), Cao, Han, Zhan, and Tong (2021), and Boulatov, Eisdorfer, Goyal, and Zhdanov (2022).

variance premiums. Thus, these regressions only use the cross sectional variations in estimations as the Fama-MacBeth regressions. The standard errors are double-clustered by firm and month to account for correlations both over time within each firm and across firms as in Thompson (2011). The coefficients of $\Delta IVar$ in panel B are all significantly positive, which are consistent with what I have shown in panel A of Table 9.[43] For example, without any controls in column (1) of Panel B, the coefficient of $\Delta IVar$ is 0.03 with a t-statistic 3.39. And this number is significant in the range of 0.02-0.04 when adding a control each time in columns (2)-(6). When adding all the controls in column (7), the coefficient of $\Delta IVar$ is 0.05 with a t-statistic 2.41.

Combining Fama-MacBeth and panel regressions results together, I conclude that investors overreact to the idiosyncratic variance change $\Delta IVar$ when forming future volatility expectations.[44]

4.3 Biased expectation: evidence from earnings announcement

To corroborate the overreaction interpretation, I leverage on firms' earnings announcements to study the relationship between variance change and zero-delta straddle returns. Engelberg, McLean, and Pontiff (2018) propose that firm information events can be utilized to differentiate risk and biased expectation explanations for anomaly returns.[45] They document that stock return anomalies are six times higher on earnings announcement days. When new information arrives in the form of an earnings announcement, investors update their beliefs resulting in a correction to the stocks price. They interpret this result as evidence that anomaly returns are due to stock mispricing.

Following the same logic, my option return predictability results should be stronger for those stock options with earnings announcements during the holding period if they mainly

[43]In Table A7, I present the result for $\Delta SVar$ and $\Delta IVar$ defined relative to Fama and French (1993). The results are very similar to the results in Table 9, which shows my results are robust to the factor models chosen in calculating these two components.

[44]Lochstoer and Muir (2022) also run a similar panel regression in their firm level analysis. They show that increases in total variance over 6 months negatively forecast variance risk premiums, which they interpret as evidence of underreaction to changes in total variance. In untabulated result, when using total variance change ΔVar in the regression, I confirm their findings. A key difference is that I decompose the total variance into two components and check them separately.

[45]Lee, Sun, Wang, and Zhang (2019) also utilize this test to rule out risk explanations for their results.

reflect the correction of option mispricing caused by investors overreaction to volatility shock. I use portfolio sorts to test this biased expectation hypothesis. Based on whether stocks have earnings announcements during the straddle holding period, I divide the straddles each month into two subsamples: no earnings sample and earnings sample.[46] Then, I implement the same portfolio sorting procedure as in Table 2 based on $\Delta Ivar$ on these two subsamples separately.

Insert Table 10 here.

Table 10 presents the portfolio sorting results for these two subsamples. First, the 10-1 straddle portfolio spreads are significantly negative in both the no earnings sample and earnings sample, which again shows the robustness of my return predictability result. In equal weight scheme, the 10-1 excess return spread for no earnings sample is -2.60% with a t-statistic -4.32 and it is -6.64% with a t-statistic -4.53 for earnings sample. And 10-factor alpha of the 10-1 portfolio for no earnings sample is -2.71% with a t-statistic -3.09 and it is -6.83% with a t-statistic -3.63 for earnings sample. Similar patterns can be found when using value weighting scheme.

Moreover, the return spread is more negative for the earnings sample as shown in the row "Difference" of Table 10. The row "Difference" is defined as the 10-1 return spread difference between earnings sample and no earnings sample. All the numbers in row "Difference" are negative and statistically significant, with a magnitude of around -5.32% to -3.03% depending on the weighting schemes and factor adjustment models used. For example, the equal weight excess return of the "Difference" is -4.04% with a t-statistic -2.56. And it is -3.34% with a t-statistic -1.71 for equal weight 10-factor alpha. Similar return difference patterns can be found in value weighting scheme. All these point to the same fact that the negative return predictability of variance change is more pronounced for earnings announcement sample options in portfolio sorting analysis.

[46]To correctly identify earnings announcement dates, I follow the procedures of DellaVigna and Pollet (2009) and Johnson and So (2018). I first compare Compustat and I/B/E/S announcement dates and assign the earlier dates as being correct. When they are more than two trading days apart from each other, I drop those observations. Second, I adjust the announcement date one trading day forward if the announcement occurred after the market close based on the I/B/E/S time stamp. With or without these adjustments have little effects on my results.

Furthermore, I also check whether the same results hold in Fama-MacBeth regressions by adding an *Earnings* dummy and its interaction with $\Delta IVar$. The *Earnings* dummy equals to 1 if the underlying stock has an earnings announcement during the holding period and 0 otherwise. Table A8 presents these results.[47] I find negative and statistically significant coefficients on $\Delta IVar$ in all the specifications and the coefficients on *Earnings* are all significantly positive.[48] More important for my test, I find that the coefficients on the interaction term of $\Delta IVar$ and *Earnings* are all significantly negative. For the regression with all controls in column (17), the coefficients on $\Delta IVar$ and the interaction term $\Delta IVar \times Earnings$ are -1.22 and -2.18. This means that the effect of $\Delta IVar$ for stocks with earnings announcement sample is -2.18% lower than that for stocks without earnings announcement in Fama-MacBeth regression.

In summary, the more pronounced return predictability results for earnings announcement subsample in Table 10 and A8 are consistent with the pattern documented in Engelberg, McLean, and Pontiff (2018) for stock market anomalies, supporting my argument that overreaction about volatility shock contributes to the option return predictability and this biased expectation gets corrected around earnings announcement.

The decomposition results in Section 4.1, the overreaction results in Section 4.2, along with the earnings announcement test results in Section 4.3 all point to the importance of investigating the idiosyncratic variance change. In the rest of the paper, I will mainly focus on the idiosyncratic variance change.

4.4 Demand pressure induced by overreaction

In this subsection, I investigate how end-user demand varies with the idiosyncratic variance change ($\Delta IVar$). I hypothesis that investors' overreaction to variance change will induce a demand pressure on the underlying options and this will make the options with large variance change overpriced. The impact of demand-pressure on the option prices has been

[47] To conserve space, I omitted the coefficients of other predictors in Table A8.

[48] Gao, Xing, and Zhang (2018) document that average at-the-money straddles from 3 days before an earnings announcement to the announcement date yield a highly significant positive return, while straddles on individual stocks generally earn negative and significant returns. Though my straddle returns are measured over the entire month instead of the daily returns around earnings announcement, the positive coefficients on *Earnings* are generally consistent with their findings.

documented in Bollen and Whaley (2004), Garleanu, Pedersen, and Poteshman (2009), Boyer and Vorkink (2014), Byun and Kim (2016), Muravyev (2016), and Boulatov, Eisdorfer, Goyal, and Zhdanov (2022).

Following Cao and Han (2013), Cao, Han, Zhan, and Tong (2021), and Ramachandran and Tayal (2021), I construct two proxies for option demand to test this demand pressure channel. The first one is relative open interest

$$\text{Relative open interest} = \frac{\text{Open interest}}{\text{Number of shares outstanding}} \tag{17}$$

and the other one is relative open value

$$\text{Relative open value} = \frac{\text{Open interest}\times\text{Option price}}{\text{Number of shares outstanding} \times \text{Stock price}} \tag{18}$$

where Option price is defined as the mid point of the bid and ask quote.

Then, I run panel regressions with both firm and time fixed effects using one of the above measures as the dependent variable option demand in the following form:

$$Option\ demand_{i,t} = a + \beta \Delta IVar_{i,t} + \gamma \mathbf{X_{i,t}} + \tau_i + \tau_t + \varepsilon_{i,t} \tag{19}$$

where $\mathbf{X_{i,t}}$ are the control vectors, τ_i and τ_t are the firm and month fixed effects respectively. To deal with the outliers, all independent variables each month are winsorized at 1% and 99%. For ease of interpretation, they are standardized to have a mean of zero and a standard deviation of one.

Insert Table 11 here.

Panel A of Table 11 presents the panel regression of relative open share on idiosyncratic variance change. In column (1) of Panel A, the coefficient on $\Delta IVar$ is 0.15 with a double clustered t-statistic 2.55, which means a one standard deviation increase in $\Delta IVar$ will lead to 0.15% higher option demand measured by relative open interest. Boulatov, Eisdorfer, Goyal, and Zhdanov (2022) document that inattention to the underlying stock prices generates a demand pressure for options on low-priced stocks. Controlling log of stock price in column

(2), the coefficient of $\Delta IVar$ is 0.16 with a t-statistic 2.61, which is almost the same as in column (1).

Also, Ramachandran and Tayal (2021) show that investors drive up the demand for put options on overpriced stocks because of short-sale constraint. Following Ramachandran and Tayal (2021), the proxy for short-sale constraint is defined as

$$\frac{RSI}{IO} = \frac{\text{Relative short interest}}{\text{Institutional ownership}} \tag{20}$$

where relative short interest is measured as short interest over the total shares outstanding and institutional ownership is the percentage of shares owned by institutions.[49] Column (3) of Panel A in Table 11 presents the result for controlling the short sale constraint. The coefficient of $\Delta IVar$ is 0.23 with a t-statistic 2.65.

In column (4) of Panel A, the coefficient of $\Delta IVar$ is 0.23 with a t-statistic 2.68 when adding these two controls at the same time. This implies that a one-standard increase in idiosyncratic variance change leads to 0.23% higher option demand.

Panel B of Table 11 presents the option demand results when option demand is measured by relative open value. In all of the four regressions, the coefficients are all significantly positive.[50] I also consider option interest scaled by the monthly stock trading volume as another proxy for option demand and these results are presented in Table A9. The coefficients of $\Delta IVar$ are all statistically significant and of large magnitudes.

In summary, high idiosyncratic variance change can lead to a demand pressure, which is induced by the overreaction to idiosyncratic component of volatility shock.[51]

[49]The short interest data is from Compustat and the institutional ownership data is from Thomson Reuters 13F holdings.

[50]The coefficients of $Log(p)$ in Panel B of Table 11 is consistent with the findings in Boulatov, Eisdorfer, Goyal, and Zhdanov (2022) that stocks with lower prices have higher option demand. But, the coefficients of $\frac{RSI}{IO}$ are all significantly positive, while Ramachandran and Tayal (2021) document significantly negative relationship between $\frac{RSI}{IO}$ and option demand. Their results are conditional results restricted to put options written on overpriced stocks. Thus, their results should be interpreted with caution.

[51]In untabulated tables, I show my results in this subsection are robust to (1) without controls of stock and option characteristics, (2) using month fixed effect only or without any fixed effect, (3) standard errors without clustering or clustered by firm or time only, (4) using alternative regression method such as Fama and MacBeth (1973).

4.5 Dealer's response

Having documented that options written on stocks with higher idiosyncratic variance change have higher demand, a natural question is how do dealers respond to this higher demand. Christoffersen, Goyenko, Jacobs, and Karoui (2018) propose that expected return and spreads together constitute dealers remuneration for taking on the risks of market making. They argue that the expected return can be viewed as a daily fee and the spread as a down payment charged by a risk averse dealer to manage or accept the risk of a position. Thus, responding to the inventory risk driven by demand pressure, they will charge higher option premiums and bid-ask spreads (Bollen and Whaley (2004), Garleanu, Pedersen, and Poteshman (2009) and Muravyev (2016)).

To begin with, I first focus on the expected return component, which is approximated by the option expensiveness. Following Garleanu, Pedersen, and Poteshman (2009) and Goyal and Saretto (2009), I define the expensiveness of options as the log difference between implied volatility and historical volatility over the past one year as defined in Section 2.4. I formally test this hypothesis by running the following panel regression :

$$IV_{i,t} - HV_{i,t} = a + \beta \Delta IVar_{i,t} + \boldsymbol{\gamma} \mathbf{X_{i,t}} + \tau_i + \tau_t + \varepsilon_{i,t} \tag{21}$$

where $\mathbf{X_{i,t}}$ are the control vectors, τ_i and τ_t are the firm and month fixed effects respectively.[52]

Insert Table 12 here.

Panel A of Table 12 present the option expensiveness results and all the coefficients in Panel A are multiplied by 100. In column (1), the coefficient of $\Delta IVar$ is 0.66 with a t-statistic 8.46, which indicates that one standard deviation increase in $\Delta IVar$ is associated with 0.66% higher option expensiveness. Column (2) and (3) include $Log(p)$ and $\frac{RSI}{IO}$ separately, the coefficients on the idiosyncratic volatility change remain positive and statistically significant, 0.65 with a t-statistic 8.39 and 0.43 with a t-statistic 5.61, which are close to the result in Column (1).

[52]Similarly, all independent variables each month are winsorized at 1% and 99%. For ease of interpretation, they are standardized to have a mean of zero and a standard deviation of one.

Lastly, I include $Log(p)$ and $\frac{RSI}{IO}$ in the same regression in column (4). The coefficient of $\Delta IVar$ is 0.43 with a t-statistic 5.57, which indicates that one standard deviation increase in $\Delta IVar$ is associated with 0.43% higher option expensiveness control. The coefficients on stock price $Log(p)$ are significantly negative, which confirms the findings in Boulatov, Eisdorfer, Goyal, and Zhdanov (2022) that options on low-priced stocks are overpriced. The coefficients on $\frac{RSI}{IO}$ are negative but not statistically significant.

Next, I turn to the option spread component. I run the same panel regressions as in equation (21) by replacing $IV - HV$ with option bid-ask spread, which is defined as the ratio of difference between ask and bid quotes over the midpoint of bid and ask quotes. These results are presented in Panel B of Table 12.[53] The coefficients of $\Delta IVar$ in Columns (1) to (4) are all significantly positive and of similar magnitudes, depending on the specifications. For example, in Column (4), the coefficient of $\Delta Ivar$ is 0.15 with a t-statistic 2.77, which indicates that a one standard deviation increase in $\Delta Ivar$ is associated 0.15% higher option bid-ask spread. The coefficients of $Log(p)$ and $\frac{RSI}{IO}$ are all statistically negative, which suggest that options written on stocks with high price and less short-sale constraint tend to have less option bid-ask spread. These are largely consistent with the findings in Boulatov, Eisdorfer, Goyal, and Zhdanov (2022) and Ramachandran and Tayal (2021).

Taken together, dealers respond strongly to the demand pressure induced by investors' overreaction to idiosyncratic variance change $\Delta IVar$. They will charge a higher option premium and option bid-ask spread to compensate the resulting inventory risk driven by demand pressure.[54] Depending on the regression specifications, a one-standard increase in $\Delta IVar$ will lead to 0.43% to 0.66% higher option expensiveness and 0.12% to 0.17% higher option bid-ask spread.

[53] For ease of interpretation, all the coefficients are also multiplied by 100.

[54] In untabulated tables, I show my results in this subsection are robust to (1) without controls of stock and option characteristics, (2) using month fixed effect only or without any fixed effect, (3) standard errors without clustering or clustered by firm or time only, (4) using alternative regression method such as Fama and MacBeth (1973).

5 Conclusion

This paper documents a novel and robust effect in option prices – equity options written on stocks with higher variance change tend to be relatively overpriced. This overpricing is manifested in zero-delta straddle portfolio returns and alphas up to adjustments with 10 option factors as in Horenstein, Vasquez, and Xiao (2020) and Heston, Jones, Khorram, Li, and Mo (2022). The negative relationship also hold in portfolios double sorted on variance change and various controls documented in the literature as well as in cross-sectional Fama and MacBeth (1973) regressions. In further robustness check, I show my results are robust to transaction costs, subperiod analysis, conditional betas in factor adjustment, controlling for the volatility uncertainty, controlling for jump risk, alternative calculations of straddle returns, and using longer maturity options.

Furthermore, I decompose the total variance change into systematic and idiosyncratic variance change components. I show that the idiosyncratic variance change is the dominant force for the return predictability. Then, I document investors overreaction to idiosyncratic variance change by showing increases in idiosyncratic variance change lead to higher variance risk premiums at firm level Fama and MacBeth (1973) and panel regressions. The overreaction explanation is further confirmed by leveraging on the earnings announcement test proposed by Engelberg, McLean, and Pontiff (2018). I show that the return predictability result is much more pronounced for the earnings announcement subsample than no earnings announcement subsample in portfolio sorting and Fama and MacBeth (1973) regressions. The overreaction to volatility shock evidence from large cross-sectional options collaborates the overreaction along the volatility term structure evidence in Stein (1989) and Poteshman (2001).

To close the loop, I show this overreaction can generate a demand pressure on the options and dealers will response this demand pressure by charging a higher option price and option bid-ask spread as argued by the demand-based option pricing framework of Garleanu, Pedersen, and Poteshman (2009).

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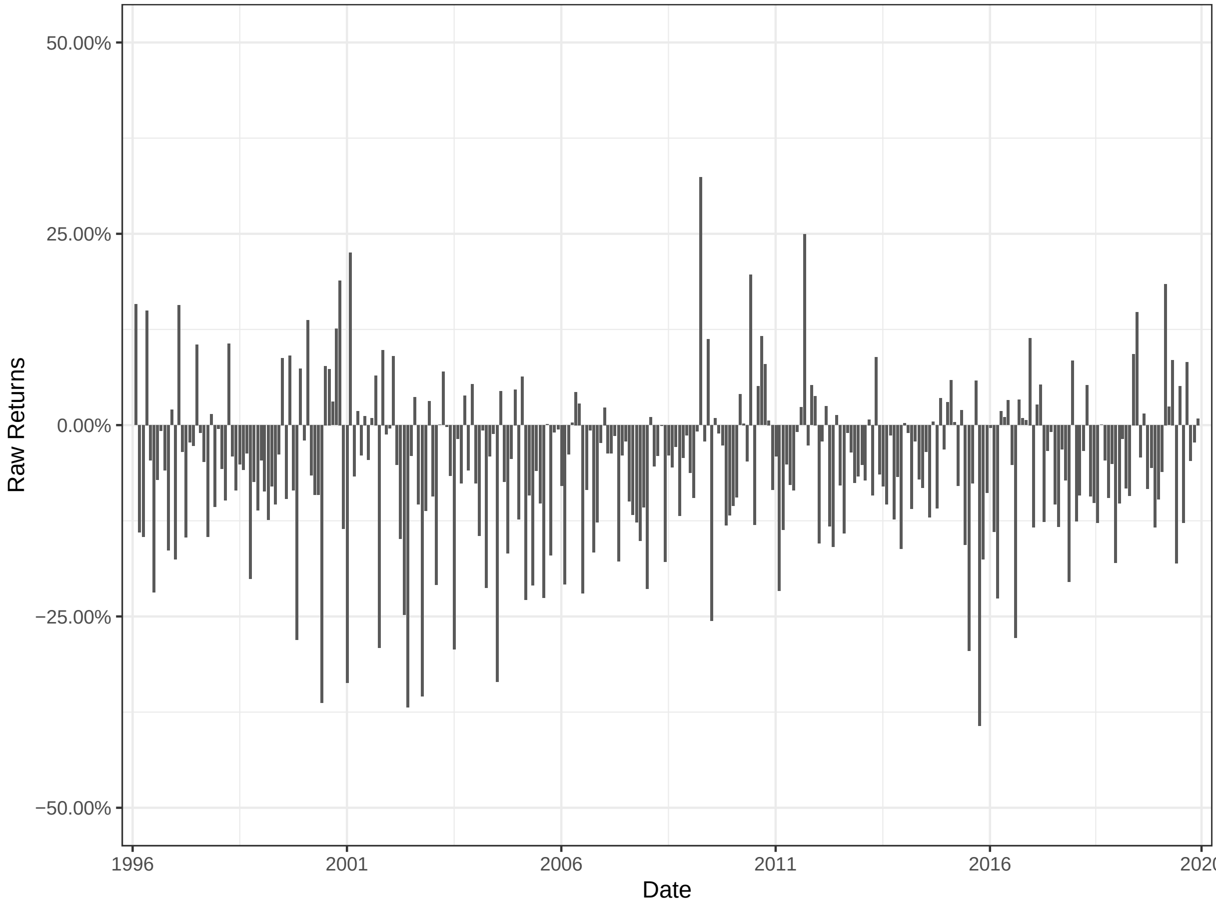
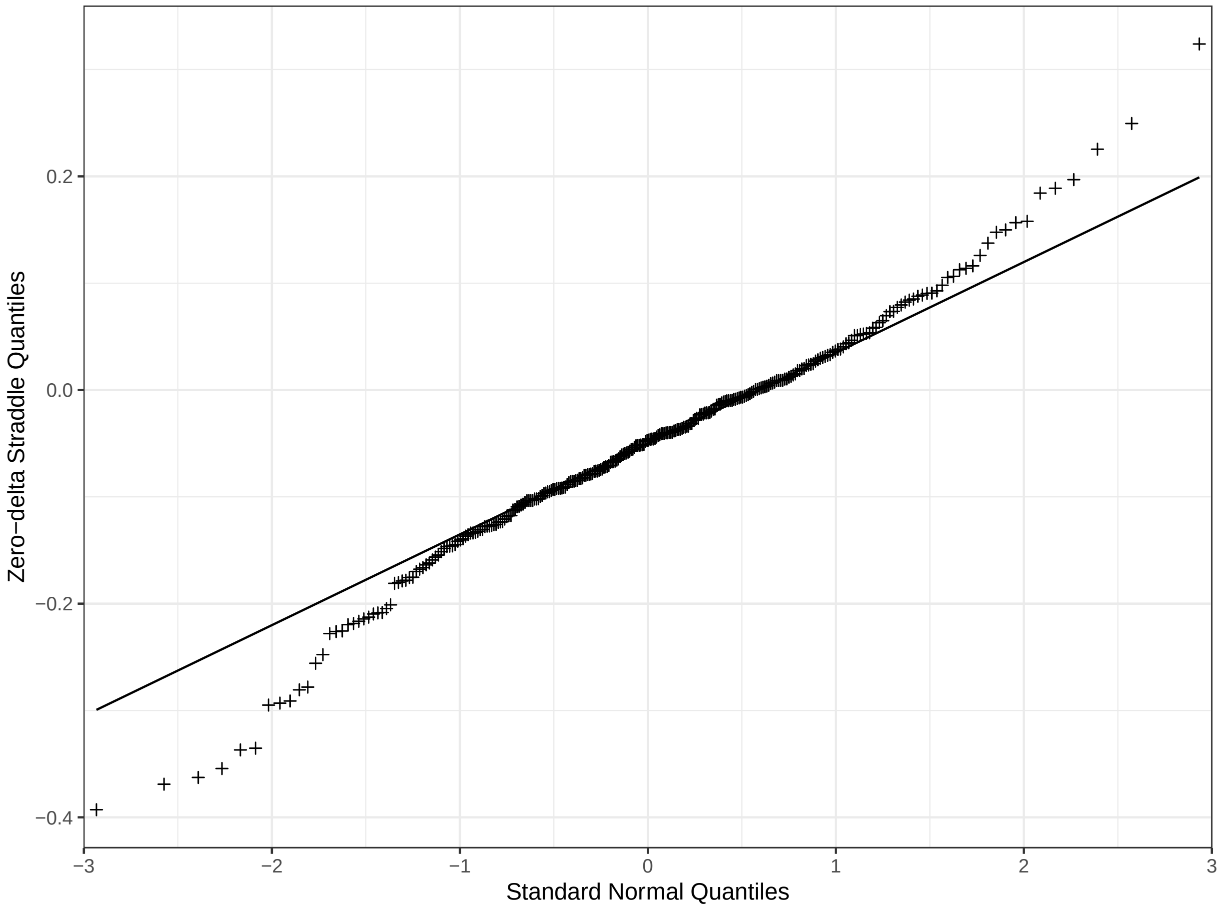
Figure 1: Time Series of Straddle Returns



This figure shows the equal weight returns of the 10-1 straddle portfolio, defined as the difference between decile 10 (highest volatility change) and decile 1 (lowest volatility change) as in Table 2. The sample period spans from 1996 to 2020.

Figure 2: QQ-Plot of Straddle Returns



This figure presents the QQ-plots of equal weight straddle returns of the 10-1 straddle portfolio, defined as the difference between decile 10 (highest volatility change) and decile 1 (lowest volatility change) as in Table 2. The sample period spans from 1996 to 2020.

Table 1: Summary statistics

This table presents summary statistics for my sample and zero-delta straddle returns after the filter procedure in Section 2.1. All the variables are extracted from Ivy DB OptionMetrics. All the numbers are statistics on the full panel of each variable. The sample period spans from 1994 to 2020. Panel A presents the summary for call options and Panel B presents the summary for put options. Panel C presents the zero-delta straddle returns. The sample period spans from 1996 to 2020.

Panel A: Call options								
Variable	N	Mean	Median	Standard deviation	10th percentile	25th percentile	75th percentile	90th percentile
Days to maturity	242226	50	50	2	46	49	51	52
$Moneyness = \frac{K}{S}(\%)$	242226	100.42	100.11	4.38	95.24	97.88	102.62	105.82
Implied volatility	242226	0.48	0.43	0.23	0.24	0.31	0.59	0.78
Open interest	242226	1018	163	3017	10	39	662	2328
Option bid-ask spread	242226	0.17	0.12	0.17	0.04	0.07	0.21	0.36
Delta	242226	0.53	0.54	0.10	0.40	0.47	0.60	0.66
Gamma	242226	0.11	0.09	0.07	0.04	0.06	0.15	0.21
Vega	242226	5.53	3.76	6.24	1.29	2.15	6.64	10.88
Panel B: Put options								
Variable	N	Mean	Median	Standard deviation	10th percentile	25th percentile	75th percentile	90th percentile
Days to maturity	242226	50	50	2	46	49	51	52
Moneyness= $\frac{K}{S}(\%)$	242226	100.42	100.11	4.38	95.24	97.88	102.62	105.82
Implied volatility	242226	0.48	0.43	0.23	0.24	0.31	0.60	0.80
Open interest	242226	633	85	2013	7	20	364	1396
Option bid-ask spread	242226	0.17	0.12	0.17	0.04	0.07	0.21	0.36
Delta	242226	-0.47	-0.46	0.10	-0.60	-0.53	-0.40	-0.34
Gamma	242226	0.11	0.09	0.07	0.04	0.06	0.15	0.21
Vega	242226	5.52	3.75	6.24	1.29	2.15	6.63	10.87
Panel C: Zero-delta straddle returns								
Variable	N	Mean	Median	Standard deviation	10th percentile	25th percentile	75th percentile	90th percentile
Hold until month-end(%)	242226	-1.69	-17.15	51.24	-43.20	-34.17	14.46	59.09
Hold until maturity(%)	241801	-1.35	-19.85	83.97	-85.32	-61.79	36.92	102.23

Table 2: Portfolio sorting result of straddle returns

This table reports the excess returns, 1-Factor, 3-Factor, 7-Factor, and 10-Factor alphas. The factors are defined in Section 3.1 and Table A1. Left panel reports the equal weight result and right panel reports the value weight result. Returns and alphas are in percent, t-statistics are shown in parentheses using Newey and West (1987) correction with 12 lags. The sample period spans from 1996 to 2020.

	Equal Weight (%)					**Value Weight (%)**				
Decile	Excess returns	1-Fator alpha	3-Factor alpha	7-Factor alpha	10-Factor alpha	Excess returns	1-Fator alpha	3-Factor alpha	7-Factor alpha	10-Factor alpha
Short	0.41	-2.10	-1.69	1.29	0.95	-0.04	-2.76	-2.10	1.30	0.90
2	-0.08	-2.00	-1.08	1.53	1.51	-0.84	-2.96	-1.80	1.29	1.28
3	-1.11	-3.20	-2.00	0.76	0.78	-1.68	-3.75	-2.38	0.60	0.39
4	-1.52	-3.31	-2.04	0.74	0.75	-2.63	-4.30	-2.61	0.66	0.54
5	-1.56	-3.99	-2.54	0.03	0.03	-3.22	-5.59	-4.04	-1.48	-1.62
6	-1.30	-3.22	-1.47	1.69	1.40	-2.60	-4.54	-2.51	0.87	0.54
7	-1.66	-4.11	-2.85	0.04	-0.34	-2.33	-5.24	-3.73	-0.83	-1.37
8	-2.65	-4.85	-3.61	-0.71	-1.14	-4.01	-6.21	-4.65	-1.33	-1.79
9	-2.61	-5.04	-4.25	-0.77	-0.92	-3.80	-6.53	-5.36	-1.70	-2.02
Long	-4.89	-7.10	-6.55	-3.48	-3.93	-6.05	-8.12	-7.36	-4.17	-4.61
10-1	-5.30	-5.00	-4.86	-4.77	-4.88	-6.01	-5.36	-5.26	-5.47	-5.50
	(-9.05)	(-7.14)	(-6.57)	(-5.30)	(-6.22)	(-8.13)	(-6.33)	(-5.77)	(-5.22)	(-5.66)
95% Bootstrap CI	[-6.48, -4.11]					[-7.45, -4.56]				

Table 3: Bivariate portfolio sorting result of straddle returns

This table reports the bivariate portfolio sorting result of straddle excess returns. At the end of each month, we first sort all options into quitiles based on a sorting characteristic. Then, the options are further sorted into deciles according to volatility change defined in equation 6 within the sorting characteristic quintile (**Dependent sort**) or independently (**Independent sort**). We average straddle returns for each volatility change decile across the characteristic quintiles, which leaves us ten decile returns. The table reports the excess return of the decile 1, decile 10 and 10-1 portfolios separately for dependent sort (left panel) and independent sort (right panel). The sample period spans from 1996 to 2020. Returns and alphas are in percent, t-statistics are shown in parentheses using Newey and West (1987) correction with 12 lags.

	Dependent sort (%)			**Independent sort (%)**		
Sorting Characteristic	1	10	10-1	1	10	10-1
$IV - HV$	-0.48	-4.35	-3.86	-0.27	-4.65	-4.37
	(-0.50)	(-4.00)	(-6.08)	(-0.28)	(-4.57)	(-6.13)
$Ivol$	-0.12	-3.57	-3.45	0.45	-3.31	-3.75
	(-0.13)	(-3.06)	(-5.54)	(0.44)	(-2.57)	(-3.56)
$Slope$	0.54	-4.03	-4.57	0.52	-3.88	-4.40
	(0.49)	(-3.28)	(-5.96)	(0.49)	(-3.01)	(-5.08)
VoV	0.11	-4.09	-4.19	0.34	-4.49	-4.82
	(0.11)	(-3.81)	(-6.95)	(0.35)	(-4.21)	(-7.83)
$Optionmom$	0.22	-4.77	-4.99	0.22	-4.82	-5.04
	(0.23)	(-4.62)	(-8.06)	(0.22)	(-4.73)	(-8.40)
$Log(p)$	0.07	-5.22	-5.28	0.30	-5.43	-5.73
	(0.07)	(-5.14)	(-8.68)	(0.29)	(-5.33)	(-8.18)
VoI	0.21	-4.71	-4.92	0.33	-4.95	-5.28
	(0.21)	(-4.76)	(-7.77)	(0.33)	(-5.04)	(-8.80)
BidAsk	0.36	-5.17	-5.53	0.21	-4.95	-5.16
	(0.38)	(-5.16)	(-9.11)	(0.21)	(-4.88)	(-8.79)
Gamma	0.18	-5.21	-5.40	0.21	-5.23	-5.45
	(0.19)	(-5.53)	(-9.23)	(0.23)	(-5.33)	(-9.02)
Vega	0.00	-5.17	-5.17	0.21	-5.47	-5.68
	(0.00)	(-5.30)	(-8.35)	(0.20)	(-5.55)	(-8.23)
Size	-0.41	-5.50	-5.10	0.21	-5.09	-5.30
	(-0.42)	(-5.53)	(-8.55)	(0.20)	(-4.94)	(-7.32)
Bm	-0.05	-5.08	-5.02	0.17	-4.91	-5.08
	(-0.05)	(-5.26)	(-7.55)	(0.17)	(-4.90)	(-7.74)
Reversal	0.44	-3.95	-4.39	0.53	-3.76	-4.28
	(0.45)	(-3.75)	(-8.16)	(0.52)	(-3.19)	(-5.62)
Mom	-0.07	-5.11	-5.04	-0.12	-5.37	-5.25
	(-0.07)	(-5.21)	(-8.40)	(-0.12)	(-5.42)	(-7.82)
Maxret	0.18	-4.44	-4.62	0.59	-4.82	-5.41
	(0.19)	(-3.85)	(-6.94)	(0.58)	(-4.47)	(-5.82)
LTreversal	0.38	-4.83	-5.22	0.40	-4.83	-5.23
	(0.38)	(-4.69)	(-9.08)	(0.40)	(-4.50)	(-8.37)
Skewness	0.51	-4.44	-4.95	0.77	-4.69	-5.46
	(0.50)	(-4.51)	(-7.85)	(0.77)	(-4.54)	(-7.94)
Kurtosis	0.73	-3.98	-4.71	0.73	-4.35	-5.08
	(0.75)	(-3.92)	(-8.20)	(0.72)	(-4.32)	(-7.37)
Amihud	-0.14	-5.20	-5.06	0.38	-4.86	-5.24
	(-0.14)	(-5.16)	(-8.59)	(0.37)	(-4.81)	(-7.55)

Table 4: Fama MacBeth Regression of Return Predictability

This table reports Fama-MacBeth regression results of straddle returns for the priod of 1996-2020. Each month we run cross-sectional Fama and MacBeth (1973) regressions of the zero-delta straddle monthly returns. The dependent variable straddle returns are multiplied by 100 and the explanatory variables are defined in Section 2.4 . All explanatory variables are based on the last non-missing variable observation for each month t and are assigned to deciles ranging from zero to one. Cross-sectional regressions are run every calendar month, and the time-series standard errors are Newey-West adjusted with 12 lags for heteroskedasticity and autocorrelation. Fama-MacBeth t-statistics are reported below the coefficients estimates. Coefficients marked with *, **, *** are significant at 10%, 5%, and 1% respectively.

	Straddle $Ret_{t+1} \times 100$																
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Δhv	-4.62***	-3.30***	-4.35***	-4.57***	-4.78***	-4.67***	-4.55***	-4.64***	-4.55***	-4.66***	-4.59***	-4.58***	-4.63***	-4.63***	-4.47***	-4.42***	-2.73***
	(-9.97)	(-6.88)	(-8.26)	(-9.62)	(-10.14)	(-10.13)	(-9.82)	(-10.31)	(-10)	(-10.2)	(-9.94)	(-9.93)	(-10.09)	(-9.98)	(-9.66)	(-9.64)	(-5.28)
$IVHV$		-8.93***															-9.15***
		(-6.85)															(-7.68)
$IVOL$			-1.39														-3.13***
			(-1.5)														(-3.98)
$Amihud$				-0.02													0.41
				(-0.02)													(0.32)
$Log(p)$					15.90***												11.76***
					(4.9)												(3.73)
CFV						-0.73											-0.51
						(-1.55)											(-1.1)
CH							-0.79										0.84
							(-1.44)										(0.79)
$DISP$								0.32									-0.18
								(0.68)									(-0.43)
$ISSUE_{1Y}$									1.62***								1.38***
									(3.27)								(3.28)
$ISSUE_{5Y}$										0.11							-0.56
										(0.27)							(-1.45)
PM											-1.16***						-1.46***
											(-2.49)						(-2.88)
$PROFIT$												-1.01***					-0.64
												(-2.4)					(-0.84)
TEF													1.23***				1.02***
													(3.19)				(2.83)
$Zscore$														0.06			-0.16
														(0.17)			(-0.44)
$Slope$															1.60***		0.34
															(3.01)		(0.79)
$Optionmom$																2.00***	1.41***
																(5.41)	(3.26)
$Intercept$	-8.63***	1.99	-8.00***	-8.63***	-9.74***	-8.62***	-8.59***	-8.83***	-9.76***	-8.59***	-8.53***	-8.51***	-9.07***	-8.54***	-8.30***	-9.66***	1.49
	(-5.38)	(1.1)	(-4.17)	(-4.52)	(-5.74)	(-5.45)	(-5.26)	(-5.24)	(-5.62)	(-5.27)	(-5.23)	(-5.26)	(-5.5)	(-5.24)	(-5.34)	(-6.3)	(0.65)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
NW-Adjusted	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
$adjR^2$	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.07

Table 5: Effect of transaction costs

This table reports the portfolio sorting excess return result for considering transaction costs. For the row $\frac{ESPR}{QSPR} = 0\%$, I assume the options are transacted at the midpoint of the bid and ask quotes and this result is the same as the result in Table 2 except I calculate 1-10 spread instead of 10-1 spread. This flipping procedure guarantees that I construct a profitable strategy. The other rows correspond to the variations of this assumption. For example, suppose an option is quoted bid at \$3 and ask at \$4, $\frac{ESPR}{QSPR} = x\%$ means that I buy the options in the bottome decile (low variance change) at $(3+4)/2 + x\%/2 \times (4-3)$ and sell the options in the top decile (high variance change) at $(3+4)/2 - x\%/2 \times (4-3)$. Panel A reports the result for the whole sample and Panel B consists the result for option sample with option bid ask spread lower than 10%. Both equal and value weight results are reported. Excess returns are in percent, t-statistics are shown in parentheses using Newey and West (1987) corection with up to 12 lags. The sample period spans from 1996 to 2020.

	Panel A: Whole Sample					
	Equal Weight (%)			**Value Weight (%)**		
	1	10	1-10	1	10	1-10
$\frac{ESPR}{QSPR} = 0\%$	0.41	-4.89	5.30	-0.04	-6.05	6.01
	(0.42)	(-4.91)	(9.05)	(-0.04)	(-6.31)	(8.13)
$\frac{ESPR}{QSPR} = 10\%$	-0.51	-3.98	3.47	-0.76	-5.35	4.59
	(-0.53)	(-3.95)	(5.87)	(-0.74)	(-5.54)	(6.23)
$\frac{ESPR}{QSPR} = 20.3\%$	-1.42	-3.00	1.58	-1.48	-4.62	3.13
	(-1.49)	(-2.95)	(2.61)	(-1.45)	(-4.74)	(4.23)
$\frac{ESPR}{QSPR} = 25\%$	-1.83	-2.54	0.71	-1.81	-4.28	2.47
	(-1.93)	(-2.49)	(1.16)	(-1.78)	(-4.37)	(3.32)
	Panel B: Option bid-ask spread below 10%					
	Equal Weight (%)			**Value Weight (%)**		
	1	10	1-10	1	10	1-10
$\frac{ESPR}{QSPR} = 0\%$	0.60	-6.07	6.67	-0.20	-7.26	7.06
	(0.52)	(-5.79)	(7.03)	(-0.16)	(-6.64)	(6.32)
$\frac{ESPR}{QSPR} = 10\%$	0.28	-5.76	6.04	-0.50	-6.98	6.48
	(0.24)	(-5.48)	(6.38)	(-0.39)	(-6.37)	(5.81)
$\frac{ESPR}{QSPR} = 20.3\%$	-0.05	-5.44	5.39	-0.80	-6.68	5.88
	(-0.05)	(-5.16)	(5.70)	(-0.64)	(-6.09)	(5.29)
$\frac{ESPR}{QSPR} = 25\%$	-0.21	-5.30	5.09	-0.94	-6.55	5.61
	(-0.18)	(-5.01)	(5.39)	(-0.75)	(-5.96)	(5.05)

Table 6: Straddle Portfolio Returns in different subperiods for the period of 1996 to 2020
This table reports the equal weight excess returns in different subperiods. The sentiment index is constructed by Baker and Wurgler (2006). The cut off of low and high market return is the median of $S\&P500$ index returns. The business cycle dates are from National Bureau of Economic Research (NBER). The cut off of low and high VIX is the median of VIX index, which is obtained from CBOE. Returns are in percent, t-statistics are shown in parentheses using Newey and West (1987) correction with 12 lags. The sample period spans from 1996 to 2020.

	Excess Returns (%)										
	1	2	3	4	5	6	7	8	9	10	10-1
1996-2008	1.08	-0.08	-1.74	-2.04	-3.33	-2.78	-2.94	-3.38	-3.63	-6.19	-7.27
	(0.70)	(-0.05)	(-1.05)	(-1.31)	(-2.19)	(-1.92)	(-1.91)	(-2.16)	(-2.42)	(-4.35)	(-7.29)
2009-2020	-1.26	-1.67	-1.61	-3.28	-3.10	-2.41	-1.67	-4.70	-3.99	-5.89	-4.63
	(-0.95)	(-1.19)	(-1.17)	(-2.16)	(-2.36)	(-1.69)	(-1.06)	(-2.66)	(-3.28)	(-4.67)	(-4.47)
January	5.25	1.86	2.70	1.07	1.20	1.72	1.99	-2.58	-0.24	-4.03	-9.29
	(1.90)	(0.43)	(0.83)	(0.39)	(0.45)	(0.44)	(0.57)	(-0.68)	(-0.06)	(-1.50)	(-6.93)
Non-January	-0.51	-1.08	-2.06	-2.96	-3.61	-2.98	-2.71	-4.14	-4.11	-6.23	-5.72
	(-0.46)	(-1.00)	(-1.77)	(-2.52)	(-3.31)	(-2.72)	(-2.30)	(-3.38)	(-3.76)	(-5.95)	(-6.93)
Low-Sentiment	-1.40	-1.71	-1.67	-3.34	-3.23	-3.40	-2.76	-5.77	-4.60	-7.41	-6.01
	(-0.90)	(-1.04)	(-0.96)	(-2.14)	(-2.09)	(-2.39)	(-1.73)	(-3.64)	(-3.23)	(-5.37)	(-5.49)
High-Sentiment	1.06	-0.29	-2.14	-2.36	-3.51	-2.35	-2.82	-3.38	-3.98	-5.11	-6.17
	(0.65)	(-0.19)	(-1.25)	(-1.39)	(-2.37)	(-1.58)	(-1.77)	(-1.97)	(-2.68)	(-3.33)	(-5.21)
Low-Market Ret	1.59	0.57	-0.44	-1.41	-1.63	-1.02	-0.03	-1.47	-2.02	-3.16	-4.75
	(1.04)	(0.32)	(-0.24)	(-0.70)	(-0.99)	(-0.60)	(-0.02)	(-0.76)	(-1.16)	(-2.01)	(-4.15)
High-Market Ret	-1.67	-2.25	-2.92	-3.86	-4.81	-4.18	-4.63	-6.56	-5.59	-8.94	-7.27
	(-1.38)	(-1.85)	(-2.51)	(-3.56)	(-4.92)	(-3.88)	(-4.62)	(-6.31)	(-4.98)	(-9.53)	(-7.06)
NBER Recession	2.63	4.62	1.64	1.45	3.32	2.73	3.06	1.63	3.73	-1.41	-4.04
	(0.60)	(0.96)	(0.35)	(0.27)	(0.69)	(0.71)	(0.52)	(0.31)	(0.88)	(-0.40)	(-1.73)
NBER Expansion	-0.32	-1.41	-2.02	-3.06	-3.90	-3.15	-2.89	-4.60	-4.58	-6.53	-6.21
	(-0.32)	(-1.39)	(-1.86)	(-2.92)	(-4.06)	(-3.12)	(-2.86)	(-4.18)	(-4.93)	(-6.86)	(-7.81)
Low VIX	-3.13	-2.99	-4.28	-5.88	-5.31	-4.94	-5.43	-6.71	-7.31	-9.04	-5.91
	(-3.47)	(-3.19)	(-4.81)	(-6.79)	(-5.74)	(-4.39)	(-5.77)	(-7.22)	(-8.33)	(-10.72)	(-6.22)
High VIX	3.04	1.30	0.92	0.62	-1.13	-0.27	0.77	-1.32	-0.29	-3.06	-6.10
	(1.64)	(0.69)	(0.44)	(0.30)	(-0.64)	(-0.15)	(0.39)	(-0.59)	(-0.18)	(-1.93)	(-5.30)

Table 7: Portfolio sorting result of straddle returns based on systematic and idiosyncratic components separately

This table is the same as Table 2 except we sort straddles into deciles based on systematic and idiosyncratic components separately. Table A contains the result for systematic volatility change defined in equation (7). Table B contains the result for idiosyncratic volatility change defined in equation (8). Both equal weight and value weight results are presented. Returns and alphas are in percent, t-statistics are shown in parentheses using Newey and West (1987) correction with 12 lags. The sample period spans from 1996 to 2020.

Panel A : Systematic Component										
	Equal Weight (%)					**Value Weight (%)**				
Decile	Excess returns	1-Fator alpha	3-Factor alpha	7-Factor alpha	10-Factor alpha	Excess returns	1-Fator alpha	3-Factor alpha	7-Factor alpha	10-Factor alpha
1	-1.56	-3.96	-3.10	-0.18	-0.44	-2.53	-4.88	-3.90	-0.42	-0.84
2	-1.89	-4.25	-3.21	-0.57	-0.63	-2.92	-5.47	-4.21	-1.20	-1.25
3	-1.59	-3.94	-2.67	0.43	0.49	-2.72	-4.88	-3.33	0.05	0.02
4	-1.94	-4.02	-2.72	-0.51	-0.41	-2.93	-5.05	-3.54	-1.01	-0.98
5	-2.15	-4.08	-2.67	0.12	-0.07	-3.24	-5.17	-3.49	-0.50	-0.83
6	-2.35	-4.43	-3.20	-0.50	-0.57	-3.41	-5.61	-4.10	-1.41	-1.46
7	-1.38	-3.40	-2.15	0.71	0.46	-2.18	-4.38	-2.79	0.46	0.15
8	-1.22	-3.24	-2.23	0.97	0.70	-2.53	-4.40	-3.03	0.18	-0.16
9	-0.98	-3.38	-2.39	0.90	0.18	-2.07	-4.44	-3.15	0.26	-0.52
10	-1.87	-4.17	-3.69	-0.21	-0.58	-2.74	-5.16	-4.45	-0.80	-1.22
10-1	-0.32	-0.21	-0.59	-0.03	-0.15	-0.21	-0.29	-0.55	-0.38	-0.37
	(-0.42)	(-0.26)	(-0.77)	(-0.03)	(-0.14)	(-0.25)	(-0.31)	(-0.60)	(-0.32)	(-0.31)
Panel B : Idiosyncratic Component										
	Equal Weight (%)					**Value Weight (%)**				
Decile	Excess returns	1-Fator alpha	3-Factor alpha	7-Factor alpha	10-Factor alpha	Excess returns	1-Fator alpha	3-Factor alpha	7-Factor alpha	10-Factor alpha
1	0.56	-1.76	-1.33	1.75	1.37	0.24	-2.44	-1.72	1.78	1.33
2	-0.04	-2.33	-1.48	1.25	0.95	-0.69	-3.18	-2.20	0.95	0.56
3	-0.57	-2.60	-1.55	1.35	1.33	-1.69	-3.67	-2.20	1.09	0.87
4	-1.08	-3.14	-1.93	0.92	1.06	-1.97	-4.02	-2.50	0.69	0.73
5	-1.44	-3.55	-1.85	0.77	0.55	-2.63	-4.58	-2.70	0.22	-0.23
6	-1.88	-3.97	-2.49	0.64	0.49	-3.46	-5.94	-4.19	-1.01	-1.32
7	-2.03	-4.30	-2.75	0.10	-0.12	-3.48	-5.63	-3.79	-0.89	-1.19
8	-2.75	-5.06	-3.89	-1.02	-1.37	-3.93	-6.39	-4.98	-1.76	-2.18
9	-2.84	-5.23	-4.38	-1.27	-1.53	-3.82	-6.43	-5.32	-1.98	-2.47
10	-4.90	-6.99	-6.44	-3.39	-3.65	-6.14	-8.19	-7.42	-4.25	-4.46
10-1	-5.46	-5.23	-5.11	-5.15	-5.02	-6.38	-5.74	-5.70	-6.03	-5.78
	(-9.13)	(-7.49)	(-6.92)	(-6.08)	(-6.31)	(-8.23)	(-6.65)	(-6.13)	(-5.71)	(-5.61)

Table 8: Systematic v.s. idiosyncratic components Fama MacBeth regression of return predictability

This table reports Fama-MacBeth regression results of straddle returns for the period of 1996-2020. This is the same as in Table except that the total volatility change $\Delta Var_{i,t}$ is decomposed into systematic component $\Delta SVar_{i,t}$ and idiosyncratic component $\Delta IVar_{i,t}$. . The dependent variable straddle returns are multiplied by 100 and the explanatory variables are defined in Section 2.4 . All explanatory variables are based on the last non-missing variable observation for each month t and are assigned to deciles ranging from zero to one. Cross-sectional regressions are run every calendar month, and the time-series standard errors are Newey-West adjusted with 12 lags for heteroskedasticity and autocorrelation. Fama-MacBeth t-statistics are reported below the coefficients estimates. Coefficients marked with *, **, *** are significant at 10%, 5%, and 1% respectively.

	Straddle $Ret_{t+1} \times 100$																
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
$\Delta SVar$	0.74	1.25***	0.71	0.81	0.68	0.72	0.76	0.74	0.75	0.68	0.76	0.76	0.75	0.76	0.82*	0.80	1.11**
	(1.46)	(2.59)	(1.43)	(1.59)	(1.35)	(1.41)	(1.52)	(1.46)	(1.51)	(1.36)	(1.51)	(1.51)	(1.51)	(1.51)	(1.66)	(1.59)	(2.32)
$\Delta IVar$	-5.04***	-3.93***	-4.98***	-5.01***	-5.18***	-5.09***	-4.98***	-5.07***	-4.98***	-5.03***	-5.03***	-5.00***	-5.06***	-5.06***	-4.92***	-4.86***	-3.45***
	(-10.6)	(-7.74)	(-8.92)	(-10.42)	(-10.79)	(-10.83)	(-10.57)	(-10.95)	(-10.7)	(-10.67)	(-10.71)	(-10.65)	(-10.76)	(-10.56)	(-10.28)	(-10.38)	(-6.59)
$IVHV$		-9.01***															-9.14***
		(-7.01)															(-7.75)
$IVOL$			-0.23														-2.16***
			(-0.25)														(-2.74)
$Amihud$				-0.62													-0.01
				(-0.48)													(-0.01)
$Log(p)$					16.16***												12.38***
					(4.97)												(3.9)
CFV						-0.74											-0.53
						(-1.56)											(-1.13)
CH							-0.79										0.79
							(-1.44)										(0.73)
$DISP$								0.32									-0.22
								(0.68)									(-0.53)
$ISSUE_{1Y}$									1.60***								1.33***
									(3.27)								(3.18)
$ISSUE_{5Y}$										0.12							-0.54
										(0.32)							(-1.37)
PM											-1.18***						-1.41***
											(-2.51)						(-2.72)
$PROFIT$												-1.01***					-0.63
												(-2.41)					(-0.81)
TEF													1.21***				1.01***
													(3.17)				(2.79)
$Zscore$														0.06			-0.17
														(0.19)			(-0.47)
$Slope$															1.67***		0.39
															(3.2)		(0.91)
$Optionmom$																1.98***	1.38***
																(5.35)	(3.2)
$Intercept$	-8.69***	1.92	-8.67***	-8.20***	-9.79***	-8.67***	-8.66***	-8.89***	-9.80***	-8.64***	-8.58***	-8.58***	-9.13***	-8.60***	-8.36***	-9.73***	1.16
	(-5.62)	(1.07)	(-4.72)	(-4.32)	(-5.98)	(-5.71)	(-5.48)	(-5.48)	(-5.86)	(-5.49)	(-5.44)	(-5.48)	(-5.72)	(-5.47)	(-5.54)	(-6.62)	(0.5)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
NW-Adjusted	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
$adjR^2$	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.08

Table 9: Overreaction to volatility change

This table presents the monthly forecast regressions of stock level variance risk premiums. The dependent variable variance risk premium VRP is defined as $IV_{i,t}^2 - RV_{i,t+1}$. All independent variables are winsorized at the 1% and 99% levels each month. Panel A reports the Fama-MacBeth regression results. To adjust for serial correlations, Fama-MacBeth t-statistics with Newey and West (1987) adjusted (up to 12 lags) are reported with parentheses. Panel B reports the panel regression results with time fixed effect. The standard errors are double-clustered by firm and time in calculating the t values. Coefficients marked with *, **, *** are significant at 10%, 5%, and 1% respectively.

	Dependent variable $IV_{i,t}^2 - RV_{i,t+1}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A : Fama-MacBeth Regression							
$\Delta SVar$	-0.05	-0.07*	-0.05	-0.05	-0.04	-0.05	-0.06
	(-1.22)	(-1.77)	(-1.2)	(-1.27)	(-1.08)	(-1.32)	(-1.64)
$\Delta IVar$	0.05***	0.04***	0.03***	0.05***	0.05***	0.04***	0.03***
	(4.87)	(3.87)	(2.97)	(4.86)	(5.21)	(4.54)	(2.48)
$IVHV$		0.24***					0.27***
		(7.56)					(9.17)
$Ivol$			0.04				0.02
			(1.39)				(0.66)
$Slope$				-0.13			0.14**
				(-1.48)			(2.02)
$Log(p)$					-0.02***		-0.02***
					(-3.86)		(-2.54)
VoV						0.14***	0.06
						(2.43)	(1.3)
$Intercept$	-0.00	-0.01	-0.01	-0.01	0.07***	-0.02***	0.04
	(-0.65)	(-0.79)	(-0.94)	(-0.76)	(3.56)	(-2.45)	(1.47)
NW-Adjusted	YES	YES	YES	YES	YES	YES	YES
adj R^2	0.01	0.04	0.03	0.02	0.03	0.02	0.07
Panel B : Panel Regression							
$\Delta SVar$	-0.09*	-0.11***	-0.09*	-0.11**	-0.09*	-0.09*	-0.13***
	(-1.85)	(-2.4)	(-1.85)	(-2.15)	(-1.82)	(-1.9)	(-2.46)
$\Delta Ivar$	0.03***	0.02**	0.03**	0.04***	0.03***	0.03***	0.05***
	(3.39)	(2.24)	(2.03)	(3.59)	(3.43)	(3.13)	(2.41)
$IVHV$		0.20***					0.13***
		(6.84)					(3.56)
$Ivol$			-0.00				-0.04
			(-0.06)				(-1)
$Slope$				0.03			0.13
				(0.17)			(0.97)
$Log(p)$					-0.02***		-0.01***
					(-5.08)		(-2.85)
VoV						0.15***	0.06
						(3.02)	(0.89)
Month FE	YES	YES	YES	YES	YES	YES	YES
Double CLuster	YES	YES	YES	YES	YES	YES	YES

Table 10: Portfolio sorting result for earnings and no-earnings subsamples
This table reports the excess returns, 1-Factor, 3-Factor, 7-Factor, and 10-Factor alphas. The sample period spans from 1996 to 2020. Left panel reports the equal-weight result and right panel reports the value-weighted result. Returns and alphas are in percent, t-statistics are shown in parentheses using Newey and West (1987) correction up to 12 lags.

	Equal Weight (%)					**Value Weight (%)**				
	Excess returns	1-Fator alpha	3-Factor alpha	7-Factor alpha	10-Factor alpha	Excess returns	1-Fator alpha	3-Factor alpha	7-Factor alpha	10-Factor alpha
No earnings sample	-2.60	-3.02	-2.61	-2.71	-2.43	-2.44	-2.29	-2.96	-2.12	-2.71
	(-4.32)	(-3.41)	(-3.80)	(-3.09)	(-3.38)	(-2.69)	(-2.73)	(-2.98)	(-2.53)	(-2.65)
Earnings sample	-6.64	-8.34	-5.64	-6.83	-5.77	-6.79	-6.45	-7.50	-6.46	-7.46
	(-4.53)	(-5.57)	(-3.20)	(-3.63)	(-3.11)	(-3.36)	(-3.24)	(-3.56)	(-3.10)	(-3.43)
Difference	-4.04	-5.32	-3.03	-4.12	-3.34	-4.34	-4.16	-4.54	-4.34	-4.75
	(-2.56)	(-3.21)	(-1.68)	(-2.10)	(-1.71)	(-2.04)	(-1.84)	(-1.92)	(-1.90)	(-1.95)

Table 11: End-users demand

This table presents panel regressions of relative open share and relative open value on volatility change. The relative open share is defined as $\frac{\text{Open interest}}{\text{Number of shares outstanding}}$ and relative open value is defined as $\frac{\text{Open interest} \times \text{Option price}}{\text{Number of shares outstanding} \times \text{Stock price}}$. All independent variables are winsorized at the 1% and 99% levels each month. Panel A reports the results for relative open share. Panel B reports results for relative open value. The standard errors are double-clustered by firm and time in calculating the t values. Coefficients marked with *, **, *** are significant at 10%, 5%, and 1% respectively.

Panel A : Relative open share				
	(1)	(2)	(3)	(4)
$\Delta IVar$	0.15***	0.16***	0.23***	0.23***
	(2.55)	(2.61)	(2.65)	(2.68)
$Log(p)$		1.09***		1.35***
		(8.27)		(6.5)
$\frac{RSI}{IO}$			1.75***	1.80***
			(8.46)	(8.52)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Double CLuster	YES	YES	YES	YES
Panel B : Relative open value				
	(1)	(2)	(3)	(4)
$\Delta IVar$	0.05***	0.05***	0.06***	0.06***
	(5.91)	(5.9)	(5.22)	(5.22)
$Log(p)$		-0.03**		-0.02
		(-2.1)		(-0.8)
$\frac{RSI}{IO}$			0.19***	0.18***
			(5.85)	(5.87)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Double CLuster	YES	YES	YES	YES

Table 12: Dealers' response

This table presents panel regressions of option expensiveness and option bid-ask spread on idiosyncratic volatility change. The option expensiveness is defined as $IV - HV$ and option bid-ask spread is the ratio of difference between ask and bid quotes over the midpoint of bid and ask quotes. All independent variables are winsorized at the 1% and 99% levels each month. Panel A reports the results for $IV - HV$. Panel B reports results for bid-ask spread. The standard errors are double-clustered by firm and time in calculating the t values. Coefficients marked with *, **, *** are significant at 10%, 5%, and 1% respectively.

Panel A : $IV - HV$				
	(1)	(2)	(3)	(4)
$\Delta IVar$	0.66***	0.65***	0.43***	0.43***
	(8.46)	(8.39)	(5.61)	(5.57)
$Log(p)$		-1.21***		-0.83***
		(-6.6)		(-3.78)
$\frac{RSI}{IO}$			-0.07	-0.12
			(-0.61)	(-0.99)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Double CLuster	YES	YES	YES	YES
Panel B : Option bid-ask spread				
	(1)	(2)	(3)	(4)
$\Delta IVar$	0.15***	0.12***	0.17***	0.15***
	(3.86)	(3.12)	(3.08)	(2.77)
$Log(p)$		-4.17***		-4.32***
		(-33.29)		(-25.94)
$\frac{RSI}{IO}$			-0.17*	-0.40***
			(-1.86)	(-4.22)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Double CLuster	YES	YES	YES	YES

APPENDICES

Appendix A Tables

Table A1: Performace of the 10 factors based on prior research
This table presents the performance of 10 factors from prior literature and the factors are constructed to have positive means. The sample period spans from 1996 to 2020. The first five are long-short factors sorted on the difference between implied volatility and historical volatility (Goyal and Saretto (2009)), idiosyncratic volatility (Cao and Han (2013)), market capitalization, the slope of the implied volatility term structure (Vasquez (2017)), and the slope of the implied volatility curve. Followed by two short factors only, one is an at-the-money $S\&P500$ index straddle and the other one is an equally weighted portfolio of straddles on individual equities. The last three factors are three option momentum factors documented in Heston, Jones, Khorram, Li, and Mo (2022). Returns are in percent, t-statistics are shown in parentheses using Newey and West (1987) correction with 12 lags.

	IV-HV	-Ivol	-Size	Slope	Smile	SPX straddle	EW straddle	Individual option mom	Option industry mom	Option factor mom
Mean	9.65	3.18	2.96	5.59	2.78	10.77	2.76	1.72	3.18	3.24
t	(11.31)	(3.57)	(4.09)	(7.38)	(3.54)	(5.33)	(2.49)	(3.56)	(2.74)	(2.91)
Sharpe ratio	0.78	0.22	0.23	0.42	0.23	0.32	0.17	0.18	0.16	0.18

Table A2: Bivariate portfolio sorting result of straddle returns

This table reports the bivariate portfolio sorting result of straddle excess returns. At the end of each month, we first sort all options into quitiles based on a sorting characteristic. Then, the options are further sorted into quintiles according to volatility change defined in equation 6 within the sorting characteristic quintile (**Dependent sort**) or independently (**Independent sort**). We average straddle returns for each volatility change quintile across the characteristic quintiles, which leaves us 5 quintile returns. The table reports the excess return of the quintile 1, quintile 5 and 5-1 portfolios separately for dependent sort (left panel) and independent sort (right panel). The sample period spans from 1996 to 2020. Returns and alphas are in percent, t-statistics are shown in parentheses using Newey and West (1987) correction with 12 lags.

	Dependent sort (%)			**Independent sort (%)**		
Sorting Characteristic	1	5	5-1	1	5	5-1
$IV - HV$	-0.37	-3.65	-3.28	-0.27	-3.45	-3.18
	(-0.38)	(-3.49)	(-6.92)	(-0.28)	(-3.36)	(-6.36)
$Ivol$	-0.08	-3.23	-3.15	-0.13	-3.00	-2.87
	(-0.08)	(-2.91)	(-6.11)	(-0.14)	(-2.72)	(-4.37)
$Slope$	-0.03	-3.06	-3.03	-0.21	-2.86	-2.64
	(-0.03)	(-2.70)	(-5.46)	(-0.21)	(-2.48)	(-4.20)
VoV	-0.06	-3.37	-3.30	-0.04	-3.41	-3.37
	(-0.07)	(-3.24)	(-6.90)	(-0.04)	(-3.31)	(-7.33)
$Optionmom$	0.08	-3.84	-3.92	0.06	-3.67	-3.73
	(0.08)	(-3.72)	(-8.55)	(0.06)	(-3.60)	(-8.17)
$Log(p)$	-0.04	-4.15	-4.12	-0.06	-4.26	-4.19
	(-0.04)	(-4.05)	(-8.83)	(-0.07)	(-4.42)	(-8.76)
VoI	0.03	-3.76	-3.79	0.12	-3.81	-3.93
	(0.03)	(-3.69)	(-8.25)	(0.12)	(-3.88)	(-8.48)
BidAsk	-0.03	-3.84	-3.81	0.03	-3.90	-3.93
	(-0.03)	(-3.77)	(-8.27)	(0.03)	(-3.93)	(-8.51)
Gamma	0.01	-4.02	-4.03	0.03	-3.99	-4.02
	(0.01)	(-4.03)	(-8.35)	(0.03)	(-4.12)	(-8.70)
Vega	-0.10	-4.14	-4.04	-0.05	-4.22	-4.18
	(-0.10)	(-4.05)	(-8.61)	(-0.05)	(-4.43)	(-8.72)
Size	-0.32	-4.37	-4.05	-0.20	-4.26	-4.06
	(-0.32)	(-4.29)	(-8.18)	(-0.20)	(-4.39)	(-8.27)
Bm	-0.13	-3.95	-3.82	-0.10	-3.87	-3.76
	(-0.14)	(-3.95)	(-7.58)	(-0.11)	(-3.89)	(-7.63)
Reversal	0.09	-3.44	-3.52	0.19	-3.15	-3.35
	(0.09)	(-3.35)	(-7.96)	(0.20)	(-2.97)	(-7.07)
Mom	-0.17	-4.10	-3.92	-0.03	-4.08	-4.05
	(-0.18)	(-4.12)	(-8.01)	(-0.03)	(-4.12)	(-8.28)
Maxret	0.09	-3.45	-3.54	-0.01	-4.10	-4.09
	(0.09)	(-3.05)	(-7.21)	(-0.01)	(-3.81)	(-6.31)
LTreversal	-0.24	-4.06	-3.82	0.06	-4.07	-4.13
	(-0.24)	(-3.88)	(-8.02)	(0.06)	(-3.93)	(-9.22)
Skewness	0.11	-3.85	-3.96	0.29	-3.72	-4.00
	(0.11)	(-3.86)	(-8.80)	(0.29)	(-3.73)	(-8.23)
Kurtosis	-0.01	-3.72	-3.71	0.20	-3.40	-3.60
	(-0.01)	(-3.68)	(-8.14)	(0.21)	(-3.40)	(-7.22)
Amihud	-0.28	-4.39	-4.11	-0.08	-4.08	-4.00
	(-0.30)	(-4.38)	(-8.93)	(-0.08)	(-4.17)	(-8.32)

Table A3: Portfolio sorting result with conditional betas

This table reports the excess returns, 1-Factor, 3-Factor, 7-Factor, and 10-Factor alphas with conditional betas as in Equation 10. The factors are defined in Section 3.1 and Table A1. Left panel reports the equal weight result and right panel reports the value weight result. Returns and alphas are in percent, t-statistics are shown in parentheses using Newey and West (1987) correction with 12 lags. The sample period spans from 1996 to 2020.

	Equal Weight (%)					**Value Weight (%)**				
Θ	Excess returns	1-Fator alpha	3-Factor alpha	7-Factor alpha	10-Factor alpha	Excess returns	1-Fator alpha	3-Factor alpha	7-Factor alpha	10-Factor alpha
IV	-5.33	-5.00	-4.58	-4.35	-4.30	-5.86	-5.26	-4.86	-4.94	-4.55
	(-9.41)	(-7.43)	(-7.26)	(-5.37)	(-5.83)	(-8.23)	(-6.42)	(-5.94)	(-5.11)	(-4.78)
$Delta$	-5.30	-4.99	-4.87	-4.73	-4.87	-5.95	-5.30	-5.17	-5.31	-5.26
	(-9.34)	(-7.41)	(-6.98)	(-5.47)	(-6.51)	(-8.28)	(-6.45)	(-6.03)	(-5.24)	(-5.40)
$Gamma$	-5.32	-5.05	-4.94	-4.98	-5.23	-6.01	-5.41	-5.33	-5.64	-5.78
	(-9.09)	(-7.29)	(-6.73)	(-5.51)	(-6.81)	(-8.13)	(-6.42)	(-5.89)	(-5.45)	(-6.06)
$Vega$	-5.30	-5.01	-4.76	-4.76	-4.91	-5.98	-5.35	-5.13	-5.33	-5.18
	(-9.11)	(-7.13)	(-6.54)	(-5.66)	(-6.00)	(-8.10)	(-6.28)	(-5.63)	(-5.24)	(-5.04)
VIX	-7.45	-8.35	-6.66	-8.50	-7.80	-7.18	-8.10	-8.89	-10.89	-10.16
	(-5.08)	(-5.01)	(-3.90)	(-4.63)	(-4.80)	(-4.04)	(-4.38)	(-4.02)	(-4.76)	(-4.72)

Table A4: Fama MacBeth regression of return predictability controlling VoV

This table reports Fama-MacBeth regression results of straddle returns for the period of 1996-2020. This is the same as in Table 4 except that I add an aditional control uncertainty about volatility (VoV) . All explanatory variables are based on the last non-missing variable observation for each month t and are assigned to deciles ranging from zero to one. Cross-sectional regressions are run every calendar month, and the time-series standard errors are Newey-West adjusted with 12 lags for heteroskedasticity and autocorrelation. Fama-MacBeth t-statistics are reported below the coefficients estimates. Coefficients marked with *, **, *** are significant at 10%, 5%, and 1% respectively.

	Straddle $Ret_{t+1} \times 100$																
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Δhv	-4.22***	-3.02***	-3.99***	-4.17***	-4.39***	-4.28***	-4.15***	-4.25***	-4.15***	-4.26***	-4.20***	-4.18***	-4.23***	-4.24***	-4.08***	-4.04***	-2.50***
	(-9.05)	(-6.25)	(-7.6)	(-8.73)	(-9.22)	(-9.19)	(-8.83)	(-9.36)	(-9.01)	(-9.23)	(-9.01)	(-8.97)	(-9.16)	(-9.07)	(-8.77)	(-8.75)	(-4.78)
VoV	-1.79***	-1.47***	-1.81***	-1.82***	-1.80***	-1.82***	-1.81***	-1.76***	-1.84***	-1.83***	-1.76***	-1.80***	-1.80***	-1.80***	-1.84***	-1.76***	-1.47***
	(-4.38)	(-3.9)	(-4.37)	(-4.53)	(-4.38)	(-4.48)	(-4.5)	(-4.28)	(-4.6)	(-4.49)	(-4.38)	(-4.51)	(-4.39)	(-4.4)	(-4.55)	(-4.31)	(-3.93)
$IVHV$		-8.83***															-9.03***
		(-6.91)															(-7.76)
$IVOL$			-1.23														-2.96***
			(-1.31)														(-3.75)
$Amihud$				-0.29													0.22
				(-0.23)													(0.17)
$Log(p)$					16.17***												12.09***
					(4.89)												(3.77)
CFV						-0.76											-0.56
						(-1.63)											(-1.21)
CH							-0.75										0.79
							(-1.38)										(0.74)
$DISP$								0.28									-0.21
								(0.59)									(-0.49)
$ISSUE_{1Y}$									1.57***								1.34***
									(3.16)								(3.2)
$ISSUE_{5Y}$										0.10							-0.55
										(0.25)							(-1.37)
PM											-1.09**						-1.43***
											(-2.35)						(-2.83)
$PROFIT$												-0.95**					-0.57
												(-2.31)					(-0.73)
TEF													1.23***				1.02***
													(3.15)				(2.82)
$Zscore$														0.02			-0.17
														(0.06)			(-0.47)
$Slope$															1.56***		0.36
															(2.99)		(0.84)
$Optionmom$																1.96***	1.38***
																(5.33)	(3.21)
$Intercept$	-8.29***	2.06	-7.73***	-8.06***	-9.41***	-8.27***	-8.24***	-8.45***	-9.37***	-8.24***	-8.20***	-8.17***	-8.73***	-8.19***	-7.97***	-9.30***	1.65
	(-5.28)	(1.15)	(-4.12)	(-4.36)	(-5.7)	(-5.36)	(-5.16)	(-5.14)	(-5.53)	(-5.18)	(-5.15)	(-5.15)	(-5.41)	(-5.14)	(-5.23)	(-6.18)	(0.73)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
NW-Adjusted	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
$adjR^2$	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.08

Table A5: Fama MacBeth regression of return predictability controlling $Jump$ risk

This table reports Fama-MacBeth regression results of straddle returns for the period of 1996-2020. This is the same as in Table 4 except that I add an aditional control risk-neutral jump risk ($Jump$) . All explanatory variables are based on the last non-missing variable observation for each month t and are assigned to deciles ranging from zero to one. Cross-sectional regressions are run every calendar month, and the time-series standard errors are Newey-West adjusted with 12 lags for heteroskedasticity and autocorrelation. Fama-MacBeth t-statistics are reported below the coefficients estimates. Coefficients marked with *, **, *** are significant at 10%, 5%, and 1% respectively.

	Straddle $Ret_{t+1} \times 100$																
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
$\Delta SVar$	-4.64***	-3.33***	-4.36***	-4.59***	-4.80***	-4.69***	-4.57***	-4.66***	-4.57***	-4.68***	-4.61***	-4.59***	-4.64***	-4.65***	-4.49***	-4.44***	-2.75***
	(-10.14)	(-7.01)	(-8.36)	(-9.77)	(-10.31)	(-10.31)	(-9.99)	(-10.49)	(-10.18)	(-10.37)	(-10.11)	(-10.09)	(-10.27)	(-10.14)	(-9.83)	(-9.81)	(-5.38)
$Jump$	0.23	0.05	0.23	0.25	0.24	0.20	0.18	0.23	0.19	0.22	0.21	0.18	0.24	0.24	0.19	0.25	-0.01
	(0.66)	(0.16)	(0.68)	(0.73)	(0.68)	(0.58)	(0.53)	(0.66)	(0.55)	(0.63)	(0.62)	(0.53)	(0.68)	(0.7)	(0.54)	(0.71)	(-0.03)
$IVHV$		-8.93***															-9.15***
		(-6.86)															(-7.68)
$IVOL$			-1.43														-3.17***
			(-1.53)														(-4.01)
$Amihud$				0.00													0.44
				(0)													(0.34)
$Log(p)$					16.07***												11.90***
					(4.94)												(3.76)
CFV						-0.72											-0.52
						(-1.53)											(-1.11)
CH							-0.77										0.85
							(-1.38)										(0.8)
$DISP$								0.32									-0.18
								(0.67)									(-0.43)
$ISSUE_{1Y}$									1.61***								1.37***
									(3.29)								(3.3)
$ISSUE_{5Y}$										0.12							-0.55
										(0.3)							(-1.39)
PM											-1.13***						-1.46***
											(-2.42)						(-2.9)
$PROFIT$												-0.98**					-0.63
												(-2.31)					(-0.82)
TEF													1.25***				1.03***
													(3.23)				(2.85)
$Zscore$														0.05			-0.16
														(0.16)			(-0.44)
$Slope$															1.58***		0.33
															(2.99)		(0.77)
$Optionmom$																2.02***	1.42***
																(5.43)	(3.3)
$Intercept$	-8.70***	2.03	-8.04***	-8.74***	-9.82***	-8.66***	-8.62***	-8.89***	-9.80***	-8.65***	-8.59***	-8.55***	-9.16***	-8.61***	-8.36***	-9.74***	1.57
	(-5.39)	(1.11)	(-4.18)	(-4.54)	(-5.75)	(-5.45)	(-5.25)	(-5.22)	(-5.62)	(-5.29)	(-5.24)	(-5.24)	(-5.51)	(-5.28)	(-5.34)	(-6.29)	(0.68)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
NW-Adjusted	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
$adjR^2$	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.07

Table A6: Portfolio sorting result of holding to maturity straddle returns

This table reports the excess returns, 1-Factor, 3-Factor, 7-Factor, and 10-Factor alphas for holding to maturity straddle portfolio returns. The factors are defined in Section 3.1 and Table A1. Left panel reports the equal weight result and right panel reports the value weight result. Returns and alphas are in percent, t-statistics are shown in parentheses using Newey and West (1987) correction with 12 lags. The sample period spans from 1996 to 2020.

	Equal Weight (%)					**Value Weight (%)**				
Decile	Excess returns	1-Fator alpha	3-Factor alpha	7-Factor alpha	10-Factor alpha	Excess returns	1-Fator alpha	3-Factor alpha	7-Factor alpha	10-Factor alpha
Short	-0.01	-3.51	-2.61	0.42	-0.25	1.25	-2.67	-1.48	1.60	0.92
2	0.82	-2.14	-0.59	2.07	1.57	1.02	-2.27	-0.70	2.19	1.58
3	-0.34	-3.62	-2.05	-0.12	-0.28	0.74	-2.53	-0.87	1.02	0.27
4	-0.46	-3.83	-1.72	0.93	0.69	-0.80	-4.01	-1.75	1.28	0.74
5	-1.16	-4.98	-2.69	-0.28	-0.31	-1.97	-5.74	-3.35	-1.04	-1.27
6	-1.00	-4.43	-1.95	1.46	0.99	-1.13	-4.42	-1.67	2.09	1.76
7	-2.17	-5.87	-3.91	-1.04	-1.92	-1.86	-6.14	-3.92	-1.17	-2.08
8	-3.26	-6.96	-5.14	-2.95	-3.37	-3.34	-7.40	-5.20	-2.84	-3.36
9	-2.41	-6.14	-4.69	-1.41	-1.66	-2.66	-6.88	-5.18	-2.40	-2.97
Long	-6.70	-9.34	-8.10	-5.21	-5.83	-6.88	-9.53	-8.21	-5.42	-5.94
10-1	-6.69	-5.83	-5.49	-5.64	-5.58	-8.13	-6.86	-6.73	-7.02	-6.87
	(-8.15)	(-6.65)	(-6.18)	(-4.77)	(-5.14)	(-7.23)	(-6.28)	(-5.78)	(-4.63)	(-4.60)
95% Bootstrap CI	[-8.46, -4.93]					[-10.46, -5.83]				

Table A7: Overreaction to volatility change when decoposing relative to Fama and French (1993)

This table presents the monthly forecast regressions of stock level variance risk premiums. The dependent variable variance risk premium VRP is defined as $IV_{i,t}^2 - RV_{i,t+1}$. All independent variables are winsorized at the 1% and 99% levels each month. Panel A reports the Fama-MacBeth regression results. To adjust for serial correlations, Fama-MacBeth t-statistics with Newey and West (1987) adjusted (up to 12 lags) are reported with parentheses. Panel B reports the panel regression results with time fixed effect. The standard errors are double-clustered by firm and time in calculating the t values. Coefficients marked with *, **, *** are significant at 10%, 5%, and 1% respectively.

	Dependent variable $IV_{i,t}^2 - RV_{i,t+1}$						
	Panel A : Fama-MacBeth Regression						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta SVar$	-0.05	-0.07*	-0.05	-0.05	-0.04	-0.05	-0.06
	(-1.22)	(-1.77)	(-1.2)	(-1.27)	(-1.08)	(-1.32)	(-1.64)
$\Delta IVar$	0.05***	0.04***	0.03***	0.05***	0.05***	0.04***	0.03***
	(4.87)	(3.87)	(2.97)	(4.86)	(5.21)	(4.54)	(2.48)
$IVHV$		0.24***					0.27***
		(7.56)					(9.17)
$Ivol$			0.04				0.02
			(1.39)				(0.66)
$Slope$				-0.13			0.14**
				(-1.48)			(2.02)
$Log(p)$					-0.02***		-0.02***
					(-3.86)		(-2.54)
VoV						0.14***	0.06
						(2.43)	(1.3)
$Intercept$	-0.00	-0.01	-0.01	-0.01	0.07***	-0.02***	0.04
	(-0.65)	(-0.79)	(-0.94)	(-0.76)	(3.56)	(-2.45)	(1.47)
NW-Adjusted	YES	YES	YES	YES	YES	YES	YES
adj R^2	0.01	0.04	0.03	0.02	0.03	0.02	0.07
	Panel B : Panel Regression						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta SVar$	-0.06*	-0.08***	-0.06*	-0.07*	-0.06	-0.06*	-0.09**
	(-1.67)	(-2.42)	(-1.67)	(-1.88)	(-1.65)	(-1.72)	(-2.25)
$\Delta Ivar$	0.05***	0.04***	0.05**	0.06***	0.05***	0.04***	0.07***
	(3.88)	(3.14)	(2.04)	(3.99)	(3.89)	(3.61)	(2.59)
$IVHV$		0.20***					0.12***
		(6.83)					(3.53)
$Ivol$			-0.00				-0.04
			(-0.12)				(-1.06)
$Slope$				0.02			0.12
				(0.16)			(0.92)
$Log(p)$					-0.02***		-0.01***
					(-5.08)		(-2.87)
VoV						0.15***	0.06
						(3.01)	(0.9)
Month FE	YES	YES	YES	YES	YES	YES	YES
Double CLuster	YES	YES	YES	YES	YES	YES	YES

Table A8: Effect of earnings announcement

This table reports Fama-MacBeth regression results of straddle returns by adding the interaction terms between volatility change and earnings announcement for the period of 1996-2020. This is the same as in Table 4 except that I add a dummy *Earnings* and its interaction with $\Delta IVar$. All explanatory variables are based on the last non-missing variable observation for each month t and are assigned to deciles ranging from zero to one within no earnings and earnings samples separately. Cross-sectional regressions are run every calendar month, and the time-series standard errors are Newey-West adjusted with 12 lags for heteroskedasticity and autocorrelation. Fama-MacBeth t-statistics are reported below the coefficients estimates. Coefficients marked with *, **, *** are significant at 10%, 5%, and 1% respectively.

	Straddle $Ret_{t+1} \times 100$																
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
$\Delta IVar$	-2.77***	-1.60***	-2.83***	-2.78***	-2.85***	-2.82***	-2.74***	-2.78***	-2.68***	-2.75***	-2.78***	-2.74***	-2.79***	-2.77***	-2.64***	-2.60***	-1.22***
	(-6.16)	(-3.53)	(-5.04)	(-6.15)	(-6.29)	(-6.32)	(-6.2)	(-6.38)	(-6.05)	(-6.14)	(-6.21)	(-6.19)	(-6.24)	(-6.11)	(-5.9)	(-5.85)	(-2.42)
Earnings	6.95***	6.72***	7.02***	6.93***	7.03***	6.92***	6.92***	6.95***	6.98***	6.94***	6.97***	6.93***	6.95***	6.95***	6.97***	6.95***	6.91***
	(10.49)	(10.41)	(10.68)	(10.58)	(10.62)	(10.38)	(10.39)	(10.61)	(10.47)	(10.38)	(10.51)	(10.47)	(10.55)	(10.56)	(10.49)	(10.46)	(10.83)
$\Delta IVar \times Earnings$	-2.05*	-1.87*	-2.20**	-2.02*	-2.20**	-2.01*	-2.00*	-2.04*	-2.09*	-2.03*	-2.09*	-2.03*	-2.01*	-2.08*	-2.07*	-2.04*	-2.18**
	(-1.89)	(-1.75)	(-2)	(-1.88)	(-2.01)	(-1.84)	(-1.85)	(-1.89)	(-1.9)	(-1.85)	(-1.93)	(-1.88)	(-1.85)	(-1.92)	(-1.89)	(-1.88)	(-2.02)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
NW-Adjusted	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
$adjR^2$	0.05	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.08

Table A9: End-users demand measured by $\frac{\text{Open interest}}{\text{Trading Volume}}$

This table presents panel regressions of relative open share on variance change. The relative open share is defined as $\frac{\text{Open interest}}{\text{Trading Volume}}$. All independent variables are winsorized at the 1% and 99% levels each month. The standard errors are double-clustered by firm and time in calculating the t values. Coefficients marked with *, **, *** are significant at 10%, 5%, and 1% respectively.

Panel A : Relative open share				
	(1)	(2)	(3)	(4)
$\Delta IVar$	0.11^{***}	0.12^{***}	0.14^{***}	0.14^{***}
	(9.88)	(9.93)	(7.94)	(7.98)
$Log(p)$		0.12^{***}		0.23^{***}
		(4.32)		(5.18)
$\frac{RSI}{IO}$			0.19^{***}	0.20^{***}
			(5.26)	(5.45)
Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Double CLuster	YES	YES	YES	YES