Long-run and short-run idiosyncratic stock volatilities and cross-section of option returns

by

Quan Gan[1] and Van Quoc Thinh Nguyen[2 *]

[1] University of Sydney, Sydney, Australia, author email: quan.gan@sydney.edu.au, work phone: +61 2 9114 0831

[2] University of Sydney, Sydney, Australia, author email: van.q.nguyen@sydney.edu.au

[*] Corresponding author

Long-run and short-run idiosyncratic stock volatilities and cross-section of option returns

Abstract: We decompose stock idiosyncratic volatility into long-run and short-run components and find that both are negatively related to delta-hedged option returns. The effects of the long-run and short-run components are explained by the limits-of-arbitrage and stock return jumps, respectively. Unlike the long-run component, the short-run component can be used to create a trading strategy that remains profitable after considering transaction costs. In downturns, only the short-run idiosyncratic volatility effect is significant. Further analysis shows that the limits-of-arbitrage's explaining power arises from its intercept and common component, while jump's explaining power arises from its residual component relating to corporate news arrivals.

JEL classification: G11, G12

Keywords: Idiosyncratic volatility; Demand-based option pricing; Transaction cost; Idiosyncratic jump; Firm news release

1 Introduction

The relationship between idiosyncratic volatility and asset prices is a research question that has attracted much attention.[1] Studying returns in the options market, Cao and Han (2013) find that stock idiosyncratic volatility is negatively related to delta-hedged option returns, and the trading strategy that buys options on low idiosyncratic volatility stocks and sells options on high idiosyncratic volatility stocks yields significant profit. However, recent research challenges the importance of the idiosyncratic volatility option premium by showing that after accounting for a reasonable level of transaction cost, the option strategy based on idiosyncratic volatility becomes unprofitable (O'Donovan & Yu, 2024). Indeed, a substantial proportion of the idiosyncratic volatility premium is attributed to limits of arbitrage (Cao & Han, 2013). Hence, to benefit from the option strategy related to idiosyncratic volatility, it is necessary to quantify the component of idiosyncratic volatility that is not significantly associated with the costs of arbitrage. In this study, we utilize idiosyncratic volatility decomposition to seek an option trading strategy that remains profitable after considering transaction costs and study the distinct roles of the idiosyncratic volatility components in option returns.

The asset pricing literature documents an important characteristic of idiosyncratic volatility that idiosyncratic volatility is persistent over long horizons and occasionally surges for short

[1] The theoretical work (Merton, 1987) and empirical evidence (Ang et al., 2006; Ang et al., 2009; Cao et al., 2021; Fu, 2009) show mixed results on the direction of the relation between idiosyncratic volatility and stock returns. Various studies investigate the economic mechanisms underlying the pricing effect of idiosyncratic volatility in stock returns (Hou & Loh, 2016).

durations (Ang et al., 2009; Bekaert et al., 2012; Brandt et al., 2010; Liu, 2022). Liu (2022) shows that idiosyncratic volatility consists of a long-run (persistent) and a short-run (transient) component, and both components have asset pricing implications for stock returns and are driven by different economic channels. Given that limits of arbitrage proxies tend to be highly persistent (Acharya & Pedersen, 2005; Bali et al., 2013), the short-run component of idiosyncratic volatility is unlikely to be driven by limits of arbitrage and may generate an option premium that remains significant after transaction costs. No less important is the need to study the distinct roles of the two idiosyncratic volatility components in the options market. It remains unknown how the long-run and short-run idiosyncratic volatility components are related to option returns and what economic mechanism drives the effect of each component.[2]

Using the volatility decomposition method as in Adrian and Rosenberg (2008) and Liu (2022), we decompose idiosyncratic volatility into the long-run and short-run components. We find that the long-run and short-run components of idiosyncratic volatility are both negatively related to delta-hedged option returns.[3] Our results suggest that the options market makers demand compensation for the idiosyncratic volatility increase in both its persistent and transient components. Further, we find that the pricing of the two components differs in terms of persistence.

[2] While the long-run and short-run components of total volatility have the same pricing direction in stock returns (Adrian & Rosenberg, 2008), the long-run and short-run components of idiosyncratic volatility have opposite pricing implications for stock returns (Liu, 2022).

[3] These relationships are not subjected to the look-ahead biases identified by Duarte et al. (2023).

The negative premium for the long-run component persists over multi-year horizons, while that for the short-run component exists only for short horizons.

Examining the economic mechanism underlying each idiosyncratic volatility component, we find that the relation between long-run idiosyncratic volatility and option returns can be explained by limits of arbitrage and that the relation between short-run idiosyncratic volatility and option returns can be explained by stock return jumps. Further analysis reveals that growth options (Cao et al., 2008), variance risk premium (Goyal & Saretto, 2009), gambling preference (Bali & Murray, 2013; Byun & Kim, 2016), earnings surprise (Jiang et al., 2009), salience theory (Cosemans & Frehen, 2021), and corporate variables identified in Zhan et al. (2022) play a little role in weakening the abovementioned relationships.

Why are the limits of arbitrage related to the effect of long-run idiosyncratic volatility? Extensive literature shows that the limits of arbitrage hinder asset pricing anomalies from disappearing, making the anomalies exist persistently (Doukas et al., 2010; Sadka & Scherbina, 2007). The limits of arbitrage proxies such as firm size and Amihud (2002) illiquidity are themselves stable firm characteristics. For example, Acharya and Pedersen (2005) and Bali et al. (2013) show that stock illiquidity is highly autocorrelated. Also, limits of arbitrage are usually considered an explanation for the pricing of idiosyncratic volatility in the options market (Cao & Han, 2013) and the stock market (Hou & Loh, 2016). Following the demand-based option pricing theory (Gârleanu et al., 2009; Ramachandran & Tayal, 2021), we use the CBOE data to compute the end-user net option demand and show that high limits of arbitrage induce high option demand. High net demand from end users, together with difficulty for market makers in hedging illiquid stocks, results in high option prices and low subsequent option returns.

Why are jumps related to the effect of short-run idiosyncratic volatility? Eraker et al. (2003) argue that the impact of jumps on stock returns is transient. Andersen et al. (2007) highlight jump occurrence as a non-persistent and important predictor of future volatility. Stock price jumps represent an unhedgeable risk faced by option market makers, inducing them to require higher option prices (Gârleanu et al., 2009). Todorov (2009) shows that when jumps occur, investors are more willing to pay for the protection offered by options against future jump increases. Tian and Wu (2023) show that historical jumps in the recent month can predict option returns. Using CBOE net option demand data, we find a strong positive relation between realized jumps and option demand by end users. Hence, the demand-based option pricing theory supports the negative relation between realized jumps and option returns. Further, being consistent with the prior literature linking corporate news arrivals to jumps (Kapadia & Zekhnini, 2019) and temporary increases in volatility (Bushee & Noe, 2000), we find that both realized jumps and short-run idiosyncratic volatility are positively related to corporate news arrivals. Thus, price jumps resulting from firm news releases can explain the effect of short-run idiosyncratic volatility in option returns.

Uncovering the mechanism behind each idiosyncratic volatility component is important for designing option trading strategies. We find that the influence of long-run idiosyncratic volatility on option returns, which is driven by limits of arbitrage, is significant only in the high transaction cost subsample. After considering transaction costs, the trading strategy based on long-run idiosyncratic volatility is not profitable. On the contrary, the effect of short-run idiosyncratic volatility, which is not explained by limits of arbitrage, is found to be significant in both high and low transaction cost subsamples. In the low transaction cost subsample, investors can still form a long-short option strategy based on short-run idiosyncratic volatility to earn a significant profit (0.46% per month) after paying transaction costs.

We also revisit the relationship between idiosyncratic volatility and delta-hedged option returns. Cao and Han (2013) show that after controlling limits of arbitrage, the relationship between idiosyncratic volatility and option returns decreases by about 40% but remains significant. It means that a full explanation for the pricing of idiosyncratic volatility remains unknown. We show that limits of arbitrage or stock realized jumps alone cannot fully explain the idiosyncratic volatility-option returns relation, but combining the two channels can.

We then examine the importance of long-run and short-run idiosyncratic volatilities in different economic states. We find that though both volatility components influence option returns in up markets, only the short-run idiosyncratic volatility is related to option returns in down markets. In downturns, stock price jumps become the dominant channel in explaining the relation between idiosyncratic volatility and option returns. This is in line with the increases in discretionary disclosure in high macroeconomic uncertainty periods to mitigate information asymmetry (Nagar et al., 2019), and aligned with the greater roles of stock jumps (Eraker et al., 2003) and news (Garcia, 2013) in asset pricing during down markets.

After decomposing idiosyncratic volatility into two components and uncovering their respective economic mechanisms, we further decompose each mechanism to understand the source of its explanation power. Particularly, we examine whether the economic mechanism's systematic or idiosyncratic component plays the dominant role in explaining the return predictability patterns documented in our study. Our approach is motivated by Herskovic et al. (2016), who show that each firm’s idiosyncratic volatility comoves with the market-wide common idiosyncratic volatility and commonality in idiosyncratic volatility has asset pricing implications. The commonality structure is also found in illiquidity (Chordia et al., 2000) and jump risk (Bégin et al., 2020). Following the literature on co-movement, we decompose illiquidity and jump each into an intercept, a common component (comoving with the market average), and a residual component (unrelated to the market average). We find that the explaining power of illiquidity in the relation between long-run idiosyncratic volatility and option returns arises exclusively from the intercept and the common illiquidity component. In contrast, the explaining power of realized jumps in the relation between short-run idiosyncratic volatility and option returns arises exclusively from the residual jump component.

Bringing our results into the stock market, we first confirm the results in Liu (2022) that the long-run idiosyncratic volatility is negatively related to stock returns and the short-run idiosyncratic volatility is positively related to stock returns. We then find that the explanation for the short-run idiosyncratic volatility based on jumps also holds in the stock market setting.

Our study advances the growing literature that studies equity option returns; for instance, research on volatility-related option mispricing (Goyal & Saretto, 2009), investors' skewness and gambling preferences (Bali & Murray, 2013; Byun & Kim, 2016), idiosyncratic volatility (Cao & Han, 2013), underlying stock's mispricing (Ramachandran & Tayal, 2021), volatility of volatility (Ruan, 2020), and a comprehensive list of firm characteristics (Zhan et al., 2022). We show that the pricing effects of the two idiosyncratic volatility components can be explained by limits of arbitrage and stock jumps. Unlike the long-run component, the short-run component can be used to create a profitable option trading strategy after considering transaction costs. In line with Gârleanu et al. (2009), Ramachandran and Tayal (2021), and Golez and Goyenko (2022), we demonstrate the crucial role of demand-based option pricing in explaining the cross-section of option returns.

Our study also contributes to the extensive literature on idiosyncratic risk and its asset pricing implications. Ang et al. (2006); Ang et al. (2009); Fu (2009) examine the relation between idiosyncratic volatility and stock returns, and other studies provide evidence that the relation between idiosyncratic volatility and stock returns arises because of return reversals (Huang et al., 2009), liquidity biases (Han et al., 2015; Han & Lesmond, 2011), arbitrage asymmetry of overpriced and underpriced stocks (Stambaugh et al., 2015), and is affected by aggregate investor sentiment (Peterson & Smedema, 2011), incomplete information (Berrada & Hugonnier, 2013). Our study reveals that idiosyncratic jumps, driven by corporate news as a major source of unhedgeable risk, matter in both the options and stock markets. Idiosyncratic jumps help us to understand the puzzle of the discrepancy between the theory prediction of Merton (1987) and empirical asset pricing findings.

The paper proceeds as follows. Section 2 discusses the data used in the study and the design of empirical analysis. Section 3 presents the empirical results, and section 4 concludes.

2 Data and model description

Data for US equity options are obtained from OptionMetrics Ivy DB from January 1996 to December 2021. Stock and firm-related information is retrieved from the Center for Research on Security Prices (CRSP) and Compustat database. Daily and monthly Fama-French common risk factors are from Kenneth French's website.

For each firm, the monthly idiosyncratic volatility is measured as the standard deviation of the residuals in the regression of daily excess stock return in each month on the three Fama and French (1993) factors and the resulting monthly idiosyncratic volatility ($ivol$) is then decomposed into long-run and short-run components ($ivollr$ and $ivolsr$) with the models (1)-(3) following Adrian and Rosenberg (2008); Christoffersen et al. (2008); Liu (2022):

Idiosyncratic volatility: $\log ivol_t^i = ivollr_t^i + ivolsr_t^i \qquad (1)$

Short-run component: $ivolsr_{t+1}^i = \rho_s^i ivolsr_t^i + \sigma_s^i \epsilon_{s,t}^i \qquad (2)$

Long-run component: $ivollr_{t+1}^{i} = \emptyset_i + \rho_l^i ivollr_t^i + \sigma_l^i \epsilon_{l,t}^i$ (3)

In models (1)-(3), $\log ivol_t^i$ (the log of idiosyncratic volatility of firm *i* in month *t*) is decomposed into the sum of two time-series components, $ivollr_t^i$ and $ivolsr_t^i$; each follows a first-order autoregressive AR(1) process. The short-run component has a zero mean, while the long-run component contains a constant $\emptyset_i$. The mean reversion parameters (ρ_l^i, ρ_s^i) in the autoregressive process are required to satisfy $\rho_l^i > \rho_s^i$ to identify the models. In other words, the long-run component is more persistent than the short-run component. We use the Kalman filter to estimate the models (1)-(3) using $\log ivol_t^i$ as the input time series (observations) to the filter and conduct the decomposition so that the expectation of each component at time *t* is predicted from observations until time *t-1*. Further discussion on the long-run and short-run decomposition with Kalman filter can be found in Liu (2022). According to Liu (2022), it is crucial to study the dynamics of idiosyncratic volatility over long and short horizons, as idiosyncratic volatility consists of a component that decays quickly and a component that persists over long horizons, and these two components can have different stock pricing implications.

The long-run and short-run decomposition of idiosyncratic volatility is aligned with the literature that idiosyncratic volatility is characterized by a relatively stable autoregressive process that sometimes switches into a higher-variance regime for short durations (Bekaert et al., 2012; Brandt et al., 2010). According to Christoffersen et al. (2008), the two-component volatility model outperforms the single-component volatility model in explaining equity market volatility. Most importantly, Adrian and Rosenberg (2008) show that the pricing effects of the long-run and short-run components of stock total volatility are attributed to different economic mechanisms. Similarly, the two components of idiosyncratic volatility can also have different interpretations. It is also worth noting that the economic mechanisms behind idiosyncratic volatility components need not be the same as the economic mechanisms in Adrian and Rosenberg (2008), because Adrian and Rosenberg (2008) refer to total volatility components. Both studying the relations between stock return and long-run/short-run volatilities, Adrian and Rosenberg (2008) show two components of total volatility are priced in the same direction, while Liu (2022) shows two components of idiosyncratic volatility are priced in the opposite directions. Our study differentiates from the above two by analyzing the long-run/short-run idiosyncratic volatilities' option pricing implications.

[*Insert Figure 1 about here.*]

We execute the decomposition and illustrate the distribution of the autoregressive parameters of long-run and short-run components in Figure 1. The long-run idiosyncratic volatility autoregressive parameters, ρ_l^i, have a mean of 0.69 and a median of 0.74. These values of ρ_l^i tend to be close to but smaller than 1, suggesting that the long-run component of idiosyncratic volatility is persistent but not permanent. Following Adrian and Rosenberg (2008), we test whether the autoregressive parameters of the long-run component equal one; with the t-statistics of -189.01, we reject the null hypothesis $\rho_l^i = 1$. The short-run idiosyncratic volatility autoregressive parameters, ρ_s^i, have the mean of -0.18 and the median of -0.19.

Our objective is to study the relation between the two idiosyncratic volatility components and equity option returns. Hence, we compute the returns of the delta-hedged call option strategy, which are a long position of one call option (with price *C*) combined with a short position in delta (Δ) shares of underlying equity (with price *S*). Following Cao and Han (2013) and Zhan et al. (2022), we form the portfolio on the first trading of each month and select the options which mature on the option expiration day of the next month (third Friday of each month). In our analysis, we select at-the-money (ATM) call options, determined by the moneyness (strike price to stock price) being closest to 1. To avoid the look-ahead biases discussed by Duarte et al. (2023), all filters are applied at the time of portfolio formation, and no future information is involved in the prediction of option returns. The delta-hedged option portfolio is held until maturity and the return to the portfolio is calculated as portfolio gain until maturity scaled by *(Δ*S-C)* (Cao & Han, 2013). This method of computing delta-hedged option returns is common in the literature (Goyal & Saretto, 2009; Zhan et al., 2022). Our final sample contains 412,049 option-month observations.

The relationship between long-run and short-run idiosyncratic volatility and option returns is examined in the following specification with Fama and MacBeth (1973) regressions:

$$dret_{i,t+1} = \beta_0 + \beta_1 ivollr_{i,t} + \beta_2 ivolsr_{i,t} + \gamma control_{i,t} + \varepsilon_{i,t} \qquad (4)$$

where $dret_{i,t+1}$ is the delta-hedged option return, $ivollr_{i,t}$ is the long-run component of idiosyncratic volatility, $ivolsr_{i,t}$ is the short-run component of idiosyncratic volatility. Following Cao and Han (2013) we control for systematic volatility $sysvol_{i,t} = \sqrt{tvol_{i,t}^2 - ivol_{i,t}^2}$, where $tvol_{i,t}$ is the monthly total volatility and $ivol_{i,t}$ is the idiosyncratic volatility of stock returns. Depending on the tests, we also control for other variables. Internet Appendix Table IA1 summarizes the definition of variables used in our study.

3 Empirical results

3.1 Summary statistics

[*Insert Table 1 about here*.]

Table 1 shows the summary statistics of our main variables. From the statistics for the full sample in panel A, we find that the average delta-hedged option returns are -0.3%. This is consistent with Bakshi and Kapadia (2003) in that delta-hedged option strategy underperforms zero and this negative premium reflects the compensation for volatility risk. In panel B, we find that the average delta-hedged option returns are more negative for small firms (-0.7%), implying that option prices tend to be higher for small firms. Since the options are selected so that they are closest to at-the-money, the average delta in our sample is about 0.5, similar for both small and large firms, in panels B and C, respectively. In terms of idiosyncratic volatility, panels B and C show that the volatility is larger for small firms than for large firms. The same is observed when it comes to systematic volatility: average *sysvol* is 1.8% for small firms versus 1.3% for large firms. In terms of limits of arbitrage, the average Amihud illiquidity is higher for small firms than for large firms, suggesting that the cost of arbitrage is higher in small firms. The average excess kurtosis (kurtosis minus three) of stock return is positive, indicating that stock return data are heavy-tailed relative to a normal distribution. Panels B and C further show that the heavy tails are more pronounced for small firms than for large firms. This suggests that the unhedgeable risk arising from jumps in the underlying asset price tends to be larger for small firms.

3.2 Long-run and short-run components of idiosyncratic volatility and option returns

We discuss our baseline results in this section. Panel A of Table 2 shows the results of Fama–MacBeth regressions where the delta-hedged option returns are regressed on idiosyncratic volatility components and systematic volatility. In column (1), we verify the result of Cao and Han (2013) by showing that idiosyncratic volatility is negatively related to delta-hedged option returns. In columns (2) to (4), we show that both long-run and short-run idiosyncratic volatilities are negatively related to delta-hedged option returns, and all coefficients are significant at the 1% level. One standard deviation of long-run idiosyncratic volatility (0.560 as shown in Table 1) is associated with -0.34% monthly returns to the delta-hedged option portfolio, and one standard deviation of short-run idiosyncratic volatility (0.171 as shown in Table 1) is associated with -0.21% monthly returns to the delta-hedged option portfolio. Both are economically significant when compared with the unconditional mean of monthly returns of the delta-hedged option portfolio (-0.30% as shown in Table 1). When either idiosyncratic volatility or long-run idiosyncratic volatility is present in the regression, the effect of systematic volatility becomes insignificant (columns (1) and (2)), and when only short-run idiosyncratic volatility is present, systematic volatility has a significantly negative relation with delta-hedged option returns (column (3)).

[*Insert Table 2 about here.*]

In panel B of Table 2, we use the portfolio sorting approach to confirm the results obtained by the regression analysis in panel A. First, we examine the equal-weighted option return spread based on sorting the idiosyncratic volatility. At the beginning of each month, we sort stocks into five quintiles based on their idiosyncratic volatility and compute the differential delta-hedged option returns between the top and bottom quintile groups. The resulting series represents the returns of the option strategy that buys delta-hedged call options on high idiosyncratic volatility stocks and sells delta-hedged call options on low idiosyncratic volatility stocks. The average delta-hedged option return spread between high and low idiosyncratic volatility quintile groups is -0.94% and is highly significant at the 1% level. We then show our new findings on the option return spreads sorted by long-run and short-run idiosyncratic volatilities. The 5-1 return spreads based on long-run idiosyncratic volatility and short-run idiosyncratic volatility sorting are -0.88% and -0.64% respectively and are significant at the 1% level. We also show that delta-hedged option returns monotonically decrease with the long-run and short-run idiosyncratic volatilities, across quintile groups. Investors pay a premium for options written on stocks with high long-run and short-run idiosyncratic volatilities.

In panel C of Table 2, we investigate the difference in persistence between the pricing effects of the long-run and short-run idiosyncratic volatilities. Specifically, we study the relation between delta-hedged option returns and idiosyncratic volatility components when idiosyncratic volatility components are estimated 12 months and 24 months before the formation of the delta-hedged option portfolios. The results show that 12-month (or 24-month) lagged long-run idiosyncratic volatility is still significantly and negatively related to delta-hedged option returns, while 12-month (or 24-month) lagged short-run idiosyncratic volatility changes to positively relate to delta-hedged option returns. This means that the negative relationship between long-run idiosyncratic volatility and delta-hedged option returns is persistent over long horizons, whereas the negative relationship between short-run idiosyncratic volatility and delta-hedged option returns is transient. This result is consistent with Liu (2022) and suggests the distinct implications of the two idiosyncratic volatility components. The result implies that the underlying economic mechanisms of the two idiosyncratic volatility components could be very different, leading us to further investigate the mechanisms that are persistent (to explain the long-run component) and transient (to explain the short-run component) separately.

3.3 Explanation for the influence of long-run idiosyncratic volatility

We investigate what explains the effect of long-run idiosyncratic volatility in delta-hedged option pricing. One potential explanatory factor is the limits of arbitrage. Idiosyncratic volatility is known to be strongly correlated with illiquidity (Spiegel & Wang, 2005) and is recognized as an important hindrance to arbitrage activity (Pontiff, 2006; Shleifer & Vishny, 1997). Further, limits of arbitrage tend to explain the pricing of idiosyncratic volatility. Particularly, in the stock market, limits of arbitrage proxies explain about 10% of the idiosyncratic volatility-stock returns relation (Hou & Loh, 2016); in the options market, limits of arbitrage explain about 40% of the idiosyncratic volatility-option returns relation (Cao & Han, 2013). An important characteristic of the limits of arbitrage is their persistence. Proxies for limits of arbitrage, such as firm size and

Amihud (2002) illiquidity, tend to be stable variables. Acharya and Pedersen (2005) and Bali et al. (2013) highlight that Amihud illiquidity measure is highly autocorrelated. Further, extensive literature shows that high limits of arbitrage hinder asset pricing anomalies from disappearing, making their effects persistent (Doukas et al., 2010; Sadka & Scherbina, 2007). Hence, we conjecture that limits of arbitrage can explain the long-run relation between idiosyncratic volatility and option returns.

[*Insert Table 3 about here.*]

In panel A of Table 3, we control for three limits of arbitrage proxies, including firm size (market capitalization), stock price, and Amihud illiquidity, in the regressions and see how these proxies affect the coefficients of long-run and short-run idiosyncratic volatility. The results in columns (1) to (3) of panel A show that when we control for either firm size or stock price or Amihud illiquidity, the coefficient of long-run idiosyncratic volatility becomes insignificant, but the coefficient of the short-run idiosyncratic volatility remains significant with larger magnitude compared with the results in Table 2. The delta-hedged option returns are negatively associated with high limits of arbitrage. Limits of arbitrage explain the effect of long-run idiosyncratic volatility but not that of short-run idiosyncratic volatility. Cao and Han (2013) find that controlling for limits of arbitrage proxies reduces the strength of the relation between idiosyncratic volatility and delta-hedged option returns by about 40%. Our findings suggest that this reduction is due to the diminished influence of the long-run idiosyncratic volatility.

Since stock illiquidity is highly persistent, we further investigate the pricing implication of the persistent stock illiquidity versus the illiquidity shock and thereby elucidate why limits of arbitrage explain the long-run effect of idiosyncratic volatility. Bali et al. (2013) show that, while illiquidity is compensated with higher stock return, illiquidity shock (illiquidity minus average of illiquidity over the prior 12 months) predicts low stock return, highlighting that the stock market underreacts to illiquidity shock. We examine the illiquidity shock underreaction in the options market by decomposing each firm's stock illiquidity into mean past 12-month illiquidity, *illiqm*, and illiquidity shock, *illiqu*, as in Bali et al. (2013). The results in panel B of Table 3 show that option returns are negatively related only to the average past illiquidity (column (1)), but not to illiquidity shock (column (2)), suggesting that the options market reacts to persistent illiquidity but not to transient illiquidity shocks. Further, columns (3) and (4) show that the average past illiquidity, rather than illiquidity shock, fully explains the pricing of long-run idiosyncratic volatility. Our results suggest that the options market tends to assess firms' limits of arbitrage in their long-run consideration.

One of our proxies for limits of arbitrage is firm size. The result that firm size explains the option pricing implication of long-run idiosyncratic volatility is consistent with the stock market result of Liu (2022) that the stock return spread based on long-run idiosyncratic volatility has the strongest correlation with the size factor among the five Fama and French (2015) factors, indicating that the persistent effect of idiosyncratic volatility can be a manifestation of firm size. Although Liu (2022) attributes the influence of long-run idiosyncratic volatility on stock returns to growth options, we rule out this explanation for option returns in the later part of this study. As options are short-lived instruments, option prices may not reflect the cross-sectional difference in firms' potential for future growth.

Finally, though limits of arbitrage serve as an important explanation for the pricing of idiosyncratic volatility, they cannot fully explain the influence of idiosyncratic volatility on stock and option returns. Prior research in the stock market (Han & Lesmond, 2011; Huang et al., 2009; Spiegel & Wang, 2005) shows that the illiquidity-stock returns relation is largely weakened with the presence of idiosyncratic volatility, thereby emphasizing the important role of idiosyncratic volatility relative to illiquidity. Ang et al. (2006); Ang et al. (2009) show that idiosyncratic volatility-stock returns relation holds after controlling for liquidity and highlight that limits of arbitrage cannot fully explain the pricing of idiosyncratic volatility. In the options market, limits of arbitrage fail to fully explain the relation between idiosyncratic volatility and delta-hedged option returns (Cao & Han, 2013). Therefore, limits of arbitrage account for only part of the idiosyncratic volatility effect, and there must be a further mechanism that drives the idiosyncratic volatility-asset returns relation. Our results suggest that it is long-run idiosyncratic volatility, not idiosyncratic volatility in its entirety, that is explained by the limits of arbitrage. The remaining effect, manifested by the short-run component's effect, should be explained by a different mechanism. We discuss our findings around this new mechanism in the next section.

3.4 Explanation for the influence of short-run idiosyncratic volatility

After showing the factor that explains the effect of long-run idiosyncratic volatility, we continue to examine what explains the relation between short-run idiosyncratic volatility and delta-hedged option returns. Todorov (2009) shows that after the occurrence of underlying stock price jumps, investors become more willing to pay for protection against jumps by increasing the variance risk premium. Similarly, Tian and Wu (2023) show that jumps in the recent month can predict option returns. According to Gârleanu et al. (2009), underlying stock jumps represent an unhedgeable risk for which market makers require higher option prices. These studies highlight the roles of underlying stock jumps in option pricing. Further, the literature suggests that the effect of jumps is transient. For instance, Eraker et al. (2003) argue for the transient impact of jumps on stock returns; Andersen et al. (2007) demonstrate jump occurrence as a non-persistent predictor of future volatility. Therefore, we conjecture that stock jumps can explain the relation between short-run idiosyncratic volatility and option returns.

[*Insert Table 4 about here*.]

Following Bali et al. (2023), we measure historical underlying stock jumps as the excess kurtosis (*kur*) of daily stock return in the month before the options portfolio formation date. Panel A of Table 4 shows that jumps are significantly and negatively related to delta-hedged option returns. This result is consistent with Todorov (2009) and Gârleanu et al. (2009) in that the occurrence of stock jumps induces higher option prices and hence lower subsequent option returns. Importantly, the result shows that after controlling for stock jumps, the relation between short-run idiosyncratic volatility and delta-hedged option returns becomes insignificant. This means that underlying stock jumps fully explain the effect of short-run idiosyncratic volatility: high short-run idiosyncratic volatility stocks tend to experience recent jumps due to which investors are willing to pay higher option prices and market makers demand higher option prices. Besides, we find that stock return skewness cannot explain the short-run idiosyncratic volatility's influence and the result is shown in Table 12.

We further investigate the cause of stock jumps. Literature suggests that corporate news arrivals can lead to stock jumps (Kapadia & Zekhnini, 2019) and temporary increases in volatility (Bushee & Noe, 2000). Following Kapadia and Zekhnini (2019) and Edmans et al. (2018), we extract firm news events from Capital IQ's Key Developments database to construct *fnews* which is the number of news events in the month before the option portfolio formation date, and *fnewsdi* which is the number of discretionary news events. We also construct the unusual discretionary news release, *fnewsdiu*, which is the number of discretionary news events in a month in excess of its trailing 4-month average (Bali et al., 2018). The results in panel B of Table 4 show that all the three measures of news arrivals, *fnews*, *fnewsdi* and *fnewsdiu*, are significantly related to stock jumps. And the results in panel C of Table 4 show that these measures of news arrivals are also positively related to short-run idiosyncratic volatility. Thus, our results suggest that price jumps resulting from corporate news releases can manifest in the relation between short-run idiosyncratic volatility in option returns.

To rule out the conjecture that news arrivals are related to the relation between long-run idiosyncratic volatility in option returns, we show in panel D of Table 4 that the three measures of news arrivals do not result in increases in limits of arbitrage – the economic mechanism behind long-run idiosyncratic volatility. Particularly, the three columns of panel D show that firm stocks become more liquid as the number of news events increases. Thus, it is unlikely that firm news arrivals can drive the relation between long-run idiosyncratic volatility in option returns.

3.5 The influence of option transaction costs

Transaction costs heavily reduce the profitability of option strategies (Chen et al., 2024; Heston et al., 2023; Vasquez & Xiao, 2024). O'Donovan and Yu (2024) show that after accounting for a reasonable level of transaction cost, the option strategy based on idiosyncratic volatility becomes unprofitable. However, by restricting the trading to low-cost options, investors can substantially improve the option trading profitability (Chen et al., 2024; Heston et al., 2023; Vasquez & Xiao, 2024). In this section, we examine whether trading low-cost options allows for significantly profitable option strategies based on long-run and short-run idiosyncratic volatilities.

[*Insert Table 5 about here.*]

First, we study how the pricing effects of idiosyncratic volatility and its long-run and short-run components differ in subsamples of high-cost and low-cost options. Following Chen et al. (2024) and Heston et al. (2023), we identify a low-cost subsample by restricting to options whose bid-ask spread is below the 25th percentile in each month. In panel A of Table 5, the Fama-MacBeth regression results in columns (1) and (3) show that the relation between idiosyncratic volatility and option returns is weakened for low-cost options, suggesting that idiosyncratic volatility premium becomes less pronounced in option liquidity. The results in columns (2) and (4) show that the effect of long-run idiosyncratic volatility is significant only in the high-cost subsample. Driven by limits of arbitrage, the effect of long-run idiosyncratic volatility should be more pronounced when transaction costs are higher and weakened when transaction costs are lower. This explains the results in columns (2) and (4). In contrast, the effect of short-run idiosyncratic volatility is highly significant in both high-cost and low-cost subsamples, consistent with our finding that the short-run effect is not driven by limits of arbitrage.

Panel B of Table 5 confirms the results in panel A with portfolio sorting analysis. The return spread between top and bottom quintiles based on sorting idiosyncratic volatility or each of the two components is highly significant in the high-cost subsample. In the low-cost subsample, the short-run idiosyncratic volatility yields a significant return spread with the same magnitude as in the high-cost subsample (0.62% per month). This highlights that the effect of short-run idiosyncratic volatility is not driven by option transaction costs. Meanwhile, the effects of idiosyncratic volatility and the long-run component weaken and disappear, respectively, for low-cost options.

Panel C of Table 5 examines the profitability after transaction costs for the option strategies based on idiosyncratic volatility and its components. Following O'Donovan and Yu (2024) and Heston et al. (2023), we consider a reasonable level of transaction cost by assuming the effective option bid–ask spread to quoted spread ratio to be 20%. We then report the equal-weighted returns to the strategies that buy options in the bottom quintile and sell options in the top quintiles sorted on idiosyncratic volatility or each of its components. The returns after transaction costs are reported for the full sample and subsamples of high-cost and low-cost options. We find that in the full sample or high-cost subsample, no strategies can be profitable after transaction costs. This is consistent with numerous studies documenting that option trading tends to be unprofitable when transaction costs are relatively high (Cao & Han, 2013; Chen et al., 2024; Heston et al., 2023; Vasquez & Xiao, 2024).[4] In the low-cost subsample, only the strategy based on short-run idiosyncratic volatility can generate significant profit (0.46% per month, *t-stat* = 3.42). The low-cost strategy based on the long-run component cannot yield significant profit before transaction cost (as shown in panel B), hence no profit after transaction cost. In terms of idiosyncratic volatility, its low-cost trading strategy is not profitable after considering transaction costs.

Given that limits of arbitrage are responsible for a substantial part of the idiosyncratic volatility effect through the long-run component, our finding highlights the importance of considering short-run idiosyncratic volatility in forming a profitable option trading strategy. We show that the trading strategy based on short-run idiosyncratic volatility remains profitable after a reasonable level of transaction costs.

3.6 Full explanation of the relation between idiosyncratic volatility and option returns

As idiosyncratic volatility is decomposed into two components and the pricing of the two components is explained by the two channels, limits of arbitrage and stock jumps, it is likely that

[4] Cao and Han (2013) advise that "only market participants who face relatively low transaction costs can take advantage of our option strategy profitably".

the combination of those two channels can fully explain the well-established relationship between idiosyncratic volatility and delta-hedged option returns. Table 6 assesses this conjecture.

[*Insert Table 6 about here*.]

In particular, we simultaneously control for limits of arbitrage and stock jumps. Limits of arbitrage are proxied by the Amihud illiquidity.[5] Stock jumps are captured by the excess kurtosis of daily stock return in a month. In column (1), when both channels are controlled for, the relationship between idiosyncratic volatility and delta-hedged option returns becomes insignificant. In columns (2) and (3), when only one channel is controlled for, the negative relationship between idiosyncratic volatility and delta-hedged option returns remains statistically significant. Thus, it is the combination of the two channels, not each standalone channel, that fully explains the pricing of idiosyncratic volatility. This finding finalizes the unfinished quest of Cao and Han (2013) to uncover the economic mechanisms driving the effect of idiosyncratic volatility in option pricing, as they show about 40% of the effect is due to limits of arbitrage. We, using the decomposition of idiosyncratic volatility into long-run and short-run components, discover the two underlying channels for the pricing of the two components, and these channels in turn fully explain the relation between idiosyncratic volatility and delta-hedged option returns.

---

[5] Limits of arbitrage proxies are usually highly correlated with investment friction proxies, e.g., asset size, (Lam and Wei 2011) and idiosyncratic volatility can be explained by growth options (Cao et al. 2008); hence, we now focus only on the measure of limits of arbitrage that reflects the price impact, i.e., Amihud illiquidity.

3.7 Up and down markets

Economic downturns substantially increase uncertainty in the financial markets, dampen investor sentiment, and influence investors' attention allocation (Garcia, 2013; Kacperczyk et al., 2016; Maslar et al., 2021). In Table 7, we rerun the baseline regression with the subsamples of options written in up markets and down markets separately.

[*Insert Table 7 about here.*]

According to Cooper et al. (2004), down (up) markets are defined as periods when the past 12-month holding-period return of the value-weighted CRSP index is negative (non-negative).[6] Columns (1) to (3) of Table 7 refer to the up-market subsample. The results in the up-market subsample are no different from the results in the full sample. Particularly, both the long-run and short-run components of idiosyncratic volatility are negatively related to option returns, and the limits of arbitrage and stock jumps, respectively, fully explain the effects of long-run and short-run components. The results in the up-market subsample, hence, serve as a robustness check for our key findings. Columns (4) to (6) of Table 7 are for the down-market subsample. The result in column (4) shows that in down markets, the long-run idiosyncratic volatility is not significantly related to option returns, but the effect of short-run idiosyncratic volatility is significant. In column

[6] Cooper et al. (2004) also have alternative definitions of up and down markets based on the 36-month holding-period return (non-negative vs negative). Such definitions result in fewer observations of down markets. Hence, we choose the definitions based on the 12-month holding-period return to alleviate the observation imbalance between up-market and down-market subsamples. In our final dataset, about 23% of observations are options written in down markets.

(5), when we control for limits of arbitrage captured by Amihud illiquidity, the effect of short-run idiosyncratic volatility remains significant. In column (6), when we control for stock jumps, the effect of short-run idiosyncratic volatility disappears. Thus, the result confirms that stock jumps fully explain the pricing of short-run idiosyncratic volatility in down markets. Our results indicate that, in down markets, investors place more emphasis on short-run idiosyncratic volatility than on long-run idiosyncratic volatility when pricing delta-hedged options. Our results are hence consistent with Eraker et al. (2003), who show evidence that, in market stress, stock return jumps play a greater role than diffusive stochastic volatility (the component that tends to be persistent) in explaining crash movements, and use this evidence to argue that jumps should command larger premia than the diffusive volatility in market stress to compensate for the risk that cannot be fully hedged away. Our results are also in line with Garcia (2013), who argues that the influence of news on asset prices is more pronounced in downturns, given the positive association between news arrivals and short-run idiosyncratic volatility we demonstrate in Section 3.4. Nagar et al. (2019) find that in high macroeconomic uncertainty periods, firms increase discretionary disclosure to mitigate information asymmetry and uncertainty about firm value; this is consistent with our results on short-run idiosyncratic volatility being the dominant component of idiosyncratic volatility in down markets.

Our results highlight the importance of considering the short-run component of idiosyncratic volatility in the options market, since the short-run component, unlike the long-run component, matter in both up and down markets.

3.8 Demand-based option pricing

The economic explanations uncovered in the previous sections can find their support in the demand-based option pricing theory (Gârleanu et al., 2009). This theory provides the valuation framework to determine the expensiveness of options based on demand and supply considerations when market makers are unable to perfectly hedge their option exposure. In our study, high costs to arbitrage between options and stocks represent difficulty for market makers to hedge their option positions and rebalance their hedging. Also, stock jumps are a source of unhedgeable risk faced by market makers. So, both limits of arbitrage and stock jumps are hindrances to options supply from market makers. Further, stocks with high limits-of-arbitrage characteristics and heavy tails can attract speculation from gamblers (Kumar, 2009). If the end-user demands for options on stocks with high limits of arbitrage and jumps are high, the equilibrium prices for such options should be high to be consistent with the demand-based option pricing theory. In Table 8, we follow the empirical work of Golez and Goyenko (2022) to compute end-user net option demand from the Chicago Board of Options Exchange (CBOE) database (data available from 2005). Internet Appendix Table IA1 provides details of the option demand variable construction. The results in columns (1) to (3) of Table 8 show that option demand by end users is higher for options written on stocks with higher illiquidity, and higher excess kurtosis. In other words, limits of arbitrage and stock jumps are associated with higher end-user option demand. Based on the prediction of the demand-based option pricing theory, it follows that higher limits of arbitrage and jumps are related to higher option prices and lower subsequent option returns.

[*Insert Table 8 about here.*]

We also examine the end-user option demand in up and down markets. Columns (4) and (5) of Table 8 are for the up-market and down-market subsamples, respectively. The result in the up-market subsample (column (4)) is similar to that in the full sample (column (3)): end-user option demand increases in both limits of arbitrage and stock jumps. This explains why both limits of arbitrage and stock jumps have strong predictive power on option returns in the full sample as well as in the up-market subsample. However, in down markets, the influence of limits of arbitrage on option demand becomes insignificant while that of jumps remains significant (column (5)). In downturns, investors are prone to a phenomenon called flight-to-liquidity, i.e., adjusting portfolios toward liquid assets (Beber et al., 2009). Investor preference for liquid securities in downturns explains the insignificant relation between end-user option demand and stock illiquidity. Specifically, higher (lower) demands for liquid (illiquid) stocks induce increased demands for options written on liquid stocks relative to options written on illiquid stocks. This preference in down markets offsets the positive relation between option demand and underlying stock illiquidity found in the full sample, making the relation insignificant in the down-market subsample. On the other hand, the significant relation between jumps and option demand in down markets is consistent with the idea of Todorov (2009) that options market investors' sensitivity to recent jumps reflects their risk aversion and the finding that investors' risk aversion tends to be heightened in downturns (Guiso et al., 2018). Our result that only jumps are related to option demand in down markets, albeit with lower significance compared with full sample results, is aligned with our finding in Table 7 that only short-run idiosyncratic volatility is significantly related to option returns in down markets. Hence, the demand-based option pricing theory illuminates why the influence of long-run and short-run idiosyncratic volatility on option returns varies over time.

3.9 Decomposition of economic mechanisms

Herskovic et al. (2016) show that firm-level idiosyncratic volatility follows a commonality structure, which means that it comoves with the aggregate common idiosyncratic volatility. Moreover, the two economic mechanisms underlying idiosyncratic volatility, limits of arbitrage and stock jumps, also have a commonality structure (Bégin et al., 2020; Chordia et al., 2000).

Thus, we further decompose each mechanism to understand the source of its explanation power, following the approach of Herskovic et al. (2016):

$$mechanism_{i,t} = intercept_i + loading_i \times \overline{mechanism}_t + \varepsilon_{i,t} \quad (5)$$

where $mechanism_{i,t}$ is the uncovered economic mechanism of each idiosyncratic volatility component (i.e., limits of arbitrage or stock jumps) for firm i in month t; $\overline{mechanism}_t$ is the equal-weighted market average of each mechanism in each month. We conduct the regression for each mechanism of each firm and term the estimated intercept the mechanism intercept, the estimated $\widehat{loading}_i \times \overline{mechanism}_t$ the common component of the mechanism and the estimated residuals the residual component of the mechanism.

Take stock illiquidity as an example. Firm-level illiquidity is decomposed into the intercept, which is the constant component of illiquidity, the common illiquidity component, which is the part of illiquidity comoving with the market average, and the residual illiquidity component, which is the part of illiquidity unrelated to the market average. The decomposition of jumps is conducted in the same manner. Similar to Yan (2011) who studies whether systematic jump or idiosyncratic jump is the dominant force that explains the jump risk-stock returns relation, we investigate whether the systematic or idiosyncratic component of each economic mechanism plays the dominant role in explaining the option return predictability of the two idiosyncratic volatility components.

[*Insert Table 9 about here.*]

In Table 9, we examine the roles of the illiquidity and jumps components in explaining the long-run and short-run idiosyncratic volatility effects. In column (1), when we control for the illiquidity intercept and the common illiquidity component, the relation between long-run idiosyncratic volatility and option returns becomes insignificant (in untabulated tests, each of the illiquidity intercept and common illiquidity component is not sufficient to explain the effect of long-run idiosyncratic volatility). In column (2), when we control for the illiquidity intercept and the residual illiquidity component, that relation remains highly significant. Controlling for those illiquidity components does not affect the coefficient of short-run idiosyncratic volatility in these two columns. In column (3), the jumps intercept and the common jumps component are not significantly related to option returns and cannot explain any of the idiosyncratic volatility components. In column (4), when we control for the jumps intercept and the residual jumps component, the residual jumps component is significantly related to option returns, and fully explains the effect of short-run idiosyncratic volatility (the coefficient of the jumps intercept is still insignificant). Controlling for jumps' components in columns (3) and (4) does not affect the coefficient of the long-run idiosyncratic volatility. Thus, we conclude on the one hand that the explaining power of illiquidity for the effect of long-run idiosyncratic volatility arises from the constant illiquidity component and the illiquidity component comoving with the market average (i.e., systematic illiquidity); and on the other hand, that the explaining power of jumps for the effect of short-run idiosyncratic volatility arises from firm idiosyncratic jumps component, rather than the systematic jumps. Our results are consistent with the stock market study of Liu (2022) that the return predictability of long-run idiosyncratic volatility is strongly correlated with systematic risk factors, while the return predictability of short-run idiosyncratic volatility lacks correlations with those systematic risk factors.

[*Insert Table 10 about here*.]

Illiquidity commonality is a research topic that attracts much attention (Acharya & Pedersen, 2005; Chordia et al., 2000; Karolyi et al., 2012; Lee, 2011), but no prior work explores its link with the idiosyncratic volatility commonality discovered by Herskovic et al. (2016). Idiosyncratic volatility is considered an important hindrance to arbitrage activity (Pontiff, 2006; Shleifer & Vishny, 1997), and is strongly related to illiquidity (Spiegel & Wang, 2005). Hence, we conjecture that illiquidity commonality is related to idiosyncratic volatility commonality. Using the specification in equation (5), we decompose idiosyncratic volatility into idiosyncratic volatility intercept, common idiosyncratic volatility component, and residual idiosyncratic volatility component. Table 10 shows that the common illiquidity component is significantly related to the idiosyncratic volatility intercept and the common idiosyncratic volatility component (column (1)), while the residual illiquidity component is significantly related to the residual idiosyncratic volatility component (column (2)). Further, in column (3), we examine the exposure of firm-level variable to the market aggregate variable using 60-month rolling window estimations (Herskovic et al., 2016), and document a strong positive relation between the exposure of firm-level idiosyncratic volatility to market aggregate idiosyncratic volatility (idiosyncratic volatility beta) and the exposure of firm-level illiquidity to market aggregate illiquidity (illiquidity beta). From the results in Table 10, we conclude that illiquidity commonality is strongly associated with idiosyncratic volatility commonality. Herskovic et al. (2016) argue that household income risk is an important driver of idiosyncratic volatility commonality. Our results hence not only bridge the two commonalities but also suggest that household income risk may be a potential determinant of illiquidity commonality besides various determinants documented in the prior literature. We leave this household income risk explanation to future research.

[*Insert Table 11 about here.*]

In the earlier section, we argued that corporate news disclosure manifests in the relation between short-run idiosyncratic volatility and option returns through stock jumps. Since it is the idiosyncratic jumps rather than the systematic jumps that can explain the influence of short-run idiosyncratic volatility (Table 9), we further show in Table 11 that the idiosyncratic jumps component is driven by corporate news releases. In columns (1) to (3), the idiosyncratic jumps component is strongly and positively related to firm news disclosure, discretionary disclosure, and unusual discretionary disclosure; while in columns (4) to (6), we find that the common jumps component is not significantly related to firm news disclosure and discretionary disclosure and only has a weak relation with unusual discretionary disclosure. According to Caporin et al. (2017), systematic co-jumps are situations when individual stock prices simultaneously jump and such systematic co-jumps can be traced to market-wide economic news arrivals. Hence, the firm-level news disclosure is unlikely to trigger systematic co-jumps. This explains the lack of significant relation between corporate disclosure and the common jumps component in our results. Our results on the positive association between corporate disclosure and idiosyncratic jumps are consistent with Kapadia and Zekhnini (2019). All in all, we highlight the role of corporate news arrivals in explaining the short-run idiosyncratic volatility effect by driving the idiosyncratic jumps.

3.10 Alternative explanations

In this section, we examine whether other corporate variables, apart from limits of arbitrage and stock jumps, can explain the influence of long-run and short-run idiosyncratic volatility. In Table 12, we test whether the relations between two idiosyncratic volatility components and delta-hedged option returns remain statistically significant after controlling for past stock return characteristics and mispricing variables. Recent month stock return is an explanation for the pricing of idiosyncratic volatility in the stock market (Huang et al., 2009); mispricing related to lottery preferences is also a potential explanation (Hou & Loh, 2016). In column (1), we control for stock return in the previous month, *rev*, and the cumulative stock return from the prior second through 12th month, *mom*. Controlling for these variables does not materially affect the statistical significance and magnitude of the coefficients of the two idiosyncratic volatility components. We also find in an untabulated test that the salience theory measure (Cosemans & Frehen, 2021) cannot explain the effects of idiosyncratic volatility components. In column (2), we control for the volatility risk premium, which is the realized stock return standard deviation in each month minus the volatility implied from stock options. Goyal and Saretto (2009) find that volatility risk premium (historical-implied volatility differential) is significantly and positively related to delta-hedged option returns. We find consistent results, and after controlling for the volatility risk premium, the effects of two idiosyncratic volatility components remain highly significant. In column (3), we control for option implied risk-neutral skewness which is extracted from the OTM call and put options using the method of Bakshi et al. (2003).[7] We find that option-implied skewness is negatively related to option returns, being consistent with investors' preference for positive skewness, and that the effects of long-run and short-run idiosyncratic volatility remain significant. In column (4), we include the variable *max5*, which is the average of the five highest daily stock returns in the last month. According to Byun and Kim (2016), max daily return captures the gambling characteristic of a stock, and options buyers are willing to pay a higher premium for

[7] The computation of implied skewness requires several options available for a firm at a time. Such data availability is more likely to be found in large firms than in small firms. Similar to Cao and Han (2013), we find that the computed implied skewness data is available for about half of the sample and concentrated in large firms. Since firm size can explain the effect of long-run idiosyncratic volatility, the implied skewness measure used in our study is firm-size adjusted, i.e., the residuals from the cross-sectional regressions of implied skewness on firm size, where regressions are conducted in each month.

options written on stocks with higher gambling characteristics. We find that after controlling for *max5*, the effects of long-run and short-run idiosyncratic volatility hold, and the coefficient of *max5* is insignificant.[8] This means that the max daily return cannot explain the effects of the two idiosyncratic volatility components. In column (5), we control for the skewness of daily stock returns in the last month, a measure of jumps that captures the asymmetry of the two tails of the distribution (Amaya et al., 2015). Unlike stock excess kurtosis, the stock skewness control variable does not affect the coefficient of the idiosyncratic volatility components and is not significantly related to option returns. Thus, from the results in Table 12, we conclude that the negative relationships between two idiosyncratic volatility components and delta-hedged option returns are robust when controlling for the abovementioned past stock return characteristics and mispricing variables.

[*Insert Table 12 about here.*]

[*Insert Table 13 about here.*]

Another potential explanation for the relation between idiosyncratic volatility components and option returns is firms' growth options because firms' growth options can explain the trend in idiosyncratic volatility (Cao et al., 2008) and is one of the explanations for the pricing of idiosyncratic volatility in stock returns (Barinov & Chabakauri, 2023). We therefore control for

[8] In the study of Byun and Kim (2016), the negative relation between max daily return and option returns is robust after controlling for idiosyncratic volatility. However, they measure option returns without delta-hedging. In our unreported results using raw option returns as dependent variable, the effect of *max5* remains significantly negative when the two idiosyncratic volatility components are included as independent variables.

growth options proxies in our regressions to examine whether our results are driven by growth options. The typical proxies for growth options in literature are market-to-book ratio, Tobin's Q ratio, and research and development expenses scaled by assets (Albuquerque, 2014; Cao et al., 2008). The results in Table 13 show that except for the R&D ratio being negatively related to delta-hedge option returns, market-to-book, and Tobin's Q ratios are not significantly related to option returns, and that growth options proxies do not explain the effect of either long-run or short-run idiosyncratic volatility. The coefficients of long-run and short-run idiosyncratic volatility remain significantly negative with relatively similar magnitude (comparable with those coefficients in Table 2) after the inclusion of growth options control variables. Given the short lifespans of options, the growth potential of a firm may not be an important consideration for financial intermediaries when writing options on the firm's equity, hence the insignificance of growth options proxies in prediction of option returns and the inability of these proxies to explain the long-run and short-run idiosyncratic volatility option premiums.

In the Internet Appendix Table IA2, we consider a comprehensive set of corporate variables documented in Zhan et al. (2022). These variables have been shown to have cross-section option return predictability. We examine whether these variables can explain the relation between long-run/short-run idiosyncratic volatility and option returns. These control variables include cash flow variance computed as the variance of the cash flow to market capitalization ratio over the 60-month window, cash-to-assets ratio, earnings forecast dispersion which is the standard deviation divided by absolute value of the mean of annual EPS forecasts, one-year and five-year new equity issues in number of shares, profit margin which is earnings before interest and tax divided by revenues, profitability which is income before extraordinary items divided by book equity, total external financing which is net share issuance minus cash dividends plus net debt issuance, scaled by total assets, and z-score defined by the formula initiated by Dichev (1998). The results in Table IA2 show that after controlling for these variables, the relations between long-run and short-run idiosyncratic volatilities and option returns remain significant. Therefore, the long-run/short-run idiosyncratic volatility-option return relation cannot be explained by the corporate variables documented in Zhan et al. (2022). In untabulated tests, we control for standardized unexpected earnings as in Jiang et al. (2009) to examine the explaining power of earnings shocks in the pricing of idiosyncratic volatility components. We find that the effects of the two components remain significant after the inclusion of this control variable.

In short, our results show that corporate and behavioral characteristics other than the limits of arbitrage and jumps are unlikely to play significant roles in explaining the relations between long-run and short-run idiosyncratic volatilities and option returns.

3.11 Insights for the stock market and the puzzle around Merton (1987)

The study of Liu (2022) on the stock market shows that long-run idiosyncratic volatility is negatively related to future stock returns and short-run idiosyncratic volatility is positively related to future stock returns. In this section, we examine whether limits of arbitrage and stock jumps can explain the influence of the two idiosyncratic volatility components on stock returns. In Table 14, we confirm the negative (positive) relation between long-run (short-run) idiosyncratic volatility and next month's stock returns (column (1)) and then find that stock jumps can fully explain the positive relation between short-run idiosyncratic volatility and stock returns (column (3)). The stock jumps measured by excess kurtosis of daily stock returns are positively related to future stock returns, being consistent with Kapadia and Zekhnini (2019), who show that higher idiosyncratic jump risk is compensated with higher future stock returns, and Amaya et al. (2015), who show that realized kurtosis positively predicts stock returns. Our result emphasizes the role of jumps in explaining the pricing effect of short-run idiosyncratic volatility.

[*Insert Table 14 about here.*]

In terms of limits of arbitrage, we find that the coefficient of illiquidity measure is insignificant (column (2)). The result is consistent with the literature that the influence of illiquidity on stock returns is often dominated and eliminated by the inclusion of idiosyncratic volatility as an explanatory variable (Han & Lesmond, 2011; Huang et al., 2009; Spiegel & Wang, 2005). The inability of limits of arbitrage to explain the pricing of long-run idiosyncratic volatility in stock returns may be because stock prices – unlike option prices that reflect mainly the compensation for volatility – contain risk premia for various factors that do not stem from volatility (Stein, 1989). For example, firm growth options increase idiosyncratic volatility (Cao et al., 2008) while inducing low stock returns compared with returns of value counterparts (Fama & French, 1992); therefore, an explanation based on growth options can be feasible in the stock market (Bhamra & Shim, 2017) but not in the options market. We indeed rule out this explanation in the options market (Table 13).

The theory of Merton (1987) predicts a positive relation between idiosyncratic volatility and stock returns, but empirical studies provide limited support for the theory. Our results suggest that the theoretical prediction of Merton (1987) is supported when the idiosyncratic volatility's influence is mainly through its short-run component and indeed the short-run component captures the truly idiosyncratic part. According to the results from our decomposition of economic channels, the long-run component captures the intercept (time-invariant) and the common component (systematic variation) in illiquidity and is not truly idiosyncratic. The Merton (1987) theory will hold well if we measure the idiosyncratic volatility only by its short-run component. To reconcile the theory of Merton (1987) and the empirical findings on the pricing of idiosyncratic volatility in stock returns, our study suggests focusing on corporate news and idiosyncratic jumps which result in the transient effect that cannot be explained either by time-invariant or systematic variation of the idiosyncratic volatility.

3.12 Further analysis

Andersen et al. (2007) demonstrate that the persistent component of volatility positively predicts future volatility, while the transient component of volatility negatively predicts future volatility. As future volatility prediction is important in determining option prices, separating the persistent and transient components is necessary for understanding the influence of idiosyncratic volatility on option returns. In the Internet Appendix Table IA3, consistent with Andersen et al. (2007), we show that long-run (short-run) idiosyncratic volatility is positively (negatively) related to next month's total volatility and that separating the two idiosyncratic volatility components improves next month's volatility prediction (adjusted R-squared increases from 30% in column (1) to 38% in column (4)). These results are in line with the volatility mean-reversion literature which posits that the future volatility tends to be closer to the long-run average historical volatility than to the current volatility (Goyal & Saretto, 2009). Hence, we highlight the value of decomposing idiosyncratic volatility into long-run and short-run components when studying the cross-section of option returns.

Cao and Han (2013) show that the relation between idiosyncratic volatility and option returns is significant across different holding horizons. In Table IA4, we also examine that relation using an alternative holding period of delta-hedged option portfolios. At the beginning of each month, instead of selecting options that mature on the option expiration day of the next month (third Friday), we use options that mature in the same month (on the third Friday of the same month) to compute delta-hedged option returns, making the average maturity drop to about 17 days (compared with about one and a half month as in the main analysis). The advantage of this holding period alternative (over other holding strategies such as liquidating the one-and-a-half-month-maturity option portfolios after holding for one month) is that it avoids the calendar effect documented in Cao et al. (2021). In particular, Cao et al. (2021) show that on the third weekend in a month, stock prices are strongly affected by selling pressure due to option expiration. Our strategy avoids holding the option portfolios beyond this third-week threshold. With the new holding horizon, we recompute delta-hedged option returns and report regression results of this new dependent variable. In Table IA4, we show that when each of the two channels, limits of arbitrage and stock jumps, is controlled, the relation between idiosyncratic volatility and option returns is weakened but still significant; and when both channels are controlled, the relation disappears. Thus, our results using different portfolio holding horizons confirm that the combination of limits of arbitrage and stock jumps still fully explains the relation between idiosyncratic volatility and option returns.

In the main tests, we focus on the delta-hedged call option returns. In Table IA5, we investigate the delta-hedged put option returns. We show that controlling for each of the two channels, limits of arbitrage and stock jumps, makes the effect of idiosyncratic volatility weakened but still significant, and controlling for both makes the effect become insignificant. Consistent with our call option results, the two channels together also explain the relation between idiosyncratic volatility and put option returns.

In Internet Appendix Table IA6, we revisit the option return spreads based on portfolio sorting as discussed in Table 2 panel B. In particular, we examine whether these return spreads remain significant after controlling for the Fama and French (2015) five common equity factors and the

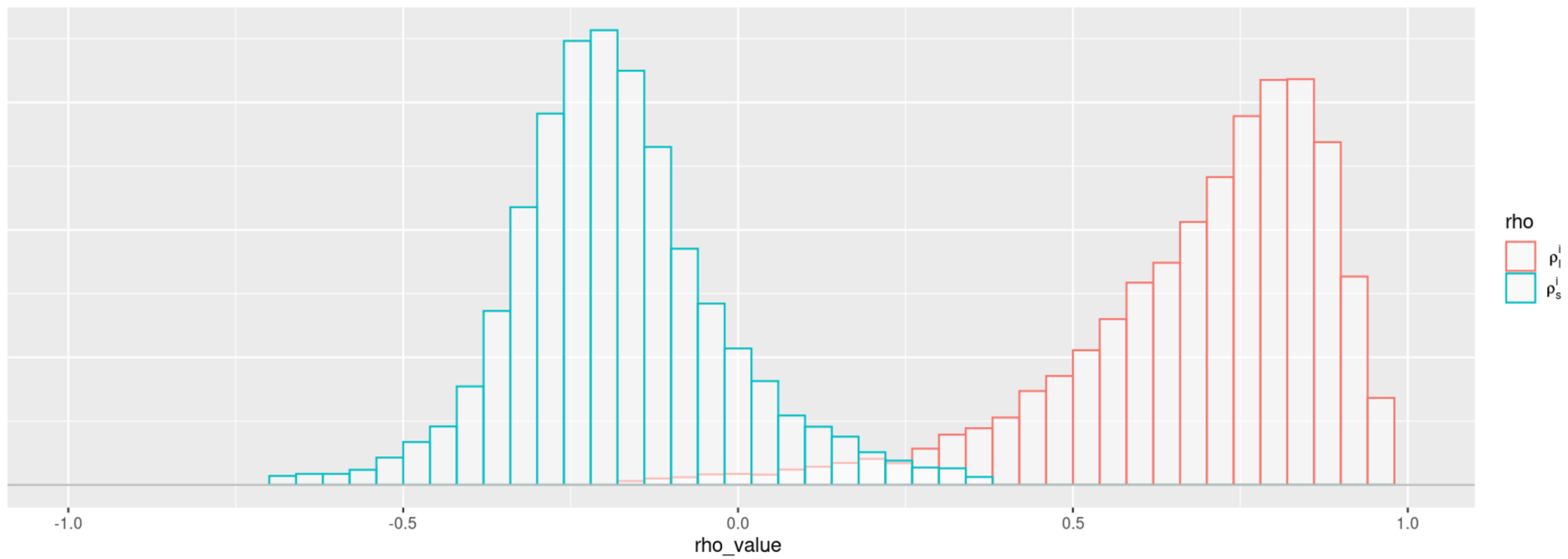
VIX index. We follow Cao and Han (2013); Goyal and Saretto (2009) to regress the monthly return spreads on idiosyncratic volatility or idiosyncratic volatility components on the monthly common equity factors and the change in the average monthly VIX index. The results show that the option trading strategies based on sorting idiosyncratic volatility or idiosyncratic volatility components yield significant alphas after controlling for five Fama and French (2015) common equity factors and the VIX index, and these market-wide control variables play little role in explaining the returns of the abovementioned option trading strategies.

4 Conclusion

In this study, we decompose idiosyncratic volatility into long-run and short-run components and find that both components are negatively related to option returns in the sample from 1996 to 2021. We then conduct comprehensive tests to explore the mechanisms behind these negative effects and find different explanations for each effect. First, the long-run idiosyncratic volatility negatively predicts option returns because stocks with high idiosyncratic volatility over a long horizon are difficult to arbitrage, and financial intermediaries require a high premium to write options on such stocks. The high option prices associated with high limits of arbitrage are justified by the demand-based option pricing theory, which posits that market markers charge higher premiums for writing options that are in high demand and difficult to hedge. Second, the short-run idiosyncratic volatility negatively predicts option returns because the short-run idiosyncratic volatility reflects the jumps in the underlying stock prices resulting from corporate news disclosure. The jumps induce investors to pay higher option premiums because underlying stock jumps represent a source of unhedgeable risk, for which market makers also demand compensation. Putting together, the limits of arbitrage and stock jumps fully explain the effect of idiosyncratic volatility on option returns. Apart from these two mechanisms, other stock and behavioural characteristics (e.g., skewness preference) seem unable to explain our findings.

The findings on the pricing of the two idiosyncratic volatility components and their economic mechanisms have important implications for option traders, especially when transaction costs are documented to eliminate the profitability of most option trading strategies (O'Donovan & Yu, 2024). We show that, unlike the long-run component, the short-run component can be used to create an option strategy that remains profitable after reasonable transaction costs. Moreover, we show that the short-run idiosyncratic volatility is the dominant component that influences option returns in down markets.

Bringing our results into the stock market, the stock jumps can fully explain the relation between short-run idiosyncratic volatility and stock returns and help researchers reconcile the Merton (1987) theory and empirical findings.



ρ_l^i: autoregressive parameter of firm's long-run idiosyncratic volatility
ρ_s^i : autoregressive parameter of firm's short-run idiosyncratic volatility

Figure 1 Histogram of autoregressive parameters of firms' long-run and short-run idiosyncratic volatilities

This figure illustrates the distribution of the autoregressive parameters of the long-run and short-run idiosyncratic volatility components.

Table 1. Summary statistics

This table provides summary statistics on mean, standard deviation, 5th, 25th, 50th, 75th, 95th percentiles of our main variables, including delta-hedged option returns, *dret*, delta, *delta*, idiosyncratic volatility, *ivol*, long-run, *ivollr*, and short-run, *ivolsr*, components of idiosyncratic volatility, systematic volatility, *sysvol*, , firm size, *size*, stock price, *price*, Amihud illiquidity measure, *illiq*, stock realized jumps, *kur*, the number of firm news events, *fnews*, volatility risk premium, *vrp*. Panel A refers to the full sample. Panel B and C refer to the subsamples of small and large firms whose market capitalization is below and above, respectively, the median in the full sample.

Panel A Full sample

	Mean	SD	Q5	Q25	Median	Q75	Q95
dret	-0.003	0.141	-0.169	-0.072	-0.021	0.039	0.230
delta	0.527	0.112	0.332	0.460	0.531	0.598	0.703
log(ivol)	-4.109	0.624	-5.083	-4.549	-4.132	-3.694	-3.056
ivollr	-4.108	0.560	-4.992	-4.507	-4.126	-3.727	-3.162
ivolsr	-0.001	0.171	-0.258	-0.110	-0.010	0.097	0.291
log(size)	7.874	1.535	5.546	6.756	7.747	8.900	10.716
price	44.850	67.057	7.350	17.500	31.030	52.250	117.490
log(illiq)	-20.867	1.899	-23.961	-22.189	-20.861	-19.562	-17.736
kur	0.446	2.084	-1.211	-0.754	-0.225	0.753	4.798
fnews	3.462	4.143	0.000	0.000	3.000	5.000	10.000
sysvol	0.016	0.012	0.004	0.008	0.013	0.019	0.037
vrp	0.063	0.253	-0.185	-0.048	0.025	0.126	0.440

Panel B Small firm sample

	Mean	SD	Q5	Q25	Median	Q75	Q95
dret	-0.007	0.163	-0.198	-0.091	-0.028	0.046	0.260
delta	0.532	0.116	0.333	0.455	0.537	0.614	0.712
log(ivol)	-3.900	0.575	-4.809	-4.294	-3.915	-3.521	-2.943
ivollr	-3.898	0.499	-4.696	-4.241	-3.909	-3.563	-3.068
ivolsr	-0.002	0.177	-0.269	-0.116	-0.011	0.101	0.304
log(size)	6.634	0.775	5.185	6.132	6.756	7.265	7.650
price	25.317	17.945	5.470	13.090	20.900	33.090	58.410
log(illiq)	-19.542	1.249	-21.334	-20.442	-19.681	-18.78	-17.258
kur	0.589	2.225	-1.194	-0.716	-0.151	0.934	5.396
fnews	2.662	2.708	0.000	0.000	2.000	4.000	8.000
sysvol	0.018	0.013	0.005	0.010	0.014	0.022	0.040
vrp	0.069	0.305	-0.236	-0.069	0.027	0.156	0.512

Panel C Large firm sample

	Mean	SD	Q5	Q25	Median	Q75	Q95
dret	0.000	0.105	-0.121	-0.055	-0.016	0.032	0.177
delta	0.520	0.107	0.329	0.463	0.525	0.580	0.689
log(ivol)	-4.371	0.565	-5.224	-4.767	-4.406	-4.013	-3.389
ivollr	-4.370	0.499	-5.122	-4.723	-4.402	-4.054	-3.497
ivolsr	-0.001	0.164	-0.248	-0.106	-0.009	0.094	0.279
log(size)	9.114	1.019	7.849	8.259	8.900	9.779	11.343
price	67.525	88.421	15.700	31.490	48.600	75.080	173.050
log(illiq)	-22.357	1.267	-24.583	-23.174	-22.266	-21.463	-20.451
kur	0.306	1.943	-1.229	-0.792	-0.299	0.583	4.229
fnews	4.635	5.118	0.000	1.000	4.000	6.000	13.000
sysvol	0.013	0.010	0.004	0.007	0.011	0.016	0.032
vrp	0.054	0.169	-0.119	-0.033	0.023	0.099	0.333

Table 2. Long-run and short-run idiosyncratic volatility components and option returns

In this table, Panel A reports results of Fama–MacBeth regressions of delta-hedged option returns, *dret*, on long-run, *ivollr*, and short-run, *ivolsr*, components of idiosyncratic volatility, *ivol*, controlling for systematic volatility, *sysvol*. Panel B reports the average delta-hedged option returns of portfolios obtained by sorting stocks into five quintile groups based on *ivol*, *ivollr*, or *ivolsr*, and the equal-weighted average return spreads between high and low volatility groups. Panel C repeats the regressions in Panel A except that the two components of idiosyncratic volatility are replaced by their respective 12-month lags, *ivollr12* and *ivolsr12*, or 24-month lags, *ivollr24* and *ivolsr24*. To adjust for serial correlation, robust Newey and West (1987) t-statistics with a lag of 6 months are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Panel A. Two idiosyncratic volatility components and option returns

	dret			
	(1)	(2)	(3)	(4)
Intercept	-0.027***	-0.026***	0.001	-0.025***
	(-4.43)	(-3.45)	(0.24)	(-3.06)
log(ivol)	-0.006***			
	(-4.95)			
ivollr		-0.006***		-0.005***
		(-3.63)		(-3.10)
ivolsr			-0.012***	-0.010***
			(-5.67)	(-3.66)
sysvol	-0.058	-0.072	-0.254***	-0.048
	(-0.79)	(-1.03)	(-2.73)	(-0.69)
Avg Adj R^2	0.0131	0.0141	0.0110	0.0150

Panel B. Portfolio sorting analysis

	dret					
	(1) - Low	(2)	(3)	(4)	(5)- High	(5) - (1) (t-value)
ivol	-0.0000	-0.0014	-0.0011	-0.0025	-0.0094	-0.0094***(-3.95)
ivollr	-0.0002	-0.0012	-0.0018	-0.0023	-0.0090	-0.0088***(-3.46)
ivolsr	-0.0009	-0.0009	-0.0022	-0.0031	-0.0073	-0.0064***(-7.43)

Panel C. Lagged idiosyncratic volatility components and option returns

	dret	
	(1)	(2)
Intercept	-0.016**	-0.021***
	(-2.22)	(-2.73)
ivollr12	-0.004**	
	(-2.31)	
ivolsr12	0.010***	
	(5.29)	
ivollr24		-0.005***
		(-2.90)
ivolsr24		0.007***
		(2.99)
sysvol	-0.195**	-0.168**
	(-2.47)	(-1.99)
Avg Adj R^2	0.0149	0.0150

Table 3. What explains the effect of long-run idiosyncratic volatility

In this table, Panel A reports results of Fama–MacBeth regressions of delta-hedged option returns, *dret*, on long-run, *ivollr*, and short-run, *ivolsr*, components of idiosyncratic volatility, controlling for systematic volatility, *sysvol*, firm size, *size*, stock price, *price*, Amihud illiquidity measure, *illiq*. Panel B examines the roles of illiquidity shock, *illiqu*, and average past illiquidity, *illiqm*, in explaining the effect of long-run idiosyncratic volatility. To adjust for serial correlation, robust Newey and West (1987) t-statistics with a lag of 6 months are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Panel A. Limits of arbitrage explanation

	dret		
	(1)	(2)	(3)
Intercept	-0.030***	-0.010	-0.058***
	(-3.79)	(-1.17)	(-5.71)
ivollr	-0.003	0.000	-0.001
	(-1.47)	(0.08)	(-0.38)
ivolsr	-0.013***	-0.013***	-0.012***
	(-4.40)	(-4.70)	(-4.58)
sysvol	-0.051	-0.124*	-0.070
	(-0.71)	(-1.76)	(-0.99)
log(size)	0.002***		
	(4.35)		
price		0.000***	
		(4.76)	
log(illiq)			-0.003***
			(-5.90)
Avg Adj R^2	0.0180	0.0201	0.0186

Panel B. Average past illiquidity and illiquidity shock

	dret			
	(1)	(2)	(3)	(4)
Intercept	-0.001	-0.002	-0.011	-0.020**
	(-0.30)	(-0.77)	(-1.41)	(-2.49)
ivollr			-0.002	-0.004**
			(-1.47)	(-2.52)
ivolsr			-0.010***	-0.009***
			(-4.02)	(-3.51)
sysvol			-0.043	-0.032
			(-0.53)	(-0.40)
illiqm	-0.459***		-0.412***	
	(-6.48)		(-5.36)	
illiqu		-0.075		-0.071
		(-1.20)		(-1.26)
Avg Adj R^2	0.0035	0.0024	0.0184	0.0178

Table 4. What explains the effect of short-run idiosyncratic volatility

In this table, Panel A reports results of Fama–MacBeth regressions of delta-hedged option returns, *dret*, on long-run, *ivollr*, and short-run, *ivolsr*, components of idiosyncratic volatility, controlling for systematic volatility, *sysvol*, realized jumps measured by excess kurtosis of daily stock returns in the last month, *kur*. Regressions results in Panel B show the positive relation between realized jumps in a month, *kur*, and the number of news events in that month: *fnews, fnewsdi,* and *fnewsdiu* referring to all corporate news events, discretionary disclosure events and unusual discretionary disclosure events, respectively. Panel C shows the positive relation between short-run idiosyncratic volatility and the number of firm news events. Comparing with the effect of news arrival on limits of arbitrage, Panel D shows the negative relation between illiquidity, *illiq*, and the number of news events. To adjust for serial correlation, robust Newey and West (1987) t-statistics with a lag of 6 months are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Panel A. Stock jumps explanation

	dret
	(1)
Intercept	-0.021***
	(-2.60)
ivollr	-0.005***
	(-2.60)
ivolsr	-0.004
	(-1.59)
sysvol	-0.039
	(-0.55)
kur	-0.001***
	(-4.91)
Avg Adj R^2	0.0158

Panel B. Firm news events and realized jumps

	kur		
	(1)	(2)	(3)
Intercept	0.304***	0.343***	0.415***
	(12.44)	(13.09)	(11.99)
fnews	0.030***		
	(4.28)		
fnewsdi		0.023***	
		(3.40)	
fnewsdiu			0.086***
			(14.20)
Avg Adj R^2	0.0045	0.0026	0.0106

Panel C. Firm news events and short-run idiosyncratic volatility

	ivolsr		
	(1)	(2)	(3)
Intercept	-0.018***	-0.013***	-0.001
	(-5.75)	(-4.52)	(-0.30)
fnews	0.005***		
	(17.14)		
fnewsdi		0.004***	
		(14.95)	
fnewsdiu			0.010***
			(16.35)
Avg Adj R^2	0.0140	0.0085	0.0261

Panel D. Firm news events and illiquidity: a comparison

	log(illiq)		
	(1)	(2)	(3)
Intercept	-20.234***	-20.252***	-20.862***
	(-289.63)	(-276.90)	(-147.04)
fnews	-0.237***		
	(-11.56)		
fnewsdi		-0.249***	
		(-12.05)	
fnewsdiu			-0.010**
			(-2.04)
Avg Adj R^2	0.1150	0.1217	0.0111

Table 5. The influence of option transaction costs

This table studies the pricing effects of idiosyncratic volatility and its two components in either the high-cost subsample, the low-cost subsample or the full sample. The low-cost (high-cost) subsample consists of options with option bid-ask spread below (above) the 25th percentile in each month. Panel A reports results of Fama–MacBeth regressions of delta-hedged option returns, *dret*, on long-run, *ivollr*, and short-run, *ivolsr*, components of idiosyncratic volatility, *ivol*, controlling for systematic volatility, *sysvol*, for each subsample. Panel B reports the equal-weighted average option return differentials based on sorting *ivol*, *ivollr*, or *ivolsr*, into quintiles for each subsample. Both panels A and B rely on option prices calculated as the option bid-ask midpoint price. Panel C reports the returns after transaction cost of the option strategies that buy the bottom quintile and sell the top quintile of options sorted on *ivol*, *ivollr*, or *ivolsr*. To account for transaction costs, we follow prior literature to assume the ratio of effective option bid–ask spread to quoted spread to be 20%. Robust Newey and West (1987) t-statistics with a lag of 6 months are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Panel A. Regressions of option returns in high-cost and low-cost subsamples

	dret (High-cost options)		dret (Low-cost options)	
	(1)	(2)	(3)	(4)
Intercept	-0.031***	-0.030***	-0.009	0.000
	(-4.97)	(-3.67)	(-0.99)	(0.02)
log(ivol)	-0.006***		-0.003*	
	(-5.22)		(-1.74)	
ivollr		-0.006***		-0.001
		(-3.53)		(-0.47)
ivolsr		-0.008***		-0.015***
		(-3.01)		(-4.32)
sysvol	-0.070	-0.055	-0.067	-0.087
	(-0.88)	(-0.71)	(-0.63)	(-0.82)
Avg Adj R^2	0.0121	0.0141	0.0222	0.0249

Panel B. Portfolio sorting analysis in high-cost and low-cost subsamples

	dret (High-cost options)			dret (Low-cost options)		
	(1) - Low	(5) - High	(5) - (1) (t-value)	(1) - Low	(5) - High	(5) - (1) (t-value)
ivol	-0.0012	-0.0122	-0.0110*** (-4.59)	0.0038	-0.0026	-0.0064** (-2.14)
ivollr	-0.0013	-0.0114	-0.0100*** (-3.78)	0.0037	-0.0011	-0.0048 (-1.45)
ivolsr	-0.0028	-0.0089	-0.0062*** (-6.47)	0.0042	-0.0020	-0.0062*** (-4.54)

Panel C. Returns to option trading strategies after transaction costs

	Option strategy returns after transaction costs		
	(1) - Full sample	(2) - High-cost subsample	(3) - Low-cost subsample
ivol	0.0025 (1.10)	0.0024 (1.08)	0.0048 (1.62)
ivollr	0.0017 (0.70)	0.0012 (0.48)	0.0032 (0.97)
ivolsr	-0.0002 (0.00)	-0.0020* (-1.78)	0.0046*** (3.42)

Table 6. Explanation for the relation between idiosyncratic volatility and option returns

This table reports results of Fama–MacBeth regressions of delta-hedged option returns, *dret*, on long-run, *ivollr*, and short-run, *ivolsr*, components of idiosyncratic volatility, *ivol*, controlling for systematic volatility, *sysvol*, Amihud illiquidity measure, *illiq*, and realized jumps, *kur*. Column (1) shows that controlling for both mechanisms, limits of arbitrage and realized jumps, can eliminate the pricing of idiosyncratic volatility, while columns (2) and (3) show that controlling for only one of the two mechanisms cannot eliminate the pricing of idiosyncratic volatility. To adjust for serial correlation, robust Newey and West (1987) t-statistics with a lag of 6 months are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	dret		
	(1)	(2)	(3)
Intercept	-0.056***	-0.061***	-0.021***
	(-5.87)	(-6.67)	(-3.12)
log(ivol)	-0.001	-0.003**	-0.004***
	(-0.55)	(-2.24)	(-3.29)
sysvol	-0.058	-0.061	-0.056
	(-0.80)	(-0.83)	(-0.78)
log(illiq)	-0.002***	-0.002***	
	(-5.84)	(-5.50)	
kur	-0.001***		-0.001***
	(-5.38)		(-4.11)
Avg Adj R^2	0.0178	0.0165	0.0142

Table 7. Up and down markets

This table reports results of Fama–MacBeth regressions, for the up-market and down-market subsamples, of delta-hedged option returns, *dret*, on long-run, *ivollr*, and short-run, *ivolsr*, components of idiosyncratic volatility, controlling for systematic volatility, *sysvol*, Amihud illiquidity measure, *illiq*, realized jumps, *kur*. To adjust for serial correlation, robust Newey and West (1987) t-statistics are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	dret (Up market subsample)			dret (Down market subsample)		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.029***	-0.065***	-0.026***	-0.011	-0.035	-0.008
	(-3.35)	(-5.76)	(-2.87)	(-0.56)	(-1.53)	(-0.39)
ivollr	-0.007***	-0.002	-0.006***	-0.001	0.002	-0.001
	(-3.32)	(-0.78)	(-2.84)	(-0.40)	(0.60)	(-0.21)
ivolsr	-0.008***	-0.011***	-0.003	-0.013**	-0.016***	-0.008
	(-2.65)	(-3.37)	(-0.92)	(-2.23)	(-2.59)	(-1.22)
sysvol	-0.111	-0.149*	-0.100	0.140	0.167	0.144
	(-1.45)	(-1.93)	(-1.29)	(0.95)	(1.15)	(0.97)
log(illiq)		-0.003***			-0.002*	
		(-6.36)			(-1.95)	
kur			-0.001***			-0.001*
			(-4.61)			(-1.90)
Avg Adj R^2	0.0120	0.0153	0.0126	0.0241	0.0283	0.0253

Table 8. Option demand analysis

This table reports the results on Fama–MacBeth regressions of the end-user net option demand, *demand*, calculated as the difference between customer buy volume and sell volume (see appendix Table IA1 for variable details), on Amihud illiquidity, *illiq*, or realized jumps measured by excess kurtosis of daily returns in the last month, *kur*. Results are reported for full sample, up-market subsample and down-market subsample. To adjust for serial correlation, robust Newey and West (1987) t-statistics are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	demand (Full sample)			demand (Up market subsample)	demand (Down market subsample)
	(1)	(2)	(3)	(4)	(5)
Intercept	91.220**	-5.450**	83.332**	95.123**	42.997
	(2.50)	(-2.49)	(2.30)	(2.05)	(0.68)
log(illiq)	4.224**		3.923**	4.422**	2.22
	(2.51)		(2.31)	(2.10)	(0.73)
kur		1.940***	1.905***	1.905***	1.905*
		(4.70)	(5.40)	(4.49)	(1.67)
Avg Adj R^2	0.0048	0.0040	0.0089	0.0101	0.0048

Table 9. Decomposition of the economic mechanisms into intercept, common and residual components

In this table, each of the two economic mechanisms is decomposed into intercept, common component (the component comoving with the market average) and residual component (the component unrelated to the market average). The following Fama–MacBeth regressions examine the explaining powers of illiquidity intercept, *illiqintercept*, common illiquidity, *illiqcom*, residual illiquidity, *illiqres*, stock jumps intercept, *kurintercept*, common stock jumps, *kurcom*, residual stock jumps, *kurres* in the relations between long-run, *ivollr*, and short-run, *ivolsr*, idiosyncratic volatilities and delta-hedged option returns, *dret*. To adjust for serial correlation, robust Newey and West (1987) t-statistics with a lag of 6 months are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	dret			
	(1)	(2)	(3)	(4)
Intercept	-0.010	-0.024***	-0.024***	-0.024***
	(-1.31)	(-3.00)	(-2.78)	(-2.85)
ivollr	-0.002	-0.005***	-0.005***	-0.005***
	(-1.41)	(-3.04)	(-2.91)	(-2.89)
ivolsr	-0.011***	-0.010***	-0.009***	-0.004
	(-4.36)	(-3.72)	(-3.17)	(-1.54)
sysvol	-0.092	-0.047	-0.046	-0.031
	(-1.32)	(-0.67)	(-0.70)	(-0.46)
illiqintercept	-0.435***	-0.045**		
	(-5.87)	(-1.97)		
illiqcom	-0.340***			
	(-5.74)			
illiqres		-0.125***		
		(-3.63)		
kurintercept			-0.001	-0.000
			(-0.34)	(-0.28)
kurcom			0.007	
			(0.83)	
kurres				-0.001***
				(-4.68)
Avg Adj R^2	0.0195	0.0185	0.0195	0.0179

Table 10. Common and residual components of illiquidity

This table shows the relations between the two components (common and residual) of illiquidity and the components (intercept, common and residual) of idiosyncratic volatility. In particular, this table reports the results of Fama–MacBeth regressions of common illiquidity, *illiqcom*, or residual illiquidity, *illiqres*, on idiosyncratic volatility intercept (*ivolintercept*), common (*ivolcom*) and residual (*ivolres*) idiosyncratic volatility. Further, the loading of individual stock illiquidity on the aggregate illiquidity, *betacilliq*, and the loading of firm idiosyncratic volatility on the common idiosyncratic volatility, *betacivol*, are each estimated using the 60-month rolling windows, and a positive relation is found between the two loadings. To adjust for serial correlation, robust Newey and West (1987) t-statistics with a lag of 6 months are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	illiqcom	illiqres	betacilliq
	(1)	(2)	(3)
Intercept	-0.007***	0.000	0.494***
	(-7.45)	(-0.96)	(9.43)
ivolintercept	0.031***	0.001	
	(11.88)	(1.24)	
ivolcom	0.035***	0.001	
	(11.32)	(1.47)	
ivolres	0.001	0.003***	
	(1.19)	(6.89)	
betacivol			0.392***
			(9.10)
Avg Adj R^2	0.0657	0.0148	0.0112

Table 11. Common and residual components of stock jumps

This table examines how the common, *kurcom*, and residual, *kurres*, components of stock jumps are related to the arrival of corporate news. In the following Fama–MacBeth regressions, each of the stock jumps component is regressed on the number of firm news events, *fnews*, discretionary disclosure events, *fnewsdi*, and unusual discretionary disclosure events, *fnewsdiu*. To adjust for serial correlation, robust Newey and West (1987) t-statistics with a lag of 6 months are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	kurres			kurcom		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.142***	-0.104***	-0.002	0.390***	0.392***	0.428***
	(-9.86)	(-9.82)	(-0.37)	(9.11)	(9.15)	(12.80)
fnews	0.040***			-0.043		
	(10.33)			(-1.04)		
fnewsdi		0.034***			-0.044	
		(9.81)			(-1.04)	
fnewsdiu			0.083***			0.003**
			(14.88)			(2.18)
Avg Adj R^2	0.0062	0.0039	0.0104	0.0015	0.0010	0.0036

Table 12. Other possible explanations

This table reports results of Fama–MacBeth regressions of delta-hedged option returns, *dret*, on long-run, *ivollr,* and short-run, *ivolsr,* components of idiosyncratic volatility, controlling for systematic volatility, *sysvol*, return in the last month, *rev*, cumulative stock return from the prior second through 12th month, *mom*, volatility risk premium, *vrp*, risk-neutral skewness adjusted for firm-size, *skew*, average of the five highest daily stock returns in the last month, *max5*, skewness of daily stock returns in the last month, *sskew*. To adjust for serial correlation, robust Newey and West (1987) t-statistics with a lag of 6 months are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	dret				
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.028***	-0.017**	-0.021**	-0.019**	-0.025***
	(-3.65)	(-2.34)	(-2.17)	(-2.32)	(-3.24)
ivollr	-0.006***	-0.005***	-0.005**	-0.004***	-0.005***
	(-3.84)	(-3.47)	(-2.55)	(-2.64)	(-3.31)
ivolsr	-0.008***	-0.051***	-0.014***	-0.009***	-0.010***
	(-3.41)	(-11.76)	(-3.77)	(-2.80)	(-3.56)
sysvol	-0.128*	-0.755***	0.038	0.010	-0.047
	(-1.74)	(-8.18)	(0.34)	(0.13)	(-0.66)
rev	0.001				
	(0.13)				
mom	0.001				
	(0.36)				
vrp		0.061***			
		(14.56)			
skew			-0.001**		
			(-2.09)		
max5				-0.063	
				(-1.47)	
sskew					0.000
					(0.75)
Avg Adj R^2	0.0223	0.0248	0.0205	0.0168	0.0154

Table 13. Growth option explanation

This table reports results of Fama–MacBeth regressions of delta-hedged option returns, *dret*, on long-run, *ivollr*, and short-run, *ivolsr*, components of idiosyncratic volatility, controlling for systematic volatility, *sysvol*, market-to-book ratio, *mb*, Tobin's Q ratio, *tobinq*, R&D expenditure scaled by total assets, *rd*. To adjust for serial correlation, robust Newey and West (1987) t-statistics with a lag of 6 months are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	dret		
	(1)	(2)	(3)
Intercept	-0.035*** (-4.61)	-0.035*** (-4.20)	-0.026*** (-2.99)
ivollr	-0.008*** (-5.18)	-0.008*** (-4.56)	-0.006*** (-3.22)
ivolsr	-0.009*** (-3.40)	-0.009*** (-3.26)	-0.013*** (-3.37)
sysvol	-0.079 (-1.16)	-0.060 (-0.86)	-0.128* (-1.68)
log(mb)	0.001 (0.79)		
tobinq		0.000 (0.21)	
rd			-0.089** (-2.44)
Avg Adj R^2	0.0208	0.0192	0.0204

Table 14. Insights for stock returns

This table reports results of Fama–MacBeth regressions of stock returns, *sret*, on long-run, *ivollr*, and short-run, *ivolsr*, components of idiosyncratic volatility, *ivol*, controlling for recent month's Amihud illiquidity, *illiq*, and realized jumps measured by excess kurtosis of daily stock returns in the last month, *kur*. To adjust for serial correlation, robust Newey and West (1987) t-statistics with a lag of 6 months are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	sret		
	(1)	(2)	(3)
Intercept	-0.026*** (-3.23)	-0.024*** (-3.17)	-0.027*** (-3.32)
ivollr	-0.007*** (-3.66)	-0.007*** (-3.47)	-0.007*** (-3.74)
ivolsr	0.004** (2.56)	0.005*** (2.59)	0.002 (1.53)
log(illiq)		0.000 (0.55)	
kur			0.000*** (3.66)
Avg Adj R^2	0.0375	0.0433	0.0394

REFERENCES

Acharya, V. V., & Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, *77*(2), 375-410.

Adrian, T., & Rosenberg, J. (2008). Stock Returns and Volatility: Pricing the Short-Run and Long-Run Components of Market Risk. *The Journal of Finance*, *63*(6), 2997-3030.

Albuquerque, A. M. (2014). Do Growth-Option Firms Use Less Relative Performance Evaluation? *The Accounting Review*, *89*(1), 27-60.

Amaya, D., Christoffersen, P., Jacobs, K., & Vasquez, A. (2015). Does realized skewness predict the cross-section of equity returns? *Journal of Financial Economics*, *118*(1), 135-167.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31-56.

Andersen, T. G., Bollerslev, T., & Diebold, F. X. (2007). Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. *The review of economics and statistics*, *89*(4), 701-720.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance*, *61*(1), 259-299.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2009). High idiosyncratic volatility and low returns: International and further U.S. evidence. *Journal of Financial Economics*, *91*(1), 1-23.

Bakshi, G., & Kapadia, N. (2003). Delta-hedged gains and the negative market volatility risk premium. *The Review of Financial Studies*, *16*(2), 527-566.

Bakshi, G., Kapadia, N., & Madan, D. (2003). Stock return characteristics, Skew laws, and the differential pricing of individual equity options. *Review of Financial Studies*, *16*(1), 101-143.

Bali, T. G., Beckmeyer, H., Mörke, M., & Weigert, F. (2023). Option Return Predictability with Machine Learning and Big Data. *Review of Financial Studies*, *36*(9), 3548-3602.

Bali, T. G., Bodnaruk, A., Scherbina, A., & Tang, Y. (2018). Unusual News Flow and the Cross Section of Stock Returns. *Management Science*, *64*(9), 4137-4155.

Bali, T. G., & Murray, S. (2013). Does Risk-Neutral Skewness Predict the Cross Section of Equity Option Portfolio Returns? *Journal of Financial and Quantitative Analysis*, *48*(4), 1145-1171.

Bali, T. G., Peng, L., Shen, Y., & Tang, Y. (2013). Liquidity Shocks and Stock Market Reactions. *The Review of Financial Studies*, *27*(5), 1434-1485.

Barinov, A., & Chabakauri, G. (2023). Idiosyncratic Volatility, Growth Options, and the Cross-Section of Returns. *The Review of Asset Pricing Studies*, *13*(4), 653-690.

Beber, A., Brandt, M. W., & Kavajecz, K. A. (2009). Flight-to-Quality or Flight-to-Liquidity? Evidence from the Euro-Area Bond Market. *Review of Financial Studies*, *22*(3), 925-957.

Bégin, J. F., Dorion, C., & Gauthier, G. (2020). Idiosyncratic Jump Risk Matters: Evidence from Equity Returns and Options. *Review of Financial Studies*, *33*(1), 155-211.

Bekaert, G., Hodrick, R. J., & Zhang, X. Y. (2012). Aggregate Idiosyncratic Volatility. *Journal of Financial and Quantitative Analysis*, *47*(6), 1155-1185.

Berrada, T., & Hugonnier, J. (2013). Incomplete information, idiosyncratic volatility and stock returns. *Journal of Banking & Finance*, *37*(2), 448-462.

Bhamra, H. S., & Shim, K. H. (2017). Stochastic idiosyncratic cash flow risk and real options: Implications for stock returns. *Journal of Economic Theory*, *168*, 400-431.

Bollerslev, T., Law, T. H., & Tauchen, G. (2008). Risk, jumps, and diversification. *Journal of Econometrics*, *144*(1), 234-256.

Brandt, M. W., Brav, A., Graham, J. R., & Kumar, A. (2010). The Idiosyncratic Volatility Puzzle: Time Trend or Speculative Episodes? *The Review of Financial Studies*, *23*(2), 863-899.

Bushee, B. J., & Noe, C. F. (2000). Corporate Disclosure Practices, Institutional Investors, and Stock Return Volatility. *Journal of Accounting research*, *38*, 171-202.

Byun, S.-J., & Kim, D.-H. (2016). Gambling preference and individual equity option returns. *Journal of Financial Economics*, *122*(1), 155-174.

Cao, C., Simin, T., & Zhao, J. (2008). Can Growth Options Explain the Trend in Idiosyncratic Risk? *The Review of Financial Studies*, *21*(6), 2599-2633.

Cao, J., Chordia, T., & Zhan, X. T. (2021). The Calendar Effects of the Idiosyncratic Volatility Puzzle: A Tale of Two Days? *Management Science*, *67*(12), 7866–7887.

Cao, J., & Han, B. (2013). Cross section of option returns and idiosyncratic stock volatility. *Journal of Financial Economics*, *108*(1), 231-249.

Caporin, M., Kolokolov, A., & Renò, R. (2017). Systemic co-jumps. *Journal of Financial Economics*, *126*(3), 563-591.

Chen, B., Gan, Q., & Vasquez, A. (2024). Does the Options Market Underreact to Firms' Left-Tail Risk? *Journal of Financial and Quantitative Analysis*, 1-32.

Chordia, T., Roll, R., & Subrahmanyam, A. (2000). Commonality in liquidity. *Journal of Financial Economics*, *56*(1), 3-28.

Christoffersen, P., Jacobs, K., Ornthanalai, C., & Wang, Y. (2008). Option valuation with long-run and short-run volatility components. *Journal of Financial Economics*, *90*(3), 272-297.

Cooper, M. J., Gutierrez Jr., R. C., & Hameed, A. (2004). Market States and Momentum. *The Journal of Finance*, *59*(3), 1345-1365.

Cosemans, M., & Frehen, R. (2021). Salience theory and stock prices: Empirical evidence. *Journal of Financial Economics*, *140*(2), 460-483.

Dichev, I. D. (1998). Is the Risk of Bankruptcy a Systematic Risk? *The Journal of Finance*, *53*(3), 1131-1147.

Doukas, J. A., Chansog, K., & Pantzalis, C. (2010). Arbitrage Risk and Stock Mispricing. *The Journal of Financial and Quantitative Analysis*, *45*(4), 907-934.

Duarte, J., Jones, C. S., Khorram, M., Mo, H., & Wang, J. L. (2023). Too good to be true: Look-ahead bias in empirical options research. *Available at SSRN 4590083*.

Edmans, A., Goncalves-Pinto, L., Groen-Xu, M., & Wang, Y. B. (2018). Strategic News Releases in Equity Vesting Months. *Review of Financial Studies*, *31*(11), 4099-4141.

Eraker, B., Johannes, M., & Polson, N. (2003). The Impact of Jumps in Volatility and Returns. *The Journal of Finance*, *58*(3), 1269-1300.

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*, *47*(2), 427-465.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3-56.
Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1-22.
Fama, E. F., & MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, *81*(3), 607-636.
Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics*, *91*(1), 24-37.
Garcia, D. (2013). Sentiment during Recessions. *The Journal of Finance*, *68*(3), 1267-1300.
Gârleanu, N., Pedersen, L. H., & Poteshman, A. M. (2009). Demand-Based Option Pricing. *The Review of Financial Studies*, *22*(10), 4259-4299.
Golez, B., & Goyenko, R. (2022). Disagreement in the Equity Options Market and Stock Returns. *The Review of Financial Studies*, *35*(3), 1443-1479.
Goyal, A., & Saretto, A. (2009). Cross-section of option returns and volatility. *Journal of Financial Economics*, *94*(2), 310-326.
Guiso, L., Sapienza, P., & Zingales, L. (2018). Time varying risk aversion. *Journal of Financial Economics*, *128*(3), 403-421.
Han, Y. F., Hu, T., & Lesmond, D. A. (2015). Liquidity Biases and the Pricing of Cross-Sectional Idiosyncratic Volatility around the World. *Journal of Financial and Quantitative Analysis*, *50*(6), 1269-1292.
Han, Y. F., & Lesmond, D. (2011). Liquidity Biases and the Pricing of Cross-sectional Idiosyncratic Volatility. *Review of Financial Studies*, *24*(5), 1590-1629.
Herskovic, B., Kelly, B., Lustig, H., & Van Nieuwerburgh, S. (2016). The common factor in idiosyncratic volatility: Quantitative asset pricing implications. *Journal of Financial Economics*, *119*(2), 249-283.
Heston, S. L., Jones, C. S., Khorram, M., Li, S., & Mo, H. (2023). Option Momentum. *The Journal of Finance*, *78*(6), 3141-3192.
Hou, K. W., & Loh, R. K. (2016). Have we solved the idiosyncratic volatility puzzle? *Journal of Financial Economics*, *121*(1), 167-194.
Huang, W., Liu, Q., Rhee, S. G., & Zhang, L. (2009). Return Reversals, Idiosyncratic Risk, and Expected Returns. *The Review of Financial Studies*, *23*(1), 147-168.
Jiang, G. J., Xu, D., & Yao, T. (2009). The Information Content of Idiosyncratic Volatility. *Journal of Financial and Quantitative Analysis*, *44*(1), 1-28.
Kacperczyk, M., Van Nieuwerburgh, S., & Veldkamp, L. (2016). A Rational Theory of Mutual Funds' Attention Allocation. *Econometrica*, *84*(2), 571-626.
Kapadia, N., & Zekhnini, M. (2019). Do idiosyncratic jumps matter? *Journal of Financial Economics*, *131*(3), 666-692.
Karolyi, G. A., Lee, K.-H., & van Dijk, M. A. (2012). Understanding commonality in liquidity around the world. *Journal of Financial Economics*, *105*(1), 82-112.
Kumar, A. (2009). Who gambles in the stock market? *The Journal of Finance*, *64*(4), 1889-1933.
Lee, K. H. (2011). The world price of liquidity risk. *Journal of Financial Economics*, *99*(1), 136-161.
Liu, Y. (2022). The short-run and long-run components of idiosyncratic volatility and stock returns. *Management Science*, *68*(2), 1573-1589.
Liu, Y. K., & Matthies, B. (2022). Long-Run Risk: Is It There? *Journal of Finance*, *77*(3), 1587-1633.

Maslar, D. A., Serfling, M., & Shaikh, S. (2021). Economic Downturns and the Informativeness of Management Earnings Forecasts. *Journal of Accounting research*, *59*(4), 1481-1520.
Merton, R. C. (1987). A Simple Model of Capital Market Equilibrium with Incomplete Information. *The Journal of Finance*, *42*(3), 483-510.
Nagar, V., Schoenfeld, J., & Wellman, L. (2019). The effect of economic policy uncertainty on investor information asymmetry and management disclosures. *Journal of Accounting and Economics*, *67*(1), 36-57.
Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, *55*(3), 703-708.
O'Donovan, J., & Yu, G. Y. (2024). Transaction Costs and Cost Mitigation in Option Investment Strategies. *Available at SSRN 4806038*.
Peterson, D. R., & Smedema, A. R. (2011). The return impact of realized and expected idiosyncratic volatility. *Journal of Banking & Finance*, *35*(10), 2547-2558.
Pontiff, J. (2006). Costly arbitrage and the myth of idiosyncratic risk. *Journal of Accounting and Economics*, *42*(1), 35-52.
Ramachandran, L. S., & Tayal, J. (2021). Mispricing, short-sale constraints, and the cross-section of option returns. *Journal of Financial Economics*, *141*(1), 297-321.
Ruan, X. F. (2020). Volatility-of-volatility and the cross-section of option returns. *Journal of Financial Markets*, *48*.
Sadka, R., & Scherbina, A. (2007). Analyst Disagreement, Mispricing, and Liquidity. *The Journal of Finance*, *62*(5), 2367-2403.
Shleifer, A., & Vishny, R. W. (1997). The Limits of Arbitrage. *The Journal of Finance*, *52*(1), 35-55.
Spiegel, M. I., & Wang, X. (2005). Cross-sectional variation in stock returns: Liquidity and idiosyncratic risk. *Working paper, Yale University*.
Stambaugh, R. F., Yu, J. F., & Yuan, Y. (2015). Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle. *Journal of Finance*, *70*(5), 1903-1948.
Stein, J. (1989). Overreactions in the Options Market. *The Journal of Finance*, *44*(4), 1011-1023.
Tian, M., & Wu, L. R. (2023). Limits of Arbitrage and Primary Risk-Taking in Derivative Securities. *Review of Asset Pricing Studies*, *13*(3), 405-439.
Todorov, V. (2009). Variance Risk-Premium Dynamics: The Role of Jumps. *The Review of Financial Studies*, *23*(1), 345-383.
Vasquez, A., & Xiao, X. (2024). Default Risk and Option Returns. *Management Science*, *70*(4), 2144-2167.
Yan, S. (2011). Jump risk, stock returns, and slope of implied volatility smile. *Journal of Financial Economics*, *99*(1), 216-233.
Zhan, X., Han, B., Cao, J., & Tong, Q. (2022). Option return predictability. *The Review of Financial Studies*, *35*(3), 1394-1442.
Zhou, G. F., & Zhu, Y. Z. (2015). Macroeconomic Volatilities and Long-Run Risks of Asset Prices. *Management Science*, *61*(2), 413-430.

INTERNET APPENDIXES

Table IA1. Variable definitions

This table provides definition of the variables used in our study.

	Definition
dret	Delta-hedged option return is return to a portfolio consisting of a long position of one call option (with price C) combined with a short position in delta (Δ) shares of underlying equity (with price S) and is calculated as portfolio gain until maturity scaled by $(\Delta * S\text{-}C)$ (Cao & Han, 2013).
ivol	Idiosyncratic volatility is measured as the standard deviation of the residuals in the regression of daily excess stock return in each month on the three Fama and French factors (Liu, 2022).
ivollr	Long-run component of idiosyncratic volatility is estimated by using Kalman filter with the specifications in Liu (2022).
ivolsr	Short-run component of idiosyncratic volatility is estimated by using Kalman filter with the specifications in Liu (2022).
sysvol	Systematic volatility is calculated as $\sqrt{tvol^2 - ivol^2}$, where *tvol* is the monthly total volatility and *ivol* is the idiosyncratic volatility of stock returns (Cao & Han, 2013).
ivollr12	Long-run idiosyncratic volatility estimated 12 months ago.
ivolsr12	Short-run idiosyncratic volatility estimated 12 months ago.
ivollr24	Long-run idiosyncratic volatility estimated 24 months ago.
ivolsr24	Short-run idiosyncratic volatility estimated 24 months ago.
size	Market capitalization is stock price multiplied by number of shares outstanding (Cao & Han, 2013).
price	Stock close price (Cao & Han, 2013).
illiq	Amihud illiquidity of each month is calculated as average of the ratio of absolute daily return to daily dollar trading volume (Amihud, 2002).
kur	Realized stock jumps measured by the excess kurtosis of daily stock return in the last month (Bali et al., 2023).
fnews	Number of corporate news events in a month (Edmans et al., 2018).
fnewsdi	Number of corporate discretionary disclosure events in a month (Edmans et al., 2018).
fnewsdiu	Unusual discretionary disclosure measured as the number of discretionary disclosure events in a month in excess of its trailing 4-month average (Bali et al., 2018).
demand	End-user net option demand computed from CBOE database. The CBOE database reports trading made by two groups, “customers” and “firms”, the former of which

	are retail investors and institutional investors, while the latter of which often act as market makers. Our calculation is based on the "customer" group. There are four types of order: buy to open a new long position (OB), buy to close an existing short position (CB), sell to open a new short position (OS), and sell to close an existing long position (CS); net demand is computed as the difference between buy volumes (OB+CB) and sell volumes (OS+CS) for all strike prices on the option portfolio formation date.
rev	Stock return in the previous month (Cao & Han, 2013).
mom	Cumulative stock return from the prior second through 12th month (Cao & Han, 2013).
vrp	Volatility risk premium is computed as standard deviation of realized return in a month using daily data minus option implied volatility (Cao & Han, 2013).
skew	Option implied risk-neutral skewness is extracted from OTM call and put options using the method of Bakshi et al. (2003).
max5	Average of the five highest daily stock returns in a month (Zhan et al., 2022).
mb	Market-to-book ratio is computed as the ratio of total assets minus total common equity plus market capitalization divided by total assets (Cao et al., 2008).
tobinq	Tobin's Q is computed as the ratio of market capitalization plus preferred stock plus current liabilities minus current asset plus long-term debt divided by total assets (Cao et al., 2008).
rd	R&D expense scaled by total assets (Albuquerque, 2014).
cfv	Cash flow variance is computed as the variance of the cash flow to market capitalization ratio over the 60-month window (Zhan et al., 2022).
ch	Cash-to-assets ratio is calculated as corporate cash holdings divided by total assets (Zhan et al., 2022).
disp	Earnings forecast dispersion is the standard deviation divided by absolute value of the mean of annual EPS forecasts (Zhan et al., 2022).
issue1y	Number of new shares issued within one year (Zhan et al., 2022).
issue5y	Number of new shares issued within five years (Zhan et al., 2022).
pm	Profit margin is earnings before interest and tax divided by revenues (Zhan et al., 2022).
profit	Profitability is income before extraordinary items divided by book equity (Zhan et al., 2022).
tef	Total external financing is net share issuance minus cash dividends plus net debt issuance, scaled by total assets (Zhan et al., 2022).
zs	Z-score is defined by the formula initiated by Dichev (1998). Particularly, Z-score equals 1.2*working capital divided by total assets + 1.4*retained earnings divided by total assets + 3.3*EBIT divided by total assets + 0.6*market value of equity divided by book value of total liabilities + revenues divided by total assets (Zhan et al., 2022).

Table IA2. Control for firm characteristics in Zhan et al. (2022)

This table reports results of Fama–MacBeth regressions of delta-hedged option returns, *dret*, on long-run, *ivollr*, and short-run, *ivolsr*, components of idiosyncratic volatility, controlling for systematic volatility, *sysvol*, cash flow variance, *cfv*, cash-to-assets ratio, *ch*, earnings forecast dispersion, *disp*, one-year and five-year new share issues, *issue1y* and *issue5y*, profit margin, *pm*, profitability, *profit*, total external financing, *tef*, z-score, *zs*. To adjust for serial correlation, robust Newey and West (1987) t-statistics are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	dret								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-0.042***	-0.021***	-0.019**	-0.027***	-0.031***	-0.025***	0.028***	-0.035***	-0.034***
	(-5.09)	(-2.61)	(-2.43)	(-3.22)	(-3.82)	(-3.3)	(-3.57)	(-5.00)	(-4.15)
ivollr	-0.009***	-0.005***	-0.004**	-0.006***	-0.007***	-0.005***	-0.006***	-0.008***	-0.007***
	(-5.04)	(-3.21)	(-2.42)	(-3.35)	(-4.05)	(-3.38)	(-3.78)	(-5.54)	(-4.39)
ivolsr	-0.009***	-0.011***	-0.011***	-0.009***	-0.008***	-0.012***	-0.011***	-0.011***	-0.009***
	(-3.16)	(-4.48)	(-4.4)	(-3.41)	(-3.15)	(-4.33)	(-3.81)	(-3.69)	(-3.39)
sysvol	0.037	-0.034	-0.049	-0.037	-0.019	0.005	-0.031	-0.012	0.037
	(0.43)	(-0.47)	(-0.64)	(-0.52)	(-0.24)	(0.06)	(-0.42)	(-0.17)	(0.48)
cfv	-0.002*								
	(-1.95)								
ch		-0.011**							
		(-2.21)							
disp			-0.001						
			(-0.97)						
issue1y				-0.000***					
				(-3.55)					
issue5y					-0.000***				
					(-3.08)				
pm						0.001***			
						(4.98)			
profit							0.008***		
							(2.76)		
tef								0.007	
								(1.59)	

zs									-0.000 (-1.4)
Avg Adj R^2	0.0183	0.0201	0.0161	0.0151	0.0158	0.0172	0.0165	0.0183	0.0162

Table IA3. Volatility forecast with long-run and short-run idiosyncratic volatility components

This table reports the results of Fama–MacBeth regressions of next month's total volatility, *leadtvol*, on long-run, *ivollr*, and short-run, *ivolsr*, components of idiosyncratic volatility, *ivol*, and systematic volatility, *sysvol*. To adjust for serial correlation, robust Newey and West (1987) *t*-statistics are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	leadtvol			
	(1)	(2)	(3)	(4)
Intercept	0.032***	0.083***	0.014***	0.087***
	(30.4)	(25.19)	(20.60)	(26.21)
log(ivol)	0.011***			
	(17.37)			
ivollr		0.015***		0.016***
		(20.33)		(21.12)
ivolsr			-0.008***	-0.015***
			(-19.11)	(-30.36)
sysvol	0.384***	0.273***	0.818***	0.294***
	(24.44)	(16.99)	(60.56)	(21.25)
Avg Adj R^2	0.3067	0.3591	0.2157	0.3852

Table IA4. Alternative portfolio holding period robustness check

In this table, we use alternative measure of delta-hedged option returns based on portfolios that are formed at the beginning of each month and mature on option expiration day of that month (rather than of next month). We report the results of Fama–MacBeth regressions of this alternative measure of delta-hedged option returns, *dret*, on idiosyncratic volatility, *ivol*, controlling for systematic volatility, *sysvol*, Amihud illiquidity measure, *illiq*, realized stock jumps measured by the excess kurtosis of daily stock return in the last month, *kur*. To adjust for serial correlation, robust Newey and West (1987) t-statistics are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	dret			
	(1)	(2	(3)	(4)
Intercept	-0.019***	-0.047***	-0.013***	-0.043***
	(-5.20)	(-7.81)	(-3.17)	(-6.87)
log(ivol)	-0.004***	-0.001*	-0.003***	0.001
	(-5.00)	(-1.85)	(-2.81)	(0.65)
sysvol	0.086	0.092*	0.078	0.088*
	(1.64)	(1.71)	(1.54)	(1.70)
log(illiq)		-0.002***		-0.002***
		(-6.93)		(-7.48)
kur			-0.001***	-0.001***
			(-4.76)	(-6.20)
Avg Adj R^2	0.0108	0.0149	0.0123	0.0167

Table IA5. Delta-hedged put option returns

This table reports the results of Fama–MacBeth regressions of delta-hedged put option returns, *dretp*, on idiosyncratic volatility, *ivol*, controlling for systematic volatility, *sysvol*, Amihud illiquidity measure, *illiq*, realized stock jumps measured by the excess kurtosis of daily stock return in the last month, *kur*. To adjust for serial correlation, robust Newey and West (1987) t-statistics are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	dretp			
	(1)	(2)	(3)	(4)
Intercept	-0.02***	-0.045***	-0.015**	-0.041***
	(-3.85)	(-6.13)	(-2.57)	(-5.34)
log(ivol)	-0.005***	-0.003**	-0.004***	-0.001
	(-4.70)	(-2.32)	(-3.00)	(-0.82)
sysvol	0.002	-0.002	0.003	0.000
	(0.02)	(-0.03)	(0.04)	(0.01)
log(illiq)		-0.002***		-0.002***
		(-4.66)		(-4.94)
kur			-0.001***	-0.001***
			(-4.13)	(-4.95)
Avg Adj R^2	0.0118	0.015	0.0128	0.0161

Table IA6. Common risk factors and return spreads based on idiosyncratic volatility components

This table reports results of time series regressions of return spreads between high and low volatility groups sorted by either idiosyncratic volatility, *ivol*, long-run idiosyncratic volatility, *ivollr*, or short-run idiosyncratic volatility, *ivolsr*, on the change of VIX index, *Δvix*, and Fama and French (2015) common factors, including market risk premium, *mrp*, small minus big, *smb*, high minus low, *hml*, conservative minus aggressive, *cma*, robust minus weak, *rmw*, factors. To adjust for serial correlation, robust Newey and West (1987) t-statistics are reported in parentheses. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	ivol spread	ivollr spread	ivolsr spread
	(1)	(2)	(3)
Alpha	-0.0088***	-0.0081***	-0.0063***
	(-3.49)	(-3.00)	(-6.03)
mrp	-0.0006	-0.0006	-0.0004
	(-1.05)	(-0.87)	(-0.81)
smb	0.0022***	0.0025***	0.0004
	(2.77)	(2.81)	(1.24)
hml	-0.0004	-0.0005	0.0008
	(-0.30)	(-0.38)	(1.37)
cma	-0.0008	-0.0011	0.0007
	(-0.75)	(-0.91)	(1.33)
rmw	-0.0015	-0.0016	-0.0011
	(-0.84)	(-0.75)	(-1.33)
Δvix	0.0008	0.0011*	-0.0008
	(1.46)	(1.94)	(-1.55)
Adj R^2	0.0372	0.0449	0.0778