Essays in Option Pricing

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Discipline of Finance

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July 2025

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This is to certify that I have made a substantial original contribution to the three studies presented in this thesis, including research idea generation, empirical data analysis, and drafting.

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As supervisor for the candidature upon which this thesis is based, I can confirm that the authorship attribution statements above are correct.

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ABSTRACT

This thesis consists of three standalone studies on option pricing. The first study explores the dynamics of idiosyncratic volatility in option returns over different horizons. 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.

The second study explains the recent puzzle of option momentum from a behavioral perspective. Motivated by the frog-in-the-pan literature, we show that option momentum exists because investors are inattentive to past option return information that arrives continuously in small amounts. Our results reveal that option momentum strengthens in continuous information. Conversely, if past option returns are accumulated suddenly and dramatically, discrete information will attract investors' attention and induce option price adjustment that eliminates option momentum. The monthly momentum profitability monotonically increases from an insignificant 0.62% for options with discrete information to 11.00% for options with continuous information during the formation period. Our study also shows that continuous information can explain the persistence of option momentum over long horizons.

The third study documents novel co-movement patterns in option returns. We show that option returns co-move among firms linked by production complementarity, industry and shared analyst coverage. The co-movements in delta-neutral option returns can be explained by the option common factors, especially the factors based on the implied-historical volatility difference and volatility-of-volatility. The stock market common factors, especially the market risk premium, can explain the co-movements in raw option returns but cannot explain the co-movements in delta-neutral returns. The co-movements in raw call returns intensify in bull markets, whereas the co-movements in raw put returns intensify in bear markets. There are also peer option momentum effects among economically linked firms.

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1.1. 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

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[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).

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 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

[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).

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. 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) and 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 understand the puzzle of the discrepancy between the theory prediction of Merton (1987) and empirical asset pricing findings.

The chapter proceeds as follows. Section 1.2 discusses the data used in the study and the design of empirical analysis. Section 1.3 presents the empirical results, and Section 1.4 concludes.

1.2. Data and model description

1.2.1. Data

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 returns 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) and Liu (2022):

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

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

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

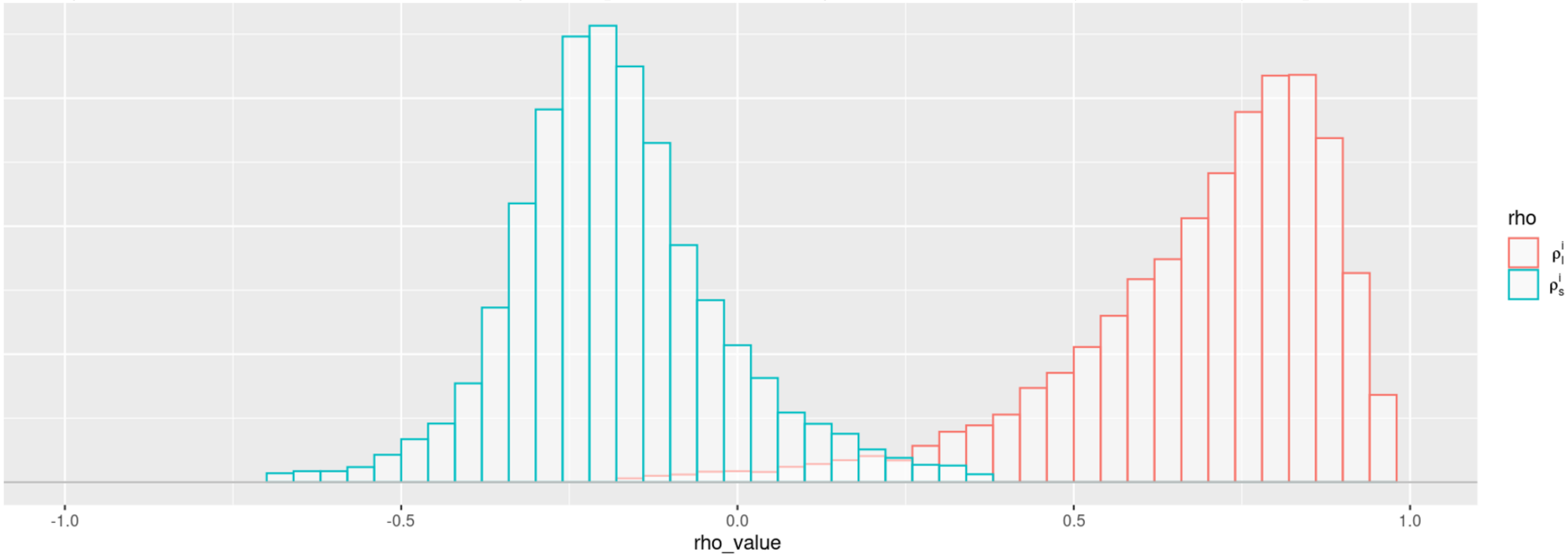
In models (1)-(3), $\log ivol_t^i$ (the log of idiosyncratic volatility of firm i in month t) is decomposed into the sum of two time-series components, $ivollr_t^i$ and $ivolsr_t^i$; each follows a first-order autoregressive AR(1) process. The short-run component has a zero mean, while the long-run component 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 and short-run idiosyncratic volatilities' option pricing implications.

We execute the decomposition and illustrate the distribution of the autoregressive parameters of long-run and short-run components in Figure 1.1. 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.

Figure 1.1. 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.



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

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 in each month and select the options which mature on the option expiration day in the next month (the 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). We follow the prior literature to not rebalance the option portfolios during the holding period to reduce the impact of transaction costs (Bali & Murray, 2013; Goyal & Saretto, 2009; O'Donovan & Yu, 2024; Vasquez & Xiao, 2024; Zhan et al., 2022). Our 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.

1.2.2. Model specification

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. Appendix Table A1.1 summarizes the definition of variables used in our study.

1.3. Empirical results

1.3.1. Summary statistics

Table 1.1. 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 1.1 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.

1.3.2. Long-run and short-run components of idiosyncratic volatility and option returns

We discuss our baseline results in this section. Panel A of Table 1.2 shows the results of the 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 1.1) is associated with -0.34% (i.e., -0.006×0.560) monthly returns to the delta-hedged option portfolio, and one standard deviation of short-run idiosyncratic volatility (0.171 as shown in Table 1.1) is associated with -0.21% (i.e., -0.012×0.171) 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 1.1). 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)).

Table 1.2. Long-run and short-run idiosyncratic volatility components and option returns

In this table, Panel A reports results of the 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

In panel B of Table 1.2, 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 1.2, 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.

In this study, we focus on delta-hedged returns. One concern is whether adopting a gamma-neutral hedging approach could change the results. Methodologically, delta-hedging the options helps reduce the impact of small underlying stock movements on the performance of the option positions, making the option performance strongly reflect the effect of option expensiveness and therefore improving the interpretation of the results. Meanwhile, gamma-hedging helps reduce the impact of large stock price movements on the performance of the options. Therefore, we expect that gamma-hedging will not alter our results since it only makes option returns more reflective of the option expensiveness and make the relations between idiosyncratic volatility components and option returns more pronounced (in a similar way as delta-hedging does).

1.3.3. 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.

Table 1.3. What explains the effect of long-run idiosyncratic volatility

In this table, Panel A reports results of the 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

In panel A of Table 1.3, 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 1.2. 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 1.3 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.

1.3.4. 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 and 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.

Table 1.4. What explains the effect of short-run idiosyncratic volatility

In this table, Panel A reports results of the 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

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 1.4 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 (probably because stock return skewness is usually priced in the OTM rather than ATM options) and the result is shown in Table 1.12.

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 1.4 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 1.4 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 1.4 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.

1.3.5. 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.

Table 1.5. 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 the 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)

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 1.5, 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 1.5 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 1.5 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

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

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.

One concern in option trading is the costs associated with daily rebalancing. Though we do not adopt daily rebalancing (to maximize the trading profitability and to follow the convention in the prior literature (Bali & Murray, 2013; Goyal & Saretto, 2009; O'Donovan & Yu, 2024; Vasquez & Xiao, 2024; Zhan et al., 2022)), it may be useful to figure out which idiosyncratic volatility component has a strong relationship with the trading costs associated with delta-hedging. Our results in Table A1.3 help answer this question. Fundamentally, to keep the option portfolio delta-neutral, investors must sell or buy more shares of the underlying asset when its price increases or decreases. The more frequently investors adjust their portfolios, the higher the transaction costs. Therefore, daily rebalancing costs are positively associated with the volatility of the underlying asset during the option lifespan. As shown in Table A1.3, the future volatility is positively related to long-run idiosyncratic volatility and negatively related to short-run idiosyncratic volatility (being consistent with prior literature). The results imply that the daily rebalancing costs should be strongly associated with the long-run component rather than the short-run component. This further highlights the key insight of our paper that the trading strategy related to short-run idiosyncratic volatility is more likely to be profitable than the one related to long-run idiosyncratic volatility, especially when daily rebalancing is considered.

1.3.6. 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 the combination of those two channels can fully explain the well-established relationship between idiosyncratic volatility and delta-hedged option returns. Table 1.6 assesses this conjecture.

Table 1.6. Explanation for the relation between idiosyncratic volatility and option returns

This table reports results of the 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

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

[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.

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.

1.3.7. 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 1.7, we rerun the baseline regression with the subsamples of options written in up markets and down markets separately.

Table 1.7. Up and down markets

This table reports results of the 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

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 1.7 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

[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.

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 1.7 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 (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 1.3.4. 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.

1.3.8. 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 1.8, 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). Appendix Table A1.1 provides details of the option demand variable construction. The results in columns (1) to (3) of Table 1.8 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.

Table 1.8. Option demand analysis

This table reports the results on the 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 A1.1 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

We also examine the end-user option demand in up and down markets. Columns (4) and (5) of Table 1.8 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 1.7 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.

1.3.9. 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.

Table 1.9. 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

In Table 1.9, 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.

Table 1.10. 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 the 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

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 1.10 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 1.10, 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.

Table 1.11. 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

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 1.9), we further show in Table 1.11 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.

1.3.10. 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 1.12, 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 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*

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[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.

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 1.12, 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.

[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.

Table 1.12. Other possible explanations

This table reports results of the 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 1.13. Growth option explanation

This table reports results of the 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***	-0.035***	-0.026***
	(-4.61)	(-4.20)	(-2.99)
ivollr	-0.008***	-0.008***	-0.006***
	(-5.18)	(-4.56)	(-3.22)
ivolsr	-0.009***	-0.009***	-0.013***
	(-3.40)	(-3.26)	(-3.37)
sysvol	-0.079	-0.060	-0.128*
	(-1.16)	(-0.86)	(-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

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 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 1.13 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 1.2) 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 Appendix Table A1.2, 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 A1.2 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.

1.3.11. 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 1.14, 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.

Table 1.14. Insights for stock returns

This table reports results of the 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***	-0.024***	-0.027***
	(-3.23)	(-3.17)	(-3.32)
ivollr	-0.007***	-0.007***	-0.007***
	(-3.66)	(-3.47)	(-3.74)
ivolsr	0.004**	0.005***	0.002
	(2.56)	(2.59)	(1.53)
log(illiq)		0.000	
		(0.55)	
kur			0.000***
			(3.66)
Avg Adj R^2	0.0375	0.0433	0.0394

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 1.13).

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.

1.3.12. 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 Appendix Table A1.3, 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 A1.4, 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 A1.4, 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 A1.5, 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 Appendix Table A1.6, we revisit the option return spreads based on portfolio sorting as discussed in Table 1.2 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) and 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.

1.4. 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.

Chapter 2. Frog in the Pan and Option Momentum

2.1. Introduction

Whether asset returns can be predicted is a central research question in finance. A striking piece of evidence of return predictability is momentum, which is the tendency of assets with good past performance to outperform in the future. The momentum effect is among the most pervasive phenomena and is considered the premier anomaly by Fama and French (2008). Much effort has been made to explain momentum in stock returns (Da et al., 2014; Favilukis & Zhang, 2024; Hoberg et al., 2022). Despite this, little is known about the cause of momentum in option returns discovered by Heston et al. (2023).

According to the behavioral finance literature, limited cognitive resources, including limited attention, prevent investors from immediately distilling all available information, resulting in market underreactions (Hirshleifer et al., 2009; Peng & Xiong, 2006), but if information is presented in a salient way, it can attract more attention and be absorbed quickly (Hirshleifer & Teoh, 2003). Da et al. (2014) propose the frog-in-the-pan hypothesis that a series of gradual changes attracts less investor attention than infrequent dramatic changes and demonstrate that past return information that appears continuously in small amounts induces stronger stock return momentum than information that arrives discretely, since investors underreact to continuous information.

In this study, we examine whether the frog-in-the-pan hypothesis can be used to explain option momentum. In the frog-in-the-pan apologue, if a frog is put into a pan of water slowly raised to a boil, it will not perceive the danger and will be cooked; otherwise, it will immediately jump out when suddenly brought into boiling water. This story is a metaphor for the inability of people to fully appreciate and react to the accumulation of small and gradual changes, and it suggests that large, dramatic changes can induce greater attention and stronger reaction. In the finance context, if a firm's past returns occurred in large amounts at discrete time points, investors will pay attention to the dramatic change and quickly incorporate past return information into the current price, hence, the return predictability based on past return will be weakened. Conversely, if a firm's past return is accrued gradually, the momentum effect will be strong. In short, the frog-in-the-pan hypothesis of Da et al. (2014) predicts that investors underreact to past stock return information that arrives continuously in small amounts, causing stock return momentum to strengthen. Testing the frog-in-the-pan momentum effect, Huang et al. (2022) further find that investors underreact to continuous return information of economically linked firms, resulting in strengthened stock return co-momentum. Motivated by this literature, we conjecture that the strength of option momentum increases in continuous information about past option returns and that option momentum will disappear if the past option return information arrives in a discrete manner.

The option momentum (Heston et al., 2023) refers to the positive relation between the return of a delta-neutral straddle and its average return in the formation period from the past second month to the past twelfth month.[9] In the spirit of Da et al. (2014), we construct the continuous information (CI) measure from monthly straddle returns to capture how continuously the option return information arrives in the formation period. Empirically, we find that CI coincides with limited attention proxies. Specifically, firms with continuous

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[9] Heston et al. (2023) demonstrate that this "2 to 12" formation period yields the strongest momentum effect.

information have low stock prices, small market capitalization, small absolute earnings surprises and low stock market liquidity.

We first investigate the influence of continuous information on the strength of option momentum using a double-sorting analysis. In each month, we sort delta-neutral straddles into quintile groups based on their CI. The bottom CI quintile consists of straddles with the most discrete past return information, while the top CI quintile group consists of straddles whose past returns are accumulated in the most continuous manner. In each CI quintile group, we further sort straddles into quintile groups based on past returns and compute the momentum profitability as the difference between average portfolio returns of the top and bottom past return quintiles. Our results show that option momentum does not exist in the most discrete information group, with the momentum profitability being 0.62% and not statistically different from zero. This suggests that discrete information about past option returns tends to be quickly reflected into option prices, hence no return momentum. Across the CI quintiles, option momentum profitability monotonically increases in information continuousness. The most continuous information group generates a profitability of 11% monthly (*t-stat* = 5.57) compared with the unconditional momentum profitability of 5%. Our double sorting results suggest that the frog-in-the-pan hypothesis explains option momentum, and when information arrives continuously, option momentum is stronger.

Our Fama and MacBeth (1973) regression analysis shows that the coefficient estimate of the interaction between past option returns and CI is significantly positive in the regression of option returns, further suggesting that option momentum strengthens in continuous information. When the interaction term is included in the regressions, the standalone option momentum (captured by the coefficient of past option returns) becomes insignificant, highlighting continuous information as an important explanation of option momentum. Moreover, controlling for the interaction of past option returns with other variables known to affect momentum strength, such as firm size, stock market liquidity, and idiosyncratic volatility, does not affect the abovementioned result about the role of CI.

Furthermore, we obtain the average momentum slope coefficients by regressing option returns on past returns in each CI quintile group. The frog-in-the-pan hypothesis predicts that the average slopes should increase from bottom to top CI groups. Indeed, we find that the momentum slope coefficients monotonically increase across CI groups. Moreover, the average momentum slope coefficient is insignificant in the bottom CI quintile, the most discrete information group.

If the effect of continuous information is due to limited attention, we should observe a stronger effect of continuous information for firms that are subject to less investor monitoring. Da et al. (2014) posit that continuous information explains more cross-sectional variation in momentum profit in subsamples of firms subjected to less investor attention. Such firms are typically identified by small firm size, low analyst coverage and low institutional ownership (Da et al., 2014; Lee et al., 2024). Using these variables as proxies for limited attention, we find that the option momentum profitability differential between the most and least continuous information groups is more pronounced in subsamples of firms with inattentive investors.

We also examine the influence of transaction costs on the increasing option momentum profitability across continuous information groups. Following Cao and Han (2013), Zhan et al. (2022) and Heston et al. (2023), we study various levels of the effective option bid–ask spread to quoted spread ratio. In all the scenarios, we find that option momentum after transaction costs monotonically increases as continuous information increases across quintile groups, and there is a significant difference in option momentum profitability between continuous and discrete information groups. Thus, our main finding holds well after considering transaction costs. Importantly, we find that when the transaction costs are high enough to eliminate momentum profitability in the full sample, investors can still earn significant momentum profit by restricting their trading to the highly continuous information group.

Prior studies show that option-implied volatility is a biased estimate of future realized volatility (Christensen & Prabhala, 1998). Goyal and Saretto (2009) argue that the implied volatility over/underpredicting future volatility is the reason why the historical-implied volatility differential is related to option returns. Investigating the implied volatility forecast error, *exvol*, which is the difference between future realized volatility and implied volatility, allows us to identify whether options are relatively cheap or expensive. We show that *exvol* is positively related to past option returns and that controlling for *exvol* makes the relation between option returns and past option returns insignificant. That means the prices of options that underperformed (outperformed) in the past are relatively expensive (cheap), making these options continue to have low (high) future returns. Linking these results with the frog-in-the-pan hypothesis, we find that the positive relation between option expensiveness and past option returns is stronger with continuous information and tends to be insignificant when past return information is discrete. Our results suggest that continuous information makes investors inattentive to past option returns and inefficient at pricing options, causing option momentum to arise.

According to Heston et al. (2023), option momentum persists over multiyear horizons. We find that continuous information can also explain this long-run option momentum effect. The long-run predictability strengthens with CI and tends to be insignificant when information about the past option returns is discrete. Thus, whether investors pay attention to the past option return information when pricing options formed in the distant future also depends on whether the past information arrives in a discrete or continuous manner.

Our study contributes to the asset pricing literature in several important ways. First, our study is related to the studies on the cross-section of option returns. Option returns can be predicted by past option returns (Heston et al., 2023), idiosyncratic volatility (Cao & Han, 2013), historical-implied volatility differential (Goyal & Saretto, 2009), a set of accounting variables (Zhan et al., 2022). Heston et al. (2023) examine various possible explanations for option momentum but fail to arrive at a conclusive answer. We find that limited investor attention due to the arrival of continuous information can explain the option momentum and the long-run option momentum.

Second, our paper advances the understanding of the role of investor attention in asset pricing. Andrei and Hasler (2015) show that investor attention is an important determinant of asset prices. DellaVigna and Pollet (2009) show that investor inattention results in price underreaction to earnings announcements and stronger announcement drift. Numerous other papers show that if investors are inattentive, they will be sluggish in incorporating available information into prices, causing greater predictability of future returns based on past information (Chen et al., 2023; Cohen & Frazzini, 2008; Hirshleifer & Teoh, 2003; Huang et al., 2022; Lee et al., 2024; Ying, 2024). Literature on the frog-in-the-pan hypothesis demonstrates that investor inattention due to information arriving continuously heightens stock momentum (Da et al., 2014) and peer stock momentum (Huang et al., 2022). Borrowing the concept of the frog-in-the-pan hypothesis, we demonstrate that investor inattention intensifies the predictability of option returns based on past option returns.

The remainder of the chapter proceeds as follows. Section 2.2 describes the data and methodology to investigate the relations between option returns and past option returns and how these relations are explained by the way in which information about past option returns arrives. Section 2.3 presents our empirical results that are consistent with the frog-in-the-pan hypothesis. Finally, Section 2.4 provides the conclusion of the chapter.

2.2. Data

We retrieve information about call and put options from the OptionMetrics Ivy DB from January 1996 to December 2023. Stock information is from CRSP, and accounting data is from Compustat.

Following Heston et al. (2023), we use at-the-money options to construct delta-neutral straddles, which consist of a pair of call and put options on the same equity with the same maturity of one month. We select options that are close to at-the-money (ATM) by requiring that the absolute delta be closest to 0.5 and neither lower than 0.25 nor greater than 0.75. To make the straddles delta-neutral, we maintain that the weights of call and put are proportional to $-\Delta_P C$ and $\Delta_C P$, respectively, where $\Delta_C (\Delta_P)$ is delta of the call (put) options and $C(P)$ is the bid-ask midpoint price of call (put) options. The weights are chosen to sum to one and are typically close to 50/50. To address the liquidity issue, we follow Heston et al. (2023) to require that the option open interest be positive. Returns to straddle positions are the weighted average of the returns on the calls and puts. Returns to each call and put option are computed from the payoff at maturity and the initial bid-ask midpoint price. We form the option positions on the option expiration day (the third Friday) of each month and hold these straddles until maturity, which is the option expiration day next month. Our final sample consists of 678,465 straddle-month observations (with 2,056 straddles per month on average).

Heston et al. (2023) show that past option returns significantly predict future option returns, and the positive association, also referred to as the option momentum, is most pronounced when the past option returns are computed using the formation period from the past second month to the past twelfth month. In our study, we investigate the effect of this "2 to 12" formation period option returns, which are the average of monthly option returns from the past second month to the past twelfth month (Heston et al., 2023).

To assess how information about past returns arrives and link it to the frog-in-the-pan hypothesis, we follow Da et al. (2014) to construct the information discreteness (ID) variable. This variable is identified by the percentage of small signals whose sign is the opposite of the sign of formation period returns relative to the percentage of small signals whose sign is the same as the sign of formation period returns.[10]

$$ID = sign(opmom_{adj}) \times [\%neg - \%pos] \qquad (1)$$

where $opmom_{adj}$ is the formation period returns $opmom$ (the average of lags 2 to 12 option returns) adjusted by (minus) the cross-sectional median of formation period returns, and $\%neg$ ($\%pos$) is the percentage of negative (positive) monthly option return within the formation period adjusted by (minus) the cross-sectional median of each respective month.[11]

Da et al. (2014) recognize the influence of market aggregate return on individual asset momentum (Cooper et al., 2004) and adjust for market aggregate returns in each signal return when computing the ID variable, and find that the results with or without adjustment are similar. Considering that delta-hedged option portfolios generally underperform zero (Bakshi & Kapadia, 2003; Cao & Han, 2013) and delta-neutral straddle returns are highly skewed

[10] Additional justification for ID being computed from the sign of individual component returns behind the formation period returns and for the appropriateness of using ID to test the frog-in-the-pan hypothesis can be found in Da et al. (2014).

[11] Alternatively, we compute $opmom_{adj}$ as the average of lags 2 to 12 adjusted option returns, i.e., we adjust the monthly option returns by deducting the cross-sectional median and then taking the average of these monthly adjusted returns to arrive at the adjusted formation period returns. Our empirical results are virtually the same.

(Heston et al., 2023), we adjust for the cross-sectional median returns in equation (1) to arrive at a meaningful ID variable in our study.

A low value of the resulting ID variable implies continuous information, while a high value of ID signifies information arriving in a discrete manner. If a past winner (high $opmom_{adj}$) accumulates its formation period return from many small monthly outperformances, the percentage of positive adjusted returns (*%pos*) will be greater than the percentage of negative adjusted returns (*%neg*), yielding a low ID value and implying continuous information. If the series of adjusted option returns are all positive, ID will equal the minimum value of -1. Otherwise, if a few substantial outperformances are responsible for high formation period return, ID will be closer to 1 to reflect that information is discrete.

The variable of interest in our study is continuous information about past option returns, as our frog-in-the-pan hypothesis posits a positive association between continuous past option return information and the strength of option momentum. To emphasize the continuousness of information, we define continuous information (CI) as one minus information discreteness ($CI = 1 - ID$). The most continuous information situation coincides with the least discrete information, and vice versa. Similar to that in Da et al. (2014), our ID variable ranges from -1 to 1 by design. Hence, the CI variable ranges from 0 to 2, with 0 indicating that past return information is most discrete.

The continuous and discrete information are the key elements to explain asset return momentum as they determine the degree to which information attracts attention and the degree to which information is reflected in asset prices.

Da et al. (2014) show that continuous information about a firm's past stock returns explain its stock return momentum. Huang et al. (2022) construct a similar measure to capture whether a firm's stock returns arrive in a discrete or continuous manner and demonstrate that continuous information determines the strength of the co-momentum of its peer's stock returns. These two papers rely on the behavioral insight that salient information attracts more attention, and higher attention induces stronger investor reaction (Hirshleifer & Teoh, 2003). Theoretically, investor attention is a necessary condition for information to be reflected in asset prices (Andrei & Hasler, 2015), since investors must be aware of the information before reacting to it. Abundant literature has demonstrated that limited attention results in sluggish price adjustment and pronounced asset pricing anomalies (Ben-Rephael et al., 2017; Chen et al., 2023; Cohen & Frazzini, 2008; Huang et al., 2022; Lee et al., 2024; Ying, 2024). Note that our measures of continuous information and discrete information are constructed from option returns and meant to explain option momentum, as opposed to those in Da et al. (2014) and Huang et al. (2022), which are constructed from stock returns and meant to explain stock momentum and stock peer momentum.

2.3. Empirical results

2.3.1. Summary statistics

We present our empirical results in this section. Table 2.1 provides the summary statistics of our main variables.

Table 2.1. Summary statistics

This table provides summary statistics on mean, standard deviation, 5th, 25th, 50th, 75th, 95th percentiles of our main variables, including straddle returns, *opret*, average past straddle returns from the prior 2nd through 12th month, *opmom*, continuous information, *CI*, option implied volatility, *iv*, forecast error of implied volatility, *exvol*, firm size, *size*, Amihud illiquidity, *ailliq*, stock idiosyncratic volatility, *ivol*. The variable definitions can be found in the appendix Table A2.1.

	Mean	SD	Q5	Q25	Median	Q75	Q95
opret	-0.017	1.326	-0.960	-0.645	-0.239	0.309	1.501
opmom	-0.012	0.399	-0.425	-0.227	-0.066	0.126	0.524
CI	1.182	0.251	0.727	1.091	1.091	1.273	1.636
iv	0.476	0.306	0.165	0.277	0.401	0.588	1.021
exvol	0.060	0.283	-0.213	-0.047	0.025	0.122	0.446
size	0.179	1.538	0.002	0.007	0.022	0.081	0.575
ailliq	0.004	0.012	0.000	0.000	0.001	0.003	0.015
ivol	0.389	0.340	0.095	0.195	0.307	0.487	0.938

The average monthly delta-neutral straddle return is -1.7%. The negative sign of average straddle return is consistent with prior literature in that the delta-hedged option strategy tends to underperform zero (Bakshi & Kapadia, 2003). The average straddle returns from the prior 2nd through 12th month (also referred to as momentum returns or formation period returns) also have a negative average of -1.2%. CI, the measure of continuous information in the formation period, has an average of 1.18 and a standard deviation of 0.25. The implied volatility of straddles is the weighted average of implied volatilities provided by OptionMetrics for the call and put that constitute the straddles. The resulting implied volatility has an average of 47.6%. The forecast error of implied volatility, *exvol*, is the difference between next month's realized volatility and implied volatility for that month. Firm size is the firm's market capitalization. Amihud (2002) illiquidity is averaged over the most recent 12 months as in Heston et al. (2023). Idiosyncratic volatility is the standard deviation of residuals from the asset pricing model as in Ang et al. (2006) and Da et al. (2014). Further details about variable construction can be found in the appendix Table A2.1.

2.3.2. Continuous information and limited investor attention

We start by investigating the relationship between our measure of continuous information and proxies of investor attention. Continuous information should coincide with less investor attention. Following Da et al. (2014), we use Fama and MacBeth (1973) regression in Table 2.2 to test this effect of continuous information in the options market.

Table 2.2. Continuous information and limited investor attention

This table reports results of the Fama–MacBeth regressions of continuous information, *CI*, on log stock price, *price*, average absolute value of earnings surprises, *asue*, firm size, *size*, Amihud illiquidity, *ailliq*, and change in analyst coverage, *dcoverage*. 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.

	CI				
	(1)	(2)	(3)	(4)	(5)
Intercept	1.191***	1.186***	1.181***	1.18***	1.181***
	(259.11)	(457.41)	(522.1)	(510.72)	(517.34)
price	-0.003**				
	(-2.36)				
asue		-0.004**			
		(-2.01)			
size			-0.002**		
			(-2.17)		
ailliq				0.162*	
				(1.88)	
dcoverage					0.000
					(0.13)
Avg Adj R^2	0.0008	0.0002	0.0000	0.0003	0.0000

Literature shows that stock prices affect option returns (Birru & Wang, 2016; Zhan et al., 2022), and this effect exists because investors do not pay enough attention to options on low-priced stocks, leading to option mispricing (Boulatov et al., 2022). Hence, we use the stock price as the first proxy for investor attention and expect that low stock price, which attracts less option investors' attention, will be associated with higher continuous information about past option returns. Column (1) of Table 2.2 confirms this relationship. The coefficient of the log stock price is negative and significant at the 5% level, suggesting that returns to options on low-priced stocks tend to arrive in a continuous manner.

Large absolute earnings surprises attract higher investor attention. Quarterly earnings surprise is calculated as realized earnings in the most recent quarter in excess of its realized earnings in the same quarter of the previous year divided by the standard deviation of earnings in the past eight quarters. The absolute earnings surprises, *asue*, is the average of the absolute value of earnings surprises in the past year. Column (2) of Table 2.2 shows a significant and inverse relationship between absolute earnings surprises and continuous information, consistent with the notion that investor attention induced by earnings surprises coincides with discrete changes in option return information.

Another proxy for investor attention is firm size, measured by market capitalization. Column (3) of Table 2.2 shows a significant and negative relation between firm size and continuous information. From the investor attention perspective, larger firms can be subject to greater attention from a large investor base. Our results show that larger firms tend to have option returns that change in a sudden and dramatic manner, while small firms tend to have past option returns that accumulate gradually and continuously.

Studies show that high investor attention promotes buying activities (Barber & Odean, 2008) and selling activities (Yuan, 2015) and that securities' liquidity strengthens as trading specialists allocate more effort and attention towards these securities (Corwin & Coughenour, 2008). Thus, high liquidity is a manifestation of high investor attention. We use the average Amihud (2002) illiquidity measure over the formation period to capture this aspect of investor attention. Column (4) of Table 2.2 shows a positive relationship between illiquidity and continuous information. For stocks that have high liquidity, their option returns can change substantially and dramatically.

The final proxy for investor attention is the change of analyst coverage, which is defined as the average number of analysts covering a firm during the twelve-month formation period in which that firm's continuous information variable is computed, minus the average analyst coverage during the twelve months before that formation period. Similar to Da et al. (2014), we do not find a significant relationship between analyst coverage change and continuous information about option returns.

The results in Table 2.2 indicate that continuous information is associated with low stock prices, low absolute earnings surprises, small market capitalization, and low liquidity. All in all, continuous information coincides with low investor attention, while discrete information coincides with high investor attention. This insight is aligned with the theoretical framework of Andrei and Hasler (2015) that return volatility increases with investor attention. Andrei and Hasler (2015) demonstrate that if investors pay little attention to news, information will be incorporated into prices gradually; therefore, return volatility will be low. Otherwise, if investors are attentive, they will immediately react to new information, causing return volatility to be substantial. The results in Table 2.2 suggest that the argument of Andrei and Hasler (2015) applies to the options market: the option returns tend to change suddenly and dramatically when investors are attentive.

2.3.3. Continuous information and option momentum: portfolio analysis

We revisit the option momentum phenomenon of Heston et al. (2023) from the one-way portfolio sorting analysis. In each month, straddles are sorted into five quintiles based on *opmom*, the average past straddle returns accumulated over the formation period from month *t-12* to *t-2*. We then compute the equally weighted average portfolio return of each straddle quintile. The results in panel A of Table 2.3 show that option returns increase monotonically from the bottom quintile to the top quintile. The average difference in return between the top and bottom quintiles, which is also referred to as option momentum profitability, is 5.00% (*t-stat* = 6.07). Thus, the option momentum profitability is highly significant and on par with the profitability level reported in Heston et al. (2023).

Table 2.3. Continuous information and option momentum

In this table, panel A reports results on unconditional option momentum, and panel B reports double sort results on option momentum conditioned on continuous information sorting to demonstrate that option momentum increases in continuous information. In panel A, straddles are sorted into quintiles based on average past straddle returns from month *t-2* to month *t-12*, *opmom*; quintile (1) represents the lowest past return straddles, and quintile (5) represents the highest past return straddles; equally weighted average returns of portfolios are reported for each quintile. In panel B, straddles are first sorted on continuous information measure into five quintiles, with quintile (1) representing discrete information and quintile (5) representing continuous information. In each quintile, straddles are then sorted based on past straddle returns, *opmom*, to obtain return differentials between top and bottom *opmom* quintiles. 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. Unconditional option momentum

Straddle return					
(1)	(2)	(3)	(4)	(5)	(5) – (1)
-0.0415	-0.0208	-0.0143	0.0050	0.0084	0.0500*** (6.07)

Panel B. Option momentum conditioned on continuous information sorting

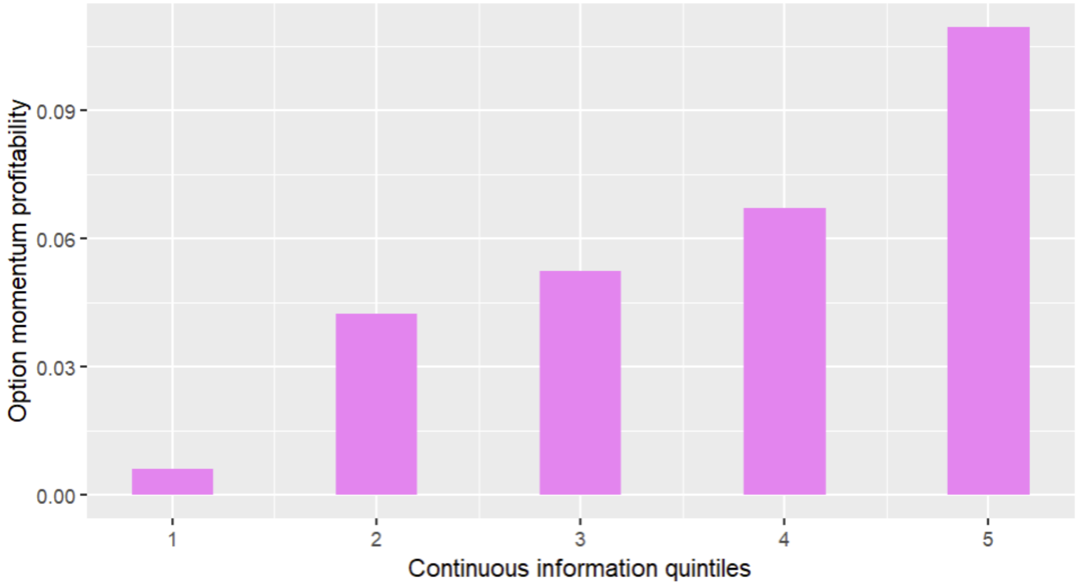
	Straddle return						
Information	(1)	(2)	(3)	(4)	(5)	(5) – (1)	
(1)-discrete	-0.0251	-0.0072	-0.0187	-0.0154	-0.0189	0.0062	(0.51)
(2)	-0.0396	-0.0094	-0.0156	0.0004	0.0029	0.0425***	(4.63)
(3)	-0.0404	-0.0251	-0.0138	0.0081	0.0121	0.0525***	(5.42)
(4)	-0.0422	-0.0211	0.0044	0.0131	0.0250	0.0672***	(4.94)
(5)-continuous	-0.0749	-0.0404	0.0299	0.0172	0.0346	0.1100***	(5.57)
(5) – (1)						0.1033***	(4.48)

We then employ the double-sorting portfolio analysis to test the frog-in-the-pan hypothesis. In each month, straddles are first sorted into five quintiles based on the continuous information variable CI. Within each continuous information group, we further sort straddles by *opmom* and compute the momentum profitability. The results in panel B of Table 2.3 show that the average option momentum profitability monotonically increases across continuous information groups. In the bottom CI group, in which information is most discrete, we find that option momentum does not exist. The option momentum profitability is only 0.62% and statistically insignificant. This indicates that if past option return information arrives in a discrete manner, it attracts high investor attention and is reflected in option prices quickly so that future returns cannot be predicted from past option return information. In the most continuous information group, the option momentum profitability increases to 11.00% and is highly significant (*t-stat* = 5.57). This means that investors are less likely to reflect information that arrives in a continuous manner in option prices, leading to a stronger option momentum effect. The differential in option momentum profitability between the continuous information and discrete information groups is 10.33% and significant at the 1% level. Our results from the double-sorting analysis support the frog-in-the-pan hypothesis and suggest that option momentum strengthens in continuous information. Our main finding is illustrated by Figure 2.1.

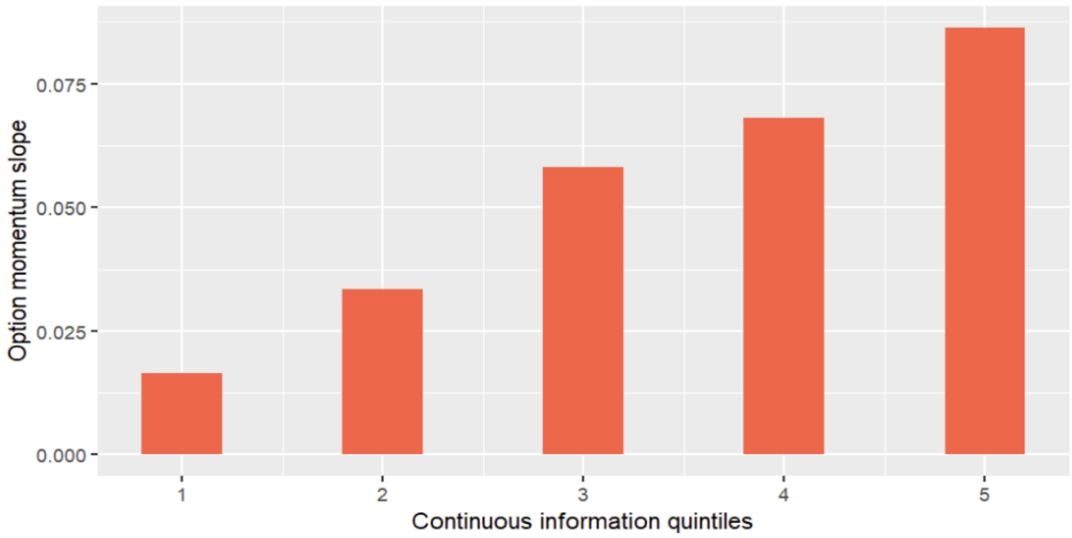
Panel A of Figure 2.1 illustrates the option momentum profitability across the five continuous information quintiles. The option momentum profitability clearly increases as information arrives more continuously. Panel B of Figure 2.1 presents the average option momentum slope coefficients across the five CI groups. The option momentum slope is obtained from the slope coefficient in the cross-sectional regression of option returns on past option returns where regressions are conducted for each CI group in each month. This slope coefficient is another measure of option momentum strength. Panel B demonstrates that the average option momentum slope coefficients monotonically increase as CI increases across the five quintiles. Not surprisingly, panel B exhibits a very similar pattern to that in panel A, suggesting that option momentum strengthens in continuous information.

Figure 2.1. Option momentum and continuous information

This figure illustrates that option momentum is stronger as information about past option returns is more continuous. In both panels, straddles are categorized into five quintiles based on the increase of continuous information *CI*. Quintile 1 represents the most discrete information quintile, and quintile 5 represents the most continuous information quintile. Panels A and B report the average option momentum profitability and the option momentum slope in each *CI* quintile, respectively. The option momentum profitability in each month is the difference in equally weighted average return between the top and bottom quintiles of straddles sorted on their past returns, and the option momentum slope is the slope coefficient in the cross-sectional regression of option returns on past option returns.



Panel A. Option momentum profitability across continuous information quintiles



Panel B. Option momentum slope across continuous information quintiles

Our continuous information measure is constructed from information in the formation period, which is available at the time of portfolio formation. This construction allows us to arrive at actionable trading implications. We further verify our finding using ex-post measure of continuous information. Particularly, we use all monthly option returns from the past 12 months together with the current month (contemporaneous to the option lifespan) to measure ex-post continuous information. Higher values of ex-post continuous information indicate that not only did the past return information arrive in a continuous manner, but the option pricing in the current month also experiences no dramatic change. We expect that this ex-post continuous information can explain option momentum even better than the continuous information in our main analysis. The results in table A2.2 confirm our conjecture. Particularly, our double-sorting results demonstrate that option momentum profitability monotonically increases as the ex-post measure of continuous information increases across quintiles. In the most discrete information quintile, option momentum profitability is significantly negative, amounting to -71.70% (*t-stat* = -28.60). This indicates that when the options market adjusts its pricing dramatically and quickly to the past return information, the option momentum strategy leads to a large loss. In the most continuous information quintile, the option momentum strategy earns significantly positive profit, 57.90% (*t-stat* = 28.50), indicating that the momentum strategy is profitable when option returns show a small and gradual variation pattern. The difference in option momentum profitability between the top and bottom continuous information quintiles is almost 130%, much higher than when we condition on an ex-ante continuous information variable. Our ex-post validation indeed confirms the explanation of continuous information for option momentum.

Besides, option momentum strategy can experience crashes (large negative returns). These shocks can significantly influence the performance of the option momentum strategy in each continuous information quintile. We continue to test whether the option momentum strategy still has best performance in the top continuous information quintile, when momentum crashes are considered. We classify a month as experiencing a momentum crash if its unconditional option-momentum profitability falls below the 10^{th} percentile of all months in our sample. The non-crash subsample consists of months without momentum crashes. Our results in table A2.3 show that in the non-crash subsample, option momentum profitability monotonically increases across continuous information quintiles, with the difference between the top and bottom quintiles of 10.58% (*t-stat* = 4.50). Thus, our main finding holds when there are no momentum crashes. When the unconditional option momentum experiences a crash, the momentum strategies in most quintiles are also significantly negative, except the top continuous information quintile (negative but insignificant). This indicates that options in the top continuous information quintile are least affected by momentum crashes. The momentum strategy in the top quintile also outperforms that in the bottom quintile by 8.03% (though the difference is not statistically significant, possibly due to small sample size). All in all, our results show that option momentum strategy generates its best performance in the most continuous information quintile, regardless of whether there are momentum crashes.

In this study, we argue that investors' limited attention is the reason why continuous information leads to investor underreaction and strengthened option momentum. Thus, we test whether the increase of option momentum in continuous information is more pronounced in subsamples where investor inattention is more likely.

Table 2.4. Continuous information, limited attention and option momentum

This table reports the double sort results of option momentum conditioned on continuous information for different subsamples. In panels A, B and C, results are reported for the subsamples based on the bottom and top 30 percent of firm size, analyst coverage and institutional ownership. In each subsample, straddles are first sorted on continuous information measure into quintiles; quintile (1) represents discrete information and quintile (5) represents continuous information; in each quintile, straddles are then sorted based on past straddle returns, *opmom*, to obtain return differentials between the top and bottom *opmom* quintiles. 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. Effect of continuous information for small and large firms

		Straddle return						
Firm size	Information	(1)	(2)	(3)	(4)	(5)	(5) – (1)	
Small	(1)-discrete	-0.0387	-0.0095	-0.0231	-0.0552	-0.0222	0.0165	(0.67)
	(2)	-0.0685	-0.0141	-0.0009	-0.0097	-0.0136	0.0549***	(2.58)
	(3)	-0.0783	-0.0098	-0.0219	-0.0141	0.0160	0.0943***	(4.13)
	(4)	-0.0736	-0.0584	0.0006	0.0297	0.0678	0.1410***	(3.78)
	(5)-continuous	-0.0994	-0.0891	-0.0280	0.1120	0.0701	0.1690***	(4.48)
	(5) – (1)						0.1528***	(3.39)
Large	(1)-discrete	0.0013	-0.0138	0.0024	0.0008	-0.0153	-0.0167	(-0.84)
	(2)	-0.0203	0.0013	0.0009	0.0284	0.0113	0.0316**	(2.40)
	(3)	-0.0203	-0.0048	-0.0034	0.0393	0.0166	0.0369**	(2.34)
	(4)	-0.0120	0.0081	0.0208	0.0198	0.0200	0.0320	(1.25)
	(5)-continuous	-0.0272	-0.0152	0.0052	0.0063	-0.0028	0.0244	(0.84)
	(5) – (1)						0.0411	(1.23)

Panel B. Effect of continuous information across low and high analyst coverage

Analyst		Straddle return						
coverage	Information	(1)	(2)	(3)	(4)	(5)	(5) – (1)	
Low	(1)-discrete	-0.0768	-0.0582	-0.0587	-0.0454	-0.0328	0.0440***	(2.75)
	(2)	-0.0677	-0.0567	-0.0349	-0.0422	-0.0253	0.0424**	(2.43)
	(3)	-0.0711	-0.0236	-0.0475	-0.0227	-0.0237	0.0474***	(3.07)
	(4)	-0.0861	-0.0488	-0.0578	-0.0063	0.0206	0.1070***	(4.33)
	(5)-continuous	-0.1160	-0.1220	-0.0327	0.0090	0.0061	0.1220***	(4.29)
	(5) – (1)						0.0776**	(2.45)
High	(1)-discrete	-0.0046	-0.0005	-0.0179	-0.0125	-0.0069	-0.0023	(-0.10)
	(2)	-0.0203	-0.0062	-0.0251	0.0174	0.0094	0.0298*	(1.89)
	(3)	-0.0360	-0.0128	-0.0108	0.0190	0.0151	0.0510***	(3.37)
	(4)	-0.0108	-0.0153	0.0191	0.0309	0.0242	0.0351	(1.53)
	(5)-continuous	-0.0166	0.0068	-0.0167	0.0078	0.0138	0.0304	(1.15)
	(5) – (1)						0.0327	(0.98)

Panel C. Effect of continuous information across low and high institutional ownership

Institutional ownership	Information	Straddle return (1)	(2)	(3)	(4)	(5)	(5) – (1)	
Low	(1)-discrete	-0.0170	-0.0183	-0.0087	-0.0451	-0.0113	0.0057	(0.18)
	(2)	-0.0562	-0.0166	-0.0104	0.0304	-0.0026	0.0537***	(2.98)
	(3)	-0.0320	-0.0370	-0.0130	0.0123	0.0070	0.0390**	(2.15)
	(4)	-0.0155	-0.0221	0.0149	-0.0103	0.0337	0.0492	(0.89)
	(5)-continuous	-0.0853	-0.0818	-0.0128	0.0031	0.0278	0.1130***	(3.65)
	(5) – (1)						0.1074**	(2.28)
High	(1)-discrete	-0.0291	-0.0155	-0.0310	-0.0149	-0.0319	-0.0028	(-0.19)
	(2)	-0.0354	-0.0154	-0.0203	-0.0024	-0.0045	0.0309**	(2.16)
	(3)	-0.0432	-0.0425	-0.0256	-0.0143	-0.0086	0.0347**	(2.11)
	(4)	-0.0448	-0.0320	-0.0138	0.0253	0.0273	0.0720***	(3.15)
	(5)-continuous	-0.0724	-0.0423	-0.0373	0.0073	0.0105	0.0829***	(2.74)
	(5) – (1)						0.0858***	(2.84)

In Table 2.4, we use three proxies of investor attention, including firm size, analyst coverage and institutional ownership (Da et al., 2014; Lee et al., 2024). We select the top 30% and bottom 30% subsamples based on attention proxies and repeat the double sorting analysis as in Table 2.3 for each subsample. In panel A of Table 2.4, we study subsamples based on firm market capitalization. The results show that the increase of option momentum profitability in continuous information is stronger in the small firm subsample, and momentum profitability maintains a monotonic pattern across CI groups. The difference in profitability between the continuous information and discrete information groups increases to 15.28% (*t-stat* = 3.39). For the large firm subsample, we do not observe a monotonic pattern of option momentum profitability across continuous information quintiles and the option momentum profitability differential between top and bottom continuous information quintiles is insignificant. The role of continuous information in intensifying option momentum is more pronounced in small firms, where investor attention is limited.

In panel B of Table 2.4, we study subsamples based on the average number of analysts covering a firm in the past 12 months. The results show that there is a significant difference of 7.76% in option momentum profitability between the continuous information and discrete information groups in the low analyst coverage subsample, while the difference is insignificant in the high analyst coverage subsample. The results suggest that the frog-in-the-pan hypothesis is more relevant to firms with low analyst coverage, a proxy of low investor attention.

Panel C of Table 2.4 reports results on subsamples based on the proportion of firm shares held by institutional investors at the beginning of the formation period. The results show that the difference in option momentum profitability between the highest and lowest CI quintiles is 10.74% for the low institutional ownership subsample and 8.58% for the high institutional ownership subsample. Although both are significant, the increase of option momentum in continuous information is still larger in magnitude when institutional ownership is low.

Overall, the results in Table 2.4 are consistent with the limited attention motivation of the frog-in-the-pan hypothesis. Among firms subjected to greater limited investor attention, continuous information about past option returns explains a larger variation in option momentum profitability.

Transaction costs reduce the profitability of trading strategies (Lesmond et al., 2004). We now examine the influence of transaction costs on our main findings. We ask whether option momentum profitability after transaction costs still increases in continuous information. To account for transaction costs, we follow Cao and Han (2013); Heston et al. (2023); Zhan et al. (2022) to assume the ratio of effective option bid–ask spread to quoted spread to be 15%, 25%, 50% and 75%, instead of using the bid-ask midpoints as the prices of call and put options. Panel A of Table 2.5 shows that for all the transaction cost levels, momentum profitability monotonically increases across CI quintiles. For instance, when the transaction cost is at the 15% level, the option momentum profitability after transaction cost is -2.80% for the bottom CI group but is 7.37% for the top CI group. The same pattern is observed for other transaction cost levels, though as transaction costs increase, option momentum in each group tends to be unprofitable. Importantly, we always observe a highly significant differential in momentum profitability between the top and bottom CI groups, which is 10.17%, 10.03%, 9.52% and

8.71% for the 15%, 25%, 50% and 75% transaction cost levels, respectively. The option momentum profitability after transaction costs still increases in continuous information.

Table 2.5. Continuous information and option momentum with transaction costs

In this table, panel A reports the results on option momentum profitability after considering transaction costs across different continuous information quintile groups. Quintile (1) represents discrete information, and quintile (5) represents continuous information. Within each continuous information group, option momentum profitability is the differential of equally weighted average portfolio returns between the top and bottom quintiles of options sorted on past option returns. Panel B reports results on unconditional option momentum profitability after considering transaction costs. To account for transaction costs, we assume the effective spread to successively be 15%, 25%, 50% and 75% of the quoted spread. 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. Continuous information and option momentum profitability

		Option momentum profitability with transaction costs			
Transaction costs		15%	25%	50%	75%
Information	(1)-discrete	-0.0280** (-2.25)	-0.0512*** (-4.00)	-0.1120*** (-7.82)	-0.1790*** (-10.50)
	(2)	0.0095 (1.03)	-0.0129 (-1.37)	-0.0712*** (-6.70)	-0.1360*** (-10.30)
	(3)	0.0194** (1.97)	-0.0032 (-0.31)	-0.0623*** (-5.4)	-0.1280*** (-8.98)
	(4)	0.0328** (2.53)	0.0093 (0.74)	-0.0528*** (-4.23)	-0.1230*** (-8.87)
	(5)-continuous	0.0737*** (3.75)	0.0491** (2.49)	-0.0164 (-0.79)	-0.0921*** (-3.96)
	(5) – (1)	0.1017*** (4.39)	0.1003*** (4.30)	0.0952*** (4.01)	0.0871*** (3.54)

Panel B. Unconditional option momentum profitability

Transaction cost	15%	25%	50%	75%
Unconditional option momentum profitability	0.0165** (2.03)	-0.0064 (-0.77)	-0.0662*** (-7.01)	-0.1334*** (-10.85)

Further, in Panel B of Table 2.5, we examine the influence of different levels of transaction costs on the unconditional option momentum in the full sample. Our results show that option momentum profitability wanes as transaction costs increase. At the 25% transaction cost level, unconditional option momentum profitability becomes insignificant, and beyond this level, option momentum profitability turns significantly negative. This result is consistent with Heston et al. (2023) in which the standard option momentum strategy is profitable only when transaction costs are around 20% or below. Studies also demonstrate that the profit to other strategies of straddle trading also turns negative at the 25% transaction cost level (Vasquez & Xiao, 2024). Table 2.5 shows that though option momentum profitability disappears at the 25% transaction cost level (Panel B), the profitability remains significantly positive if we condition the trading on the continuous information (Panel A). At the 25% transaction cost level, investors still earn a significant monthly profit of 4.91% (*t-stat* = 2.49) by restricting the option momentum strategy in the top CI quintile. By using continuous information as a conditioning variable, we enhance the profitability of option momentum strategy, allowing investors to earn significant and positive returns after transaction costs, even when the unconditional option momentum strategy becomes unprofitable.

2.3.4. Continuous information and option momentum: the Fama–MacBeth regression

To formally assess the role of continuous information in the option momentum effect, we employ the Fama and MacBeth (1973) regressions with the specification as follows:

$$opret_{i,t} = \beta_0 + \beta_1 opmom_{i,t-2-12} + \beta_2 opmom_{i,t-2-12} \times CI_{i,t-2-12} + \beta_3 CI_{i,t-2-12} + \gamma control_{i,t} + \varepsilon_{i,t} \quad (2)$$

where option return, $opret_{i,t}$, is the return of a one-month straddle that is held until maturity for firm i in month t, option momentum, $opmom_{i,t-2-12}$, is the average option return in the past twelve months after skipping the most recent month, $CI_{i,t-2-12}$ is the continuous information measure for the same formation period. Control variables $control_{i,t}$ include firm size, Amihud illiquidity, and idiosyncratic volatility, and the interactions of these variables with $opmom_{i,t-2-12}$. All the control variables are known at the time of straddle formation.

Table 2.6. Continuous information and option momentum – the Fama-MacBeth regression

This table reports results of the Fama–MacBeth regressions of straddle returns, *opret*, on average past straddle returns from month *t-2* to month *t-12*, *opmom*, and its interaction with continuous information, *CI*, firm size, *size*, Amihud illiquidity, *ailliq*, stock idiosyncratic volatility, *ivol*. 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.

	opret				
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.012	-0.025	-0.026	-0.029	0.006
	(-0.57)	(-1.17)	(-1.21)	(-1.31)	(0.19)
opmom	0.046***	-0.036	-0.036	-0.033	-0.042
	(5.59)	(-1.64)	(-1.43)	(-1.03)	(-1.40)
opmom*CI		0.068***	0.069***	0.066***	0.067***
		(3.80)	(3.57)	(2.80)	(3.00)
opmom*size			-0.020*	-0.018	-0.013
			(-1.81)	(-0.95)	(-0.75)
opmom*ailliq				0.075	0.296
				(0.11)	(0.45)
opmom*ivol					0.059***
					(3.07)
CI		0.011	0.010	0.006	0.006
		(1.58)	(1.37)	(0.90)	(1.01)
size			0.016	0.021*	0.013
			(1.53)	(1.82)	(1.30)
ailliq				-1.645***	-0.895***
				(-4.10)	(-2.73)
ivol					-0.107***
					(-4.50)
Avg Adj R^2	0.0011	0.0013	0.0029	0.0048	0.0094

The results are reported in Table 2.6. Column (1) of Table 2.6 confirms the option momentum effect. Past option returns are significantly and positively associated with future option returns. In column (2), we include the interaction between past option returns and continuous information. Our result shows that the coefficient of the interaction is positive and significant at the 1% level. That means option momentum strengthens in the continuous information in the formation period. Besides, the coefficient of the standalone past option returns, *opmom*, can be interpreted as the option momentum effect when the conditioning variable CI equals 0 (a zero value of CI implies that the past option return information is most discrete). We find that the coefficient of *opmom* is insignificant. This indicates that when return information in the formation period is very discrete, option momentum does not exist. This result is consistent with the results in the double-sorting analysis. It suggests that when information about past option returns is discrete, investors are likely to incorporate this information into option prices, rendering no predictability of future returns based on past returns. Together, our results highlight CI as an important variable to explain the strength of option momentum.

In terms of the coefficient of CI, we find that CI is not significantly related to option returns. Da et al. (2014) suggest that continuous information is relevant to future returns only when interacting with formation-period returns. Huang et al. (2022) find that discrete information from peer firms only has an interaction effect but not a direct effect on stock returns. Consistently, we find no significant relation between CI and option returns. The lack of direct relation between option returns and continuous information suggests that CI is unlikely to capture the effects of other predictors of option returns present in literature but rather reflects merely how the formation-period return information manifests.

We continue to ask whether continuous information explains option momentum beyond what other factors known to influence momentum do. Literature shows that stock momentum is stronger in small firms (Hong et al., 2000; Zhang, 2006). Heston et al. (2023) also find weak evidence that market capitalization influences option momentum. In column (3) of Table 2.6, we additionally include the interaction between past option returns and firm size measured by market capitalization. Our results show that the option momentum is stronger for smaller firms, with the coefficient of the interaction term being significant at the 10% level. Most importantly, the inclusion of firm size interaction does not influence the interaction effect of continuous information. In addition, stock momentum anomaly attenuates in liquidity (Chordia et al., 2014). Heston et al. (2023) also show that option momentum profitability tends to be larger when stock illiquidity, measured by the average past 12-month Amihud (2002) illiquidity, is higher. We also include this measure of illiquidity in column (4) of Table 2.6. The results show that the interaction between past option return and illiquidity has a positive but insignificant coefficient, and this interaction does not affect the role of continuous information. The standalone illiquidity is negatively related to option returns, consistent with Cao and Han (2013). Finally, as Da et al. (2014) suggest, idiosyncratic volatility as in Ang et al. (2006) strengthens stock momentum. Hence, we also test whether idiosyncratic volatility, $ivol$, also increases option momentum. Column (5) of Table 2.6 examines this variable. Indeed, the significantly positive coefficient of the $opmom * ivol$ interaction suggests that option momentum is stronger in idiosyncratic volatility, while the negative coefficient of the standalone $ivol$ is consistent with Cao and Han (2013). The inclusion of $ivol$ interaction does not affect the interaction between past option returns and continuous information. Thus, our result that option momentum is explained by continuous information is robust after controlling for the interaction terms involving firm size, illiquidity and idiosyncratic volatility.

We also investigate the role of continuous information in determining option momentum strength by examining the average momentum slope coefficients across different continuous information groups. We categorize straddles into quintile subsamples based on continuous information in the formation period. In each continuous information subsample, we obtain the average option momentum slope coefficient from Fama and MacBeth (1973) regression by regressing straddle returns on past straddle returns. The frog-in-the-pan hypothesis holds if we observe increasing average slopes across CI groups. Table 2.7 reports the results.

Table 2.7. Continuous information and option momentum slope

This table reports the coefficients of option momentum in the Fama–MacBeth regressions of straddle returns, *opret*, on average past straddle returns from month *t-2* to month *t-12*, *opmom*, across quintile groups based on sorting continuous information, *CI*, firm size, *size*, Amihud illiquidity, *ailliq*, stock idiosyncratic volatility, *ivol*. Quintile (1) represents low values of the conditioning variables, and quintile (5) represents high values of the conditioning variable. 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.

	Option momentum slope for each quintile group			
	CI	size	ailliq	ivol
	(1)	(2)	(3)	(4)
(1)-Low	0.0164	0.0506***	0.0191	0.0095
	(1.34)	(3.03)	(1.26)	(0.75)
(2)	0.0334***	0.0760***	0.0495***	0.0524***
	(2.86)	(5.57)	(4.10)	(3.64)
(3)	0.0582***	0.0489***	0.0491***	0.0872***
	(5.13)	(3.67)	(3.78)	(8.31)
(4)	0.0682***	0.0443***	0.0639***	0.0759***
	(4.95)	(3.84)	(4.30)	(6.53)
(5)-High	0.0863***	-0.0013	0.0767***	0.0718***
	(6.71)	(-0.09)	(5.76)	(6.21)

In column (1) of Table 2.7, we find that the average option momentum slope monotonically increases from an insignificant 0.016 to a highly significant 0.086 (*t-stat* = 6.71) when moving from the most discrete information group to the most continuous information group. The results are consistent with those in our double-sorting analysis and demonstrate that when past option returns are accumulated in a discrete manner, the options market adjusts to past option returns so that no future returns can be predicted from past option returns, and that when information is more continuous, option return momentum is stronger. In column (2) of Table 2.7, instead of conditioning on CI, we sort straddles into quintile groups based on firm size and report the average option momentum slope for each group. Columns (3) and (4) repeat this exercise for illiquidity and idiosyncratic volatility as conditioning variables, respectively. We do not observe a monotonic increase of average option momentum slope coefficient across firm size quintiles and idiosyncratic volatility quintiles. Instead, the patterns are hump shaped. When conditioning on Amihud illiquidity, option momentum slopes in general increase, but not monotonically. This pattern is consistent with the vast literature on the strengthening of financial anomalies in illiquidity (Avramov et al., 2006; Chordia et al., 2014; Sadka & Scherbina, 2007) and also with Heston et al. (2023). Note that the result here should be considered in addition to the regression results in Table 2.6, where we have already shown that the interaction with illiquidity is insignificant when there is an interaction with continuous information. All in all, our results show that continuous information is an important variable that explains option momentum while other control variables are unlikely to play a key role in explaining the option momentum effect.

2.3.5. Continuous information and option pricing

Option-implied volatility is an important parameter in the options market. However, empirical studies show that option-implied volatility is a biased estimate of future realized volatility (Christensen & Prabhala, 1998).[12] Goyal and Saretto (2009) demonstrate that the negative relation between implied-historical volatility deviation and option returns exists because high volatility deviation options have excessively high implied volatility that is not justified by future events. Thus, the forecast error of implied volatility (*exvol*), the difference between future realized volatility and implied volatility, manifests in the differences in option returns. If this forecast error is too high, the option is too cheap and has a high return; if the forecast error is too low, the option is too expensive and has a low return. Lochstoer and Muir (2022) also use the difference between option-implied variance for the next month and the

[12] Stein (1989) argues that if the volatility of the underlying asset is known, option prices can be completely determined by the Black and Scholes (1973) model, and implied volatility should equal the volatility that is expected to be realized over the option lifespan so that any speculation on volatility is unprofitable.

actual realized variance over the next month to measure the options market's reaction to past information.

Heston et al. (2023) posit that past option returns can induce option-implied volatility adjustment that is not justified by the future realized volatility, resulting in the relationship between past option returns and future option returns. Thus, the pricing of options is an important consideration to understanding the option momentum phenomenon. We study the option cheapness/expensiveness by investigating the behavior of *exvol* with respect to option momentum and the frog-in-the-pan hypothesis.

In Table 2.8, we regress implied volatility forecast error, *exvol*, on average past option returns in the prior 2 to 12 months, *opmom*. The result in column (1) shows that the forecast error of implied volatility is positively related to past option returns, with the coefficient being significant at the 1% level. In other words, options with past high (low) returns tend to have implied volatility lower (higher) than the subsequent realized volatility. This suggests that prices of options that outperformed in the past are relatively cheap, and prices of options that underperformed are relatively expensive, resulting in the momentum pattern: past outperformers continue to outperform, and past underperformers continue to underperform.

Table 2.8. Continuous information and option pricing

This table reports results of Fama–MacBeth regressions of the difference between next month's realized stock total volatility and option implied volatility, *exvol*, on average past option returns from month *t-2* to month *t-12*, *opmom*, and its interaction with continuous information, *CI*, firm size, *size*, Amihud illiquidity, *ailliq*, stock idiosyncratic volatility, *ivol.* 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.

	exvol				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.065***	0.061***	0.062***	0.063***	0.049***
	(8.05)	(7.93)	(7.90)	(7.82)	(7.82)
opmom	0.040***	-0.009	-0.007	0.005	-0.015
	(7.61)	(-1.01)	(-0.71)	(0.50)	(-1.36)
opmom*CI		0.040***	0.039***	0.033***	0.027***
		(6.80)	(6.67)	(4.55)	(4.41)
opmom*size			-0.008***	-0.008***	-0.004**
			(-3.12)	(-3.65)	(-2.35)
opmom*ailliq				1.072***	0.337
				(2.89)	(0.92)
opmom*ivol					0.073***
					(5.81)
CI		0.003	0.003	0.003	0.002
		(1.56)	(1.51)	(1.59)	(0.88)
size			-0.002	-0.003*	0.000
			(-1.51)	(-1.88)	(0.13)
ailliq				-0.136	-0.406**
				(-0.70)	(-2.23)
ivol					0.033***
					(3.74)
Avg Adj R^2	0.0042	0.0050	0.0047	0.0143	0.0269

In the appendix Table A2.4, we examine the relevance of *exvol* in the option momentum phenomenon by regressing option returns on past option returns controlling for *exvol*. Our results show that controlling for *exvol* makes the relation between option returns and past option returns insignificant, while controlling for other variables such as firm size, Amihud illiquidity, stock idiosyncratic volatility, does not affect this relation. We conclude that option pricing captured by *exvol* fully explains the option momentum effect. Hence, we further examine the explanatory power of continuous information in option momentum from the option pricing perspective.

In column (2) of Table 2.8, we find that the positive relation between the implied volatility forecast error *exvol* and past option returns *opmom* is stronger in continuous information. The coefficient of the $opmom * CI$ interaction is positive and significant at the 1% level. With the presence of this interaction, the standalone *opmom* becomes insignificant, implying that when information is very discrete (CI equals 0), there is no relation between *opmom* and *exvol*. This suggests that the options market adjusts to information that arrives in a sudden and dramatic manner, hence, there is no volatility discrepancy related to past option returns that arrive discretely. The forecast error of implied volatility increases in past option returns because investors are inattentive about past return information that arrives continuously.

In columns (3), (4) and (5) of Table 2.8, we include the interactions between *opmom* and firm size, Amihud illiquidity and idiosyncratic volatility, respectively. The results show that the increase of forecast error of implied volatility in past option returns is more pronounced in firms with smaller market capitalization, higher illiquidity and higher idiosyncratic volatility. Importantly, the interaction between *opmom* and CI remains highly significant after including those variables. Hence, continuous information plays a key role in explaining the increase of implied volatility forecast error with respect to past option returns. This represents a dynamic behind the option momentum phenomenon. If information about past option returns arrives in a continuous manner, it fails to attract investors' attention, hence the inefficient adjustment of option prices. This inefficient pricing manifests in option momentum.

2.3.6. Long-run option momentum

Table 2.9. Long-run option momentum profitability

This table investigates the long-run option momentum and its relation to continuous information. The insights from this table are that there exists a long-run option momentum where the average past option returns in months *t-2* to *t-12* positively predict each future option return in months *t+1* to *t+36* and that this long-run option momentum is more pronounced as continuous information in the *t-2* to *t-12* formation period is higher. In each month from *t+1* to *t+36*, straddles are first sorted on continuous information into five quintiles, with quintile (1) representing discrete information and quintile (5) representing continuous information. In each quintile, straddles are then sorted based on average past straddle returns in months *t-2* to *t-12*, *opmom*, to obtain the option momentum profitability, which is the return differential between top and bottom *opmom* quintiles. We report the variation in option momentum profitability across continuous information groups for each month from *t+1* to *t+36*. In parentheses are the robust Newey and West (1987) *t*-statistics with a lag of 6 months. ***, **, * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	Continuous information quintile groups				
Profitability	(1)-Discrete	(2)	(3)	(4)	(5)-Continuous
Month t+1	0.0039 (0.32)	0.0412*** (3.48)	0.0306*** (2.79)	0.0786*** (5.24)	0.1139*** (4.98)
Month t+2	0.0124 (1.00)	0.0319*** (2.89)	0.0291** (1.97)	0.0601*** (4.05)	0.1166*** (5.86)
Month t+3	0.0162 (1.26)	0.0184* (1.85)	0.0422*** (4.06)	0.0644*** (3.36)	0.106*** (4.98)
Month t+4	0.0175 (1.41)	0.0073 (0.76)	0.0266** (2.08)	0.0668*** (4.59)	0.0982*** (4.15)
Month t+5	0.0198* (1.81)	0.0064 (0.43)	0.0464*** (3.89)	0.0705*** (4.91)	0.0934*** (3.44)
Month t+6	0.0093 (0.67)	0.0064 (0.38)	0.0607*** (5.1)	0.0707*** (4.58)	0.0884*** (2.95)
Month t+7	0.0079 (0.61)	0.0069 (0.49)	0.0646*** (4.44)	0.088*** (4.58)	0.0802*** (3.1)
Month t+8	-0.0001 (-0.01)	0.0361*** (2.86)	0.0456*** (3.64)	0.0741*** (4.24)	0.065** (2.4)
Month t+9	-0.0194 (-1.23)	0.0213* (1.88)	0.0617*** (4.87)	0.0582*** (2.95)	0.0623** (2.24)
Month t+10	-0.0124 (-0.75)	0.0296*** (2.62)	0.0519*** (3.9)	0.0717*** (4.05)	0.0672*** (2.83)
Month t+11	-0.0111 (-0.66)	0.0272* (1.85)	0.0529*** (4.18)	0.0692*** (3.26)	0.0672*** (2.67)
Month t+12	0.0119 (0.69)	0.0346** (2.28)	0.0489*** (4.2)	0.0668*** (3.64)	0.0678*** (2.96)
Month t+13	0.0112 (0.68)	0.0302** (2.21)	0.034*** (2.62)	0.0625*** (2.97)	0.0622*** (2.77)
Month t+14	0.0121 (0.83)	0.02 (1.58)	0.0387*** (3.6)	0.0449** (2.06)	0.0476* (1.88)
Month t+15	0.009 (0.75)	0.023* (1.79)	0.0443*** (3.53)	0.0585** (2.35)	0.0849*** (3.15)
Month t+16	0.0174 (1.22)	0.0073 (0.69)	0.0397** (2.56)	0.0443** (2.5)	0.0916*** (3.89)
Month t+17	0.0199* (1.78)	0.007 (0.66)	0.0359*** (2.71)	0.07*** (3.55)	0.0709*** (2.75)
Month t+18	0.0197* (1.78)	0.0267* (1.87)	0.0277* (1.88)	0.0848*** (4.86)	0.0694** (2.43)

Month t+19	0.0104 (0.91)	0.0205 (1.43)	0.0115 (0.65)	0.0857*** (4.79)	0.0801*** (2.73)
Month t+20	-0.0053 (-0.50)	0.0356*** (2.66)	0.0204 (1.25)	0.0477** (2.56)	0.1167*** (3.91)
Month t+21	1e-04 (0.01)	0.0249** (2.13)	0.0112 (0.67)	0.0705*** (4.09)	0.1076*** (3.34)
Month t+22	0.0276** (2.22)	0.0447*** (3.18)	0.0194 (1.54)	0.0611*** (2.72)	0.0891*** (2.75)
Month t+23	0.0214* (1.93)	0.0084 (0.69)	0.0339** (2.56)	0.0234 (1.25)	0.097*** (3.36)
Month t+24	0.0147 (1.00)	0.0039 (0.3)	0.0318** (2.27)	0.0614*** (3.88)	0.0628** (2.08)
Month t+25	0.0058 (0.47)	0.0247** (1.99)	0.0119 (0.95)	0.0422** (2.16)	0.0641** (2.32)
Month t+26	-0.0108 (-0.73)	0.0256** (1.98)	0.0373*** (3.01)	0.0398*** (2.6)	0.0616** (2.42)
Month t+27	-0.0013 (-0.09)	0.0168 (1.21)	0.0303** (2.53)	0.0675*** (3.77)	0.0441* (1.73)
Month t+28	0.0039 (0.25)	0.0225* (1.95)	0.0138 (1.01)	0.076*** (4.32)	0.0381* (1.68)
Month t+29	0.0134 (0.88)	0.0054 (0.41)	0.0427*** (3.45)	0.0513** (2.4)	0.0573*** (2.84)
Month t+30	0.0112 (0.66)	0.0126 (0.97)	0.0384** (2.32)	0.048*** (3.54)	0.0261 (0.82)
Month t+31	0.0078 (0.50)	0.0198 (1.62)	0.0403*** (2.66)	0.0633*** (3.2)	0.0598* (1.72)
Month t+32	0.0129 (1.00)	0.0371*** (2.82)	0.0166 (1.3)	0.0767*** (4.67)	0.0309 (0.94)
Month t+33	-0.0024 (-0.13)	0.0254* (1.84)	0.0264** (2.28)	0.0529*** (3.27)	0.0592* (1.79)
Month t+34	-0.0018 (-0.10)	0.0268** (2.33)	0.0346** (2.43)	0.0489** (2.47)	0.0608* (1.73)
Month t+35	-0.0147 (-0.89)	0.0181 (1.6)	0.0207* (1.86)	0.084*** (3.14)	0.0473** (2.07)
Month t+36	-0.0241 (-1.58)	0.0233 (1.62)	0.045*** (3.45)	0.0638*** (3)	0.0517* (1.77)

Heston et al. (2023) demonstrate that option momentum persists over multiyear horizons. Straddle returns can be positively predicted not only by the “2 to 12” past returns but also by the earlier past returns. This means that the same formation period return information is relevant not only to the next month’s option returns but also to option returns many months later. In this section, we examine whether the continuous information in the formation period can explain this long-run option momentum pattern.

We construct various straddle positions at different time points in the future – from month *t+1* to month *t+36* – and examine the influence of continuous information on the long-run option momentum using double sorting analysis. In each future month *t+1* to *t+36*, we first sort straddles on continuous information, CI, in the *t-12* to *t-2* period into quintiles. In each quintile, straddles are then sorted based on average past straddle returns from month *t-12* to month *t-2*, *opmom.* To evaluate long-run option momentum, we compute the differential return between the top and bottom quintiles based on *opmom* for each CI quintile group. The return differentials, hence, reflect the response of option returns at each future time point (from *t+1* to *t+36*) to information in the *t-12* to *t-2* formation period. Table 2.9 shows the results on the long-run option momentum profitability for each CI group. The long-run option momentum in each future time point tends to be stronger as continuous information in the formation period increases across quintiles. In each month from month *t+1* to month *t+36*, the return differential based on the formation period returns is almost always insignificant for the most discrete information group and strongest for the most continuous information group. We observe no significantly negative return differential in any future month for any CI group; this is consistent with the lack of long-run option return reversal demonstrated by Heston et al. (2023). Overall, the results of the double sorting analysis in Table 2.9 suggest that the long-run option momentum strengthens in continuous information in the formation period.

Figure 2.2. Long-run option momentum and continuous information

In this figure, we examine returns of straddles formed from 1 to 36 months after the formation date of the straddles in our main analysis and use continuous information together with past option returns to predict returns of these distant future straddles. The distant future straddles are first sorted on continuous information into quintiles. In each continuous information quintile, we further sort these straddles on past option returns to compute the return differentials between the top and bottom past option return quintiles. This procedure results in the long-run option momentum profitability for each continuous information quintile, where distant future straddle (formed 1 to 36 months from now) returns are predicted from past straddle return information. The dashed red line represents the average long-run momentum profitability of the most continuous information (top *CI*) quintile. The solid blue line represents the average long-run momentum profitability of the most discrete information (bottom *CI*) quintile.

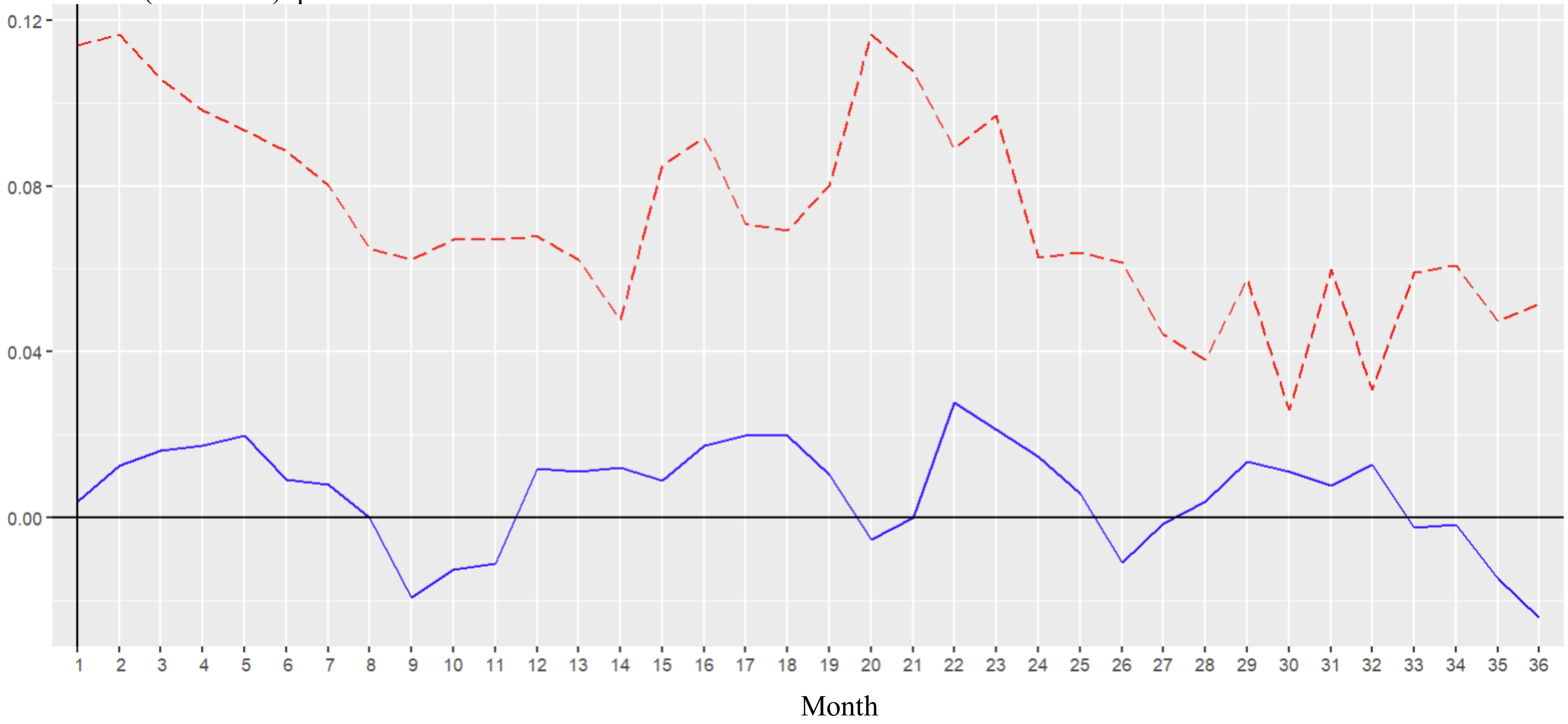


Figure 2.2 illustrates how the long-run option momentum is conditioned on continuous information in the formation period. In each month when future straddles are established, we first sort straddles into quintile groups based on CI in the “2 to 12” formation period and then sort them into quintiles based on past option returns *opmom*. We compute the return differentials between the top and bottom quintiles based on past returns for each of the five continuous information groups. The red dashed line and the blue solid line represent the average return differentials in 1 to 36 months for the top CI group and the bottom CI group, respectively. It is clear that the long-run option momentum profitability of the continuous information group is always positive and above that of the discrete information group. The future option momentum profitability for the discrete information is close to zero. This implies that the market constantly adjusts to salient past information so that no consistent momentum profit can be generated in the discrete information group.

Table 2.10. Long-run option momentum

This table investigates the long-run option momentum and its relation with continuous information. Panel A reports results of Fama–MacBeth regressions of straddle returns in each future month, *opret1* to *opret12*, on average past option returns from month *t-2* to month *t-12*, *opmom*, where *opret1* to *opret12* represent monthly returns of straddles formed in month *t+1* to month *t+12*. Panel B additionally considers interaction with continuous information about option returns in the formation period, *CI*. 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. Long-run option momentum

	opret1	opret2	opret3	opret4	opret5	opret6	opret7	opret8	opret9	opret10	opret11	opret12
Intercept	-0.012	-0.012	-0.013	-0.013	-0.013	-0.012	-0.012	-0.011	-0.012	-0.011	-0.011	-0.010
	(-0.57)	(-0.56)	(-0.64)	(-0.66)	(-0.69)	(-0.66)	(-0.66)	(-0.60)	(-0.67)	(-0.63)	(-0.63)	(-0.58)
opmom	0.046***	0.043***	0.041***	0.037***	0.041***	0.041***	0.049***	0.049***	0.044***	0.043***	0.044***	0.044***
	(5.60)	(5.57)	(4.99)	(4.81)	(4.61)	(4.36)	(4.69)	(5.29)	(4.58)	(4.75)	(4.57)	(4.58)
Avg Adj R^2	0.0011	0.0010	0.0009	0.0009	0.0009	0.0009	0.0012	0.0011	0.0008	0.0008	0.0009	0.0009

Panel B. Continuous information and long-run option momentum

	opret1	opret2	opret3	opret4	opret5	opret6	opret7	opret8	opret9	opret10	opret11	opret12
Intercept	-0.014	-0.011	-0.011	-0.012	-0.003	-0.010	-0.002	-0.014	-0.015	-0.009	-0.016	-0.004
	(-0.57)	(-0.44)	(-0.49)	(-0.61)	(-0.16)	(-0.51)	(-0.12)	(-0.69)	(-0.75)	(-0.46)	(-0.84)	(-0.21)
opmom	-0.035	-0.047	-0.037	-0.036	-0.027	-0.051	-0.026	-0.037	-0.044	-0.061**	-0.059*	-0.064**
	(-1.18)	(-1.53)	(-1.46)	(-1.44)	(-0.95)	(-1.64)	(-0.79)	(-1.00)	(-1.26)	(-2.33)	(-1.95)	(-2.20)
opmom*CI	0.066***	0.074***	0.064***	0.06***	0.054**	0.075***	0.061**	0.067**	0.068**	0.082***	0.082***	0.086***
	(2.87)	(3.15)	(3.20)	(3.03)	(2.51)	(3.20)	(2.28)	(2.21)	(2.54)	(3.67)	(3.46)	(3.47)
CI	0.002	-0.001	-0.001	-0.001	-0.008	-0.002	-0.008	0.003	0.003	-0.002	0.005	-0.005
	(0.21)	(-0.13)	(-0.19)	(-0.16)	(-1.20)	(-0.26)	(-1.03)	(0.41)	(0.34)	(-0.29)	(0.57)	(-0.74)
Avg Adj R^2	0.0014	0.0012	0.0011	0.0012	0.0012	0.0014	0.0020	0.0019	0.0010	0.0010	0.0014	0.0012

In Table 2.10, we use the Fama-MacBeth regressions to test whether the continuous information in the formation period can explain the relations between past option returns in the *t-12* to *t-2* period, *opmom*, and option returns in future months from *t+1* to *t+12*. In panel A of Table 2.10, the results show that *opmom* positively predicts option returns in months *t+1* to *t+12*. All the coefficients are highly significant at the 1% level. The results are consistent with the persistence of option momentum over long horizons. In panel B of Table 2.10, we regress future option returns on *opmom* and its interaction with continuous information in this formation period. We find that the positive coefficients of past option returns *opmom* disappear or even turn negative after 10, 11 and 12 months in future. The standalone continuous information variable CI has no significant relationship with option returns at various future time points as it does with next month's option returns in our earlier analysis. Most importantly, the interactions between past option returns and continuous information are positive and highly significant. This suggests that long-run option momentum strengthens in continuous information. If the information in the formation period is continuous, investors are inattentive to that information and do not reflect that information into option prices when they trade options at future time points, generating long-run momentum. Thus, continuous information about past option returns can explain not only option momentum but also the persistence of option momentum over long horizons.

Heston et al. (2023) posit that the persistence in momentum is a peculiar characteristic of the options market as in the long run, momentum tends to reverse for other asset classes such as stocks (Daniel et al., 1998) and corporate bonds (Bali et al., 2021). According to Heston et al. (2023), the lack of long-run reversal in option returns makes the explanation based on delayed overreaction of Daniel et al. (1998) unlikely for the options market; instead, their results are in agreement with the explanation based on underreaction, such as conservatism (Barberis et al., 1998) and gradual information diffusion (Hong & Stein, 1999). Our results in the option market are in line with those in Da et al. (2014) for the stock market, which demonstrate that continuous information induces investor underreaction and results in strong and persistent stock return momentum that does not reverse in the long run. Our study reveals that the persistence in option momentum is indeed driven by investors' underreaction to past information arriving in a continuous manner.

2.4. Conclusion

In this study, we use the frog-in-the-pan hypothesis to explain the option momentum phenomenon in Heston et al. (2023). The existence of option momentum depends on whether the past option return information arrives in a continuous or discrete manner. If formation period returns are accumulated in a sudden and dramatic manner, investors can recognize the substantial changes and reflect past returns in option prices; hence, the momentum of option returns does not exist. On the contrary, if past return information arrives continuously in small amounts, investors are less likely to pay attention to this information and fail to adjust option prices adequately, making past outperformers continue to outperform and past underperformers continue to underperform. This explanation of option momentum is analogous to the frog-in-the-pan story: if a frog is put in boiling water, it will immediately react and jump out of the pan; conversely, if it is put in water slowly raised to a boil, it cannot recognize the gradual changes and fails to react. Our explanation of option momentum is in line with the underreaction-based explanation of stock momentum (Chan et al., 1996; Da et al., 2014). Our study demonstrates that option momentum exists because investors underreact to information that arrives continuously.

Our paper enriches the growing literature on the cross-section of option returns. Besides explaining the origin of option momentum, we offer insights to improve the profitability of option momentum strategy. We also highlight the importance of investor attention to understanding financial anomalies in the options market. Continuous information can explain not only option momentum but also long-run option momentum. When information about past returns is continuous, it results in option momentum that persists over multiyear horizons.

Chapter 3. Option Return Co-movements

3.1. Introduction

Security return co-movements play an important role in asset pricing literature and have practical implications for asset allocation strategies. Despite tremendous growth in the options market, little is known about the co-movement in option returns. In stock market literature, the traditional view on co-movement holds that stock return co-movement reflects the co-movement in fundamentals. Empirical studies show that firms linked by production complementarity (Lee et al., 2024), shared analyst coverage (Ali & Hirshleifer, 2020; Muslu et al., 2014), or horizontal industry (Hoberg & Phillips, 2018) tend to have co-movements in fundamentals and hence co-movements in stock returns. Given that stock returns are exposed to market risk premium, the co-movement in stock returns can reflect firms' common exposure to stock market risk factors. In contrast, delta-neutral straddles have a market beta of zero and generate returns that are independent of the performance of the underlying equity. Hence, studying co-movement in delta-neutral straddle returns not only offers insights for option portfolio diversification but also deepens the understanding of asset return co-movements across firms.

In this study, we examine whether delta-neutral straddle returns of firms linked by different economic channels (production complementarity, industry or shared analyst coverage) tend to comove and what factors can help explain the return co-movements the options market. Following Heston et al. (2023), we construct delta-neutral straddles consisting of call and put options with weights that neutralize the delta of the straddles, making the performance of the straddles unaffected by the performance of the underlying equity. We study the co-movements in option returns of economically linked firms by examining the relations between straddle returns of the focal firm and the average straddle returns of its peers, where peers are identified as firms linked by either production complementarity (Lee et al., 2024), industry (Hoberg & Phillips, 2018), or shared analyst coverage (Muslu et al., 2014). Our results show that there exist strong co-movements in the option returns of firms linked by each of these mechanisms. A straddle return of a firm tends to be high if its peers also experience high straddle returns. Given the co-movements in option returns of firms having complementary relationships, operating in the same industry, or being covered by same analysts, our results suggest the potential diversification benefits of investing in options of unrelated firms.

Campbell et al. (2010) demonstrate that a firm's systematic risk, or the stock beta, depends on its fundamentals, hence, firms in the same fundamental category (e.g., value or growth firms) have similar degrees of systematic risk and similar stock return movements. Similarly, Bekaert et al. (2009) argue that the same market risk exposure is an important driver of stock return co-movements. According to Israelsen (2016), to demonstrate excess return co-movement, it is necessary to rule out the explanation based on similar systematic risk exposures. While Lee et al. (2024), Muslu et al. (2014) and Hoberg and Phillips (2018) show the network-based returns co-movements, these studies remain silent about whether such co-movements are due to similar market risk exposures. Our results on the co-movements in delta-neutral straddles, the assets with zero betas (Coval & Shumway, 2001), suggest that asset return co-movements can arise beyond the explanation of systematic risk exposures.

Unlike delta-neutral returns that are not related to the performance of the underlying equity, raw option returns can be driven by the underlying stock returns. Hence, we conjecture that raw option returns also display co-movements to reflect, to some extent, the co-movements in underlying stock returns. Our results show that there are indeed co-movements in raw option returns and the co-movements are stronger for raw returns than for delta-neutral returns, evident by significantly higher adjusted R-squared in the regressions of focal firm's return on peers' average return. Hence, the co-movements in raw option returns can reflect both the co-movements in option pricing and the co-movements in underlying equity performance.

According to Chan et al. (1998), the co-movement in stock returns can be driven by the common risk factors. However, not all common factors can capture stock return co-movement. A common factor could explain stock return co-movement if the attribute associated with that factor helps partition stocks into separate groups. For example, the return on the group of small stocks tends to behave in a systematically different way from the large stock group's return; therefore, the size factor can significantly capture covariation in stock returns. Motivated by the literature linking the time-varying return co-movement and common factors, we ask whether and which option and stock common factors can explain the network-based option return co-movements documented in our paper. According to Horenstein et al. (2023), the common factors in the options market can effectively explain the variation in option returns, and these factors are distinct from the stock market common factors. In our study, we examine the effect of both option and stock common factors. In line with Barberis et al. (2005) and Green and Hwang (2009), we measure the time-varying strength of return co-movement by the slope coefficient in the regression of focal firm returns on peer average returns. Using the option factors suggested by Horenstein et al. (2023), we find that the strength of delta-neutral straddle return co-movements is related to the option common factors based on the difference between implied and historical volatilities, and volatility-of-volatility. Furthermore, consistent with the idea that delta-neutral option returns are independent of underlying stock performance, our results show that the stock markets factors do not have relations with the strength of delta-neutral return co-movements.

Examining the co-movements in raw option returns, we find that these co-movements are, on the other hand, strongly related to the stock market factor, especially the market risk premium. Particularly, the call option return co-movements are stronger when the market is on the rise, and the put option return co-movements are stronger when the market is on the decline. This can be because the return co-movement becomes stronger when the difference in return between subgroups of assets is more striking. In bear markets, call options are more likely to expire out-of-the-money or deep out-of-the-money. However, there is no difference in returns between out-of-the-money calls and deep out-of-the-money calls. Therefore, call return co-movement becomes less evident in bear markets. In contrast, put return co-movement can be more pronounced in bear markets, because in bear markets, put options are more likely to expire in-the-money (and less likely to expire out-of-the-money or deep out-of-the-money), making the difference in return among subgroups of connected firms become more distinct.

According to Lochstoer and Muir (2022), the realized volatility risk premium, which is the difference between implied volatility for the next month and the actual realized volatility over the next month, captures the expensiveness of the claims that provide insurance against future volatility (a straddle is one of these claims). Goyal and Saretto (2009) also argue that implied volatility exceeding the subsequent realized volatility indicates relatively expensive options. Investigating the expensiveness of straddles, we find that there are co-movements in realized volatility risk premium of firms linked by production complementarity, industry, and shared analyst coverage. The synchronicity in straddle pricing among economically linked firms suggests that equity options of a firm tend to be expensive if options of its peers are also expensive. There is a co-movement in the expensiveness of volatility claims among economically linked firms. This can be the reason why there are co-movements in straddle returns among linked firms.

After documenting the co-movements in option returns among linked firms, we ask whether the option return of a focal firm can be predicted by the information from its peers. A typical spillover effect in return predictability is the peer momentum, a phenomenon in which the focal firms' returns can be predicted by past returns of peer firms (Ali & Hirshleifer, 2020; Hoberg & Phillips, 2018; Lee et al., 2024). According to Heston et al. (2023), the average option return of a firm in the past 12th to 2nd months is a predictor of option return of that firm. To examine the peer momentum effect, we calculate, for each focal firm, the average past option returns of its peers. The results show that option returns of the focal firms are positively related to past returns of their peers, confirming the existence of peer momentum. The peer momentums based on production complementarity, industry and shared analyst coverage provide incremental information to momentum of the focal firm as they are robust after controlling for the focal firm's past option returns. Thus, our results suggest that a firm's option return can be predicted not only by its own characteristics but also by its peers' characteristics.

The economic theory suggests that the degree of co-movement between two firms depends on the degree of linkage between them (Conley & Dupor, 2003). Based on this theoretical guidance, Lee et al. (2024) identify three degrees of production complementarity linkage (strong, medium and weak) and find that stock return co-movement is stronger among firms with stronger production complementarity link. Utilizing the data provided by Lee et al. (2024), we find that the co-movement in option returns based on production complementarity is also positively related to the strength of the linkage.

Our study contributes to literature in important ways. First, we contribute to the literature on return co-movements. The traditional view of co-movement holds that return co-movement is due to co-movements in fundamental values. Later studies show that excess return co-movement can arise from reasons unrelated to fundamentals, such as index inclusion (Barberis et al., 2005), similarity in stock prices (Green & Hwang, 2009) or similarity in headquarter location (Chan et al., 2003; Pirinsky & Wang, 2006). However, Chen et al. (2016) call the evidence of excess co-movement into question, showing that changes in market betas account for the changes in co-movement structures documented in Barberis et al. (2005) and Green and

Hwang (2009). Our findings on delta-neutral return co-movements are not vulnerable to the critique that they are driven by market beta, as delta-neutral options have a market beta of zero. Our study suggests that return co-movement can arise beyond the explanation of systematic risk. Besides the stock market literature, the literature on the options market documents a common structure in implied volatility (Engle & Figlewski, 2015). Our paper differs from Engle and Figlewski (2015) in that we study co-movements in option returns and that we document co-movements of focal firms with their related firms rather than with the aggregate market.

Second, our study enriches the growing literature on option common factors. Studies show that option prices and option returns follow a factor structure (Büchner & Kelly, 2022; Christoffersen et al., 2018; Fournier et al., 2024). Zhan et al. (2022) and Goyal and Saretto (2025) show that a parsimonious factor model can summarize the performance of various option strategies. Horenstein et al. (2023) show that three common factors effectively explain the cross-section of option returns. While these studies show the common structures in return of options in the whole market, our study shows that there exists a commonality structure in each subset of economically linked firms.

Third, our study contributes to the literature on option return predictability. Prior studies show that option return can be predicted by past option returns (Heston et al., 2023), difference between implied volatility and historical volatility (Goyal & Saretto, 2009), stock idiosyncratic volatility (Cao & Han, 2013), default risk (Vasquez & Xiao, 2024) and various accounting characteristics (Zhan et al., 2022). In general, these studies show that a firm's option return can be predicted by its own characteristics. In this study, we show that the option return of one firm can be predicted by the characteristics of its connected firms.

The remainder of the chapter continues as follows. Section 3.2 describes the data and methodology to investigate the co-movements in option returns among economically linked firms. Section 3.3 presents our empirical results on the network-based return co-movements and how these co-movements are influenced by the common factors. Finally, section 3.4 provides the conclusion of the chapter.

3.2. Data

The information about call and put options is retrieved from the OptionMetrics Ivy DB. The sample period is from January 1996 to December 2023. We refer to CRSP and Compustat for stock information and corporate accounting data.

We follow Heston et al. (2023) to construct delta-neutral straddles from at-the-money call and put options on the same equity with one-month maturity. To select options that are close to at-the-money (ATM), we require that the absolute delta be closest to 0.5 and in the range of 0.25 to 0.75. The weights of call and put are chosen to make the straddles delta neutral. Particularly, they are proportional to $-\Delta_P C$ and $\Delta_C P$, respectively, where $\Delta_C(\Delta_P)$ is delta of the call (put) options and $C(P)$ is the bid-ask midpoint price of call (put) options. The weights should sum to one and are typically close to 50/50. We calculate returns of delta-neutral straddles as the weighted average of the returns on the calls and puts. The call and put returns depend on the payoffs at maturity and the initial bid-ask midpoint prices. Options are formed on the option expiration day (the third Friday) of each month and held until maturity, which is the option expiration day next month. In our final sample, there are 678,465 straddle observations.

In this study, we examine the co-movements based on three economic links, including production complementarity (Lee et al., 2024), industry (Hoberg & Phillips, 2018), and shared analyst coverage (Ali & Hirshleifer, 2020). First, we employ the data that are made publicly available by Lee et al. (2024) to identify firms with production complementarity relationships.[13] Using data from the Benchmark Input-Output Surveys of the Bureau of Economic Analysis, Lee et al. (2024) develop a measure of production complementarity between any two firms. This measure captures the extent to which the two firms' outputs are used as complementary inputs in the same downstream production process using the data of five-year rolling windows. To make the production complementarity link distinct from industry link, Lee et al. (2024) discard any pair of firms that are in the same industry and focus on inter-industry complementors. Then, if the production complementarity measure is above the 98th percentile, two firms are considered strong complementors. If the measure is between 96th and 98th percentiles or between 94th and 96th percentiles, two firms are considered medium or weak complementors, respectively. In the baseline results, we use all strong, medium and weak complementors as peer firms for each focal firm. In subsequent tests, we study each group separately. In line with Lee et al. (2024), we calculate the equal-weighted straddle return of the complementors for each focal firm and examine the relation between this average return and focal firm's return.

[13] The production complementarity data provided by Lee et al. (2024) is available up to 2016. Thus, our results on co-movement among product complementors rely on a sample that extends up to 2016 (instead of 2023 as for other economic links in this study). Further, due to the lag in data release by the Bureau of Economic Analysis, the data Lee et al. (2024) use to identify production complementarity peers may not be observable at the time of straddle formation. For the predictive purpose, Lee et al. (2024) develop another dataset using only available information to identify peers. Following the recommendation of Lee et al. (2024), we use their co-movement dataset when studying return co-movement, and their predict dataset when studying return predictability.

Second, we use the text-based industry data from Hoberg and Phillips (2018) to identify firms in the same industry. Hoberg and Phillips (2018) analyze 10-K annual filings with text parsing algorithms to arrive at the business descriptions of each firm and identify firms in the same industry. Hoberg and Phillips (2018) demonstrate that compared with the Standard Industrial Classification (SIC) codes, the text-based industry classifications generate stronger and more robust industry momentum. In our study, we match the monthly straddle of the focal firm and the monthly straddles of the peers if these firms are in the same industry in the last year according to the Hoberg and Phillips (2018) dataset. Similar to Hoberg and Phillips (2018), we calculate the equal-weighted straddle return of peer firms for each focal firm to study return co-movement.

Third, we use the Institutional Brokers Estimate System (IBES) database to identify firms that are covered by the same analysts in the month before the option formation date and use the formula of Ali and Hirshleifer (2020) to calculate the average return of the peers. Particularly, in the average return formula, each peer's return is weighted by the number of analysts who cover stocks of the peer and the focal firm, since Ali and Hirshleifer (2020) argue that the higher the number of shared analysts, the stronger the connection.

In our main test for the co-movement in option returns among economically linked firms, we follow Lee et al. (2024) and Hoberg and Phillips (2018) to use Fama and MacBeth (1973) regression with the following specification:

$$opret_{i,t} = \alpha + \beta peer\_ret_{i,t} + \gamma control_{i,t} + \epsilon_{i,t} \qquad (1)$$

where $opret_{i,t}$ is the focal firm's delta-neutral straddle return, i refers to firm i, t refers to month t, the main independent variable $peer\_ret_{i,t}$ is the peer firms' average option return and can be either $peer\_pc_{i,t}$, $peer\_in_{i,t}$ or $peer\_cf_{i,t}$ ($peer\_pc_{i,t}$ is the average delta-neutral straddle returns of peer firms linked by production complementarity, $peer\_in_{i,t}$ is the average delta-neutral straddle returns of peer firms linked by industry, $peer\_cf_{i,t}$ is the average delta-neutral straddle returns of peer firms linked by shared analyst coverage). We also control for focal firms' characteristics, including the average past straddle returns from lag 2 to lag 12, $opmom$ (Heston et al., 2023), the difference between implied volatility and last month's realized volatility, $ivhv$ (Goyal & Saretto, 2009) , and last month's stock idiosyncratic volatility, $ivol$ (Cao & Han, 2013). Table A3.1 provides the definitions of the key variables used in our study.

The equation (1) is used to assess the co-movements in delta-neutral straddle returns among linked firms. We also study the co-movements in raw call and put option returns in a similar fashion. Particularly, we use the focal firm's raw call (put) option returns as the dependent variable and the average raw call (put) returns of peer firms as the independent variable in the regression to examine the raw call (put) return co-movements.

3.3. Empirical results

3.3.1. Summary statistics

Table 3.1 provides the summary statistics of the key variables in our study. The delta-neutral straddle position, which consists of positions in call and put options on equity of a firm, has a mean return of -0.017. The negative average delta-neutral straddle return is consistent with the negative volatility risk premium predicted by Bakshi and Kapadia (2003). In the theoretical framework of Bakshi and Kapadia (2003), delta-hedged option strategies should underperform zero because investors are willing to pay a premium for option positions that hedge against future increases in volatility. Empirical studies also agree that delta-hedged option returns are negative on average (Cao & Han, 2013; Heston et al., 2023; Vasquez & Xiao, 2024).

Table 3.1. Summary statistics

This table provides summary statistics on mean, standard deviation, 5th, 25th, 50th, 75th, 95th percentiles of our main variables, including delta-neutral straddle returns, *opret*, delta of the call, *deltacall*, and put, *deltaput*, of each straddle, implied volatility, *iv*, which is the weighted average of implied volatilities of the call and put that constitute the straddle, the average of delta-neutral straddle returns of the peers, *peer_pc*, *peer_in*, and *peer_cf*, where peers are identified as firms linked by production complementarity, industry, and shared analyst coverage, focal firm's option momentum, *opmom*, which is the average past delta-neutral straddle returns from the prior 2nd through 12th month, peers' option momentum, *peer_pc_opmom*, *peer_in_opmom*, and *peer_cf_opmom*, which are the average of option momentum of the peers based on production complementarity, industry, and shared analyst coverage.

	Mean	SD	Q5	Q25	Median	Q75	Q95
opret	-0.017	1.326	-0.960	-0.645	-0.239	0.309	1.501
deltacall	0.500	0.105	0.320	0.430	0.501	0.569	0.681
deltaput	-0.493	0.109	-0.683	-0.566	-0.493	-0.420	-0.307
iv	0.476	0.306	0.165	0.277	0.401	0.588	1.021
peer_pc	-0.045	0.373	-0.451	-0.252	-0.112	0.070	0.589
peer_in	-0.033	0.569	-0.585	-0.313	-0.135	0.114	0.777
peer_cf	-0.023	0.630	-0.600	-0.350	-0.143	0.146	0.860
opmom	-0.012	0.399	-0.425	-0.227	-0.066	0.126	0.524
peer_pc_opmom	-0.039	0.111	-0.190	-0.106	-0.047	0.018	0.144
peer_in_opmom	-0.026	0.175	-0.238	-0.128	-0.049	0.046	0.270
peer_cf_opmom	-0.010	0.178	-0.245	-0.122	-0.034	0.073	0.306

The average deltas of the calls and puts that constitute the straddles are approximately 0.5 and -0.5, respectively, suggesting that these calls and puts are close to at-the-money. The positive average delta of call options implies that the value of a call option increases when the underlying stock price increases. The negative average delta of put options implies that the value of a put option decreases when the underlying stock price increases. By constructing delta-neutral straddles, we create the positions that are approximately independent of the performance of the underlying equities. We also report the summary statistics of straddle's implied volatility, which is the weighted average of implied volatilities provided by OptionMetrics for the call and put that constitute the straddles. The *peer_pc*, *peer_in*, and *peer_cf* refer to the average of delta-neutral straddle returns of the peers linked by production complementarity, industry, and shared analyst coverage, respectively. These three variables have negative means, suggesting that portfolios of peers' delta-neutral straddles tend to underperform zero as well. The variable *opmom* refers to the focal firm's option momentum, which is the average of monthly delta-neutral straddle returns in the past 12 months excluding the most recent month. The *peer_pc_opmom*, *peer_in_opmom*, and *peer_cf_opmom* refer to the averages of option momentum of the peers based on production complementarity, industry, and shared analyst coverage, respectively. The results also show negative means for these momentum returns.

3.3.2. Delta-neutral straddle return co-movements

Theoretical work of Barberis and Shleifer (2003) suggests that when making portfolio allocation decisions, institutional and individual investors group similar assets into categories (e.g., small stocks or government bonds) to simplify the processing of large amounts of information, thereby inducing the commonalities in returns of assets in the same categories. Consistent with Barberis and Shleifer (2003), many empirical papers document evidence of the category-based stock return co-movement (Barberis et al., 2005; Boyer, 2011; Claessens & Yafeh, 2013; Green & Hwang, 2009; Pirinsky & Wang, 2006). If grouping assets help simplify the processing of information, such activity is especially important to option traders. For while a firm typically has only one common stock, it can have many outstanding options with different strike prices and maturities. Therefore, as the group-based return co-movement exists in the stock market, it is even more likely to exist in the options market. This section provides results on the co-movements in delta-neutral straddle returns of firms in the same production complementarity network, in the same industry or covered by the same analyst.

Table 3.2. Delta-neutral straddle return co-movements

Panels A, B, and C of this table shows the co-movements in delta-neutral straddle returns between focal firms and their peers by using Fama–MacBeth regressions of delta-neutral straddle returns, *opret*, on peer returns calculated as the average of delta-neutral straddle returns of the peers (*peer_pc*, *peer_in*, and *peer_cf*), where peers are identified as firms linked by production complementarity, industry, and shared analyst coverage, respectively. Panel D of this table considers all three types of co-movement and shows that they are not subsumed by each other. In the regression, we control for focal firms' characteristics including average past straddle returns from lag 2 to lag 12, *opmom*, implied-historical volatility difference, *ivhv*, and idiosyncratic volatility, *ivol*. 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. Co-movement based on the production complementarity link

	opret			
	(1)	(2)	(3)	(4)
Intercept	-0.057***	-0.050***	-0.052***	0.027
	(-4.77)	(-3.95)	(-3.99)	(1.23)
peer_pc	0.180***	0.194***	0.189***	0.182***
	(9.30)	(11.22)	(10.91)	(10.62)
opmom		0.060***	0.056***	0.062***
		(5.45)	(5.12)	(6.01)
ivhv			-0.031**	-0.215***
			(-2.52)	(-7.18)
ivol				-0.226***
				(-6.65)
Avg Adj R2	0.0096	0.0116	0.0120	0.0181

Panel B. Co-movement based on industry link

	opret			
	(1)	(2)	(3)	(4)
Intercept	-0.048***	-0.042***	-0.042***	0.024
	(-5.71)	(-4.71)	(-4.78)	(1.30)
peer_in	0.319***	0.333***	0.330***	0.320***
	(20.25)	(22.65)	(22.35)	(22.02)
opmom		0.051***	0.049***	0.054***
		(6.19)	(6.06)	(6.95)
ivhv			-0.018*	-0.159***
			(-1.84)	(-7.4)
ivol				-0.182***
				(-6.92)
Avg Adj R2	0.0314	0.0346	0.0348	0.0392

Panel C. Co-movement based on shared analyst coverage link

	opret			
	(1)	(2)	(3)	(4)
Intercept	-0.040***	-0.040***	-0.046***	0.016
	(-4.87)	(-4.77)	(-5.49)	(0.97)
peer_cf	0.363***	0.360***	0.366***	0.356***
	(22.08)	(22.01)	(21.34)	(21.35)
opmom		0.035***	0.038***	0.043***
		(3.75)	(4.32)	(5.20)
ivhv			0.000	-0.149***
			(0.04)	(-7.01)
ivol				-0.178***
				(-6.77)
Avg Adj R2	0.0425	0.0433	0.0461	0.0501

Panel D. Co-movement based on all three links

	opret			
	(1)	(2)	(3)	(4)
Intercept	-0.050***	-0.048***	-0.049***	0.021
	(-5.91)	(-5.71)	(-5.50)	(1.10)
peer_pc	0.070***	0.068***	0.065***	0.064***
	(5.28)	(5.11)	(4.86)	(4.60)
peer_in	0.203***	0.202***	0.201***	0.197***
	(22.13)	(22.09)	(21.64)	(20.85)
peer_cf	0.245***	0.243***	0.241***	0.235***
	(14.74)	(14.75)	(14.57)	(14.47)
opmom		0.044***	0.042***	0.049***
		(3.97)	(3.82)	(4.67)
ivhv			-0.000	-0.180***
			(-0.03)	(-6.29)
ivol				-0.201***
				(-6.00)
Avg Adj R2	0.0511	0.0523	0.0517	0.0555

Table 3.2 shows the results on Fama–MacBeth regressions of focal firm's delta-neutral straddle return on peers' average delta-neutral straddle return. In panels A, B and C, the peers are identified by the production complementarity, industry and shared analyst coverage links, respectively. As can be seen from panel A, a focal firm's delta-neutral straddle return has a strong and positive relation with its peers' average delta-neutral straddle return, with the coefficients being significant at the 1% level. Thus, there are co-movements in delta-neutral straddle returns of firms in a same production complementarity network. If the average straddle return of the peers is higher, the straddle return of the focal firm is also likely to be higher. When we successively control for focal firm's option momentum *opmom*, implied-historical

volatility difference *ivhv*, and idiosyncratic volatility *ivol*, the coefficient of peers' average straddle return *peer_pc* is not affected much. Thus, the return co-movement based on production complementarity link is not likely to be explained by the focal firm's characteristics. As to the control variables, their effects are consistent with prior literature: the option momentum positively predicts future straddle return (Heston et al., 2023), the implied-historical volatility difference and idiosyncratic volatility have negative relations with future straddle return (Cao & Han, 2013; Goyal & Saretto, 2009). In panels B and C, we obtain similar results for return co-movements based on the industry and shared analyst coverage links. In panel D, we include three types of peer return based on the three economic links as independent variables and find that each peer return variable remains highly significant. The option return co-movements based on production complementarity, industry and shared analyst coverage are not subsumed by each other. The distinction in peer return information based on different economic links has been discussed in prior literature. As Lee et al. (2024) argue, the production complementarity peers are those from different industries while analysts tend to cover firms in a particular industry or sector, hence the production complementarity link is not only different from the industry link but also likely to be different from the shared analyst coverage link. Israelsen (2016) demonstrate empirically that though analysts usually cover firms within a certain industry, the information on return of peers linked by the same analysts does not merely capture the information on return of peers linked by industry. Our study is consistent with prior studies in that the returns of peers linked by production complementarity, industry and shared analyst coverage appear to represent different sources of information.

In summary, the results in Table 3.2 show that delta-neutral option returns co-move among firms linked by production complementarity, industry and shared analyst coverage. As straddles are the strategy for trading on volatility (Ni et al., 2008), the co-movements in straddle returns imply that if trading on volatility of one firm is profitable, trading on volatility of the peers of that firm is likely to be profitable. From the asset allocation perspective, investors can have diversification benefits by investing in options of unrelated firms, since a loss in one position can be offset by a gain in another.

Literature suggests that return co-movements among a group of firms can be explained by their common exposure to market risk. Firms with similar fundamentals (e.g., value or growth stocks) have similar systematic risks, and hence exhibit stock return co-movement (Campbell et al., 2010). According to Bekaert et al. (2009), the same market risk exposure is an important driver of stock return co-movements. Also, the changes in market beta explain the changes in stock return co-movements after index inclusion and stock split (Chen et al., 2016). As delta-neutral straddles have a market beta of zero (Coval & Shumway, 2001), the co-movements in delta-neutral straddle returns are unlikely to be driven by similar systematic risks and therefore not subject to the critique raised by Chen et al. (2016). Further, noticing that raw options have non-zero betas, we continue to investigate the co-movements in raw option returns and examine the difference between raw return co-movements and delta-neutral return co-movements in the following sections.

3.3.3. Co-movements in raw option returns

Table 3.3 examines the co-movements in raw option returns in addition to the co-movements in delta-neutral option returns. Panels A, B and C investigate the co-movements based on production complementarity, industry and shared analyst coverage links, respectively. In the first column of each panel, we report the co-movements in delta-neutral option returns. In column (2) and (3), we show the co-movements in raw call and put returns in a similar fashion. Particularly, we use the Fama–MacBeth regressions of raw option return of the focal firm on the average raw option return of the peers linked to that focal firm. For the production complementarity link in panel A, we find that the raw call (put) option return of the focal firm is positively related to the average raw call (put) return of the peers with the coefficients highly significant at the 1% level (the *t-stat* of 16.14 for the call return co-movement and 9.82 for the put return co-movement). Noticeably, we find that the adjusted R-squared in the regression of focal firm's return on average peer return is significantly higher for raw returns than for delta-neutral returns. Specifically, the co-movements in raw call and put returns exhibit the adjusted R-squared of 1.98% and 1.45%, respectively, while the co-movement in delta-neutral straddle returns only has an adjusted R-squared of 0.96%. Thus, the variation in peer returns explains a greater proportion of the variation in focal firm's return when using raw option returns than when using delta-neutral option returns. Huang et al. (2019) and Green and Hwang (2009) use the adjusted R-squared to measure the strength of return co-movement between one firm and related firms. Our results suggest that the co-movement in raw option returns is stronger than the co-movement in delta-neutral option returns, when the same economic link is employed.

Table 3.3. Co-movements in raw option returns

This table shows that besides the co-movements in delta-neutral option returns, there exist co-movements in raw option returns. Panels A, B, and C show return co-movements based on production complementarity, industry and shared analyst coverage links, respectively. In each panel, column (1) shows the regression of delta-neutral straddle returns *opret*, on average delta-neutral straddle returns of linked firms (*peer_pc*, *peer_in*, or *peer_cf*), column (2) shows the regression of raw call returns *retc*, on average raw call returns of linked firms (*peer_pc_retc*, *peer_in_retc*, or *peer_cf_retc*), and column (3) shows the regression of raw put returns *retp*, on average raw put returns of linked firms (*peer_pc_retp*, *peer_in_retp*, or *peer_cf_retp*). 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. Co-movement based on production complementarity link

	opret	retc	retp
Intercept	-0.057***	-0.033	-0.121***
	(-4.77)	(-1.37)	(-3.50)
peer_pc	0.180***		
	(9.30)		
peer_pc_retc		0.325***	
		(16.14)	
peer_pc_retp			0.230***
			(9.82)
Avg Adj R2	0.0096	0.0198	0.0145

Panel B. Co-movement based on industry link

	opret	retc	retp
Intercept	-0.048***	-0.020	-0.109***
	(-5.71)	(-1.19)	(-5.17)
peer_in	0.319***		
	(20.25)		
peer_in_retc		0.464***	
		(39.43)	
peer_in_retp			0.397***
			(20.56)
Avg Adj R2	0.0314	0.0583	0.0526

Panel C. Co-movement based on shared analyst coverage link

	opret	retc	retp
Intercept	-0.040***	-0.004	-0.102***
	(-4.87)	(-0.23)	(-4.97)
peer_cf	0.363***		
	(22.08)		
peer_cf_retc		0.521***	
		(47.42)	
peer_cf_retp			0.473***
			(20.29)
Avg Adj R2	0.0425	0.0790	0.0746

In panels B and C, we find very similar results to those in panel A. Specifically, there are co-movements in raw call and put option returns among firms linked by industry and shared analyst coverage, and the co-movements in raw returns are stronger than the co-movements in delta-neutral returns, as evidenced by significant higher adjusted R-squared for raw return co-movements.

Unlike delta-neutral straddle returns, raw call and put option returns are related to the performance of the underlying equity during the options' lifespan. If the stock prices go up, call options are more likely to expire in-the-money. If the stock prices go down, put options are more likely to expire in-the-money. Hence, the co-movements in raw option returns may reflect not only the co-movements in option pricing but also the co-movements in the underlying stock returns. This explains why the co-movement in raw option returns is stronger than the co-movement in delta-neutral option returns.

3.3.4. Common factors and option return co-movements

Common factors reflect shared sources of variation in asset returns. Studies show that options follow factor structures and that the option factor models can effectively explain the time-series and cross-sectional variations on option returns (Fournier et al., 2024; Goyal & Saretto, 2025; Horenstein et al., 2023). In this section, we ask whether the network-based option return co-movements can be explained by option and stock common factors.

We use time series regressions to examine the association between option return co-movements and common factors in the options and stock markets. In line with Barberis et al. (2005) and Green and Hwang (2009), we measure the strength of the network-based return co-movements over time by the slope coefficient in the cross-sectional regression of focal firm returns on peer average returns. We follow Horenstein et al. (2023) to compute the three option common factors based on the implied-historical volatility difference (IV-HV), volatility-of-volatility and the ratio of cash holdings to total assets. For instance, the common factor based on IV-HV is the spread in equal-weighted average option return between the top and bottom quintiles sorted on the IV-HV. Volatility-of-volatility refers to the standard deviation scaled by the mean of ATM implied volatility where ATM implied volatility is the average of the ATM call and put implied volatilities (the call and put having an absolute delta of 0.50 and maturity of 30 days in OptionMetrics Volatility Surface). In terms of stock market common factors, we use the three Fama and French (1993) factors, including the market risk premium, small-minus-big factor and high-minus-low factor. We compute the monthly stock factors as the average daily stock factors within a month. The data on stock common factors are made available by WRDS.

Table 3.4. Can option return co-movements be explained by option and stock common factors?

This table shows results on the regressions of the strength of option return co-movements on option and stock common factors. The strength of return co-movement is measured by the slope coefficient in the cross-sectional regression of focal firm returns on peer average returns. The dependent variables in panel A are the strength of delta-neutral return co-movements based on production complementarity, industry and shared analyst coverage *(beta_peer_pc, beta_peer_in, beta_peer_cf)*. Similarly, the dependent variables in panel B are the strength of raw call and put return co-movements based on these three links. The *beta_peer_pc_retc (beta_peer_pc_retp)*, *beta_peer_in_retc (beta_peer_in_retp)*, *beta_peer_cf_retc (beta_peer_cf_retp)* refer to the strength of call (put) return co-movements based on production complementarity, industry and shared analyst coverage, respectively. The option common factors include the option return spreads based on implied-historical volatility difference, volatility-of-volatility and cash holdings to total assets ratio *(factor_ivhv, factor_vov, factor_ch)*. The stock common factors include market risk premium *(mrp)*, size factor *(smb)*, and value factor *(hml)*. 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. Co-movements in delta-neutral returns and market factors

	beta_peer_pc		beta_peer_in		beta_peer_cf	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.137***	0.134***	0.294***	0.293***	0.339***	0.338***
	(7.502)	(7.40)	(18.51)	(18.41)	(19.92)	(19.19)
factor_ivhv	-0.453***	-0.478***	-0.297***	-0.294***	-0.204***	-0.206***
	(-3.98)	(-4.00)	(-4.05)	(-3.94)	(-3.43)	(-3.44)
factor_vov	-0.513***	-0.507***	-0.214***	-0.220***	-0.192**	-0.197**
	(-3.95)	(-4.02)	(-2.91)	(-3.07)	(-2.00)	(-2.06)
factor_ch	-0.067	-0.084	-0.020	-0.028	-0.099*	-0.107**
	(-0.80)	(-0.94)	(-0.42)	(-0.62)	(-1.96)	(-2.23)
mrp		3.795		-2.079		-0.077
		(0.66)		(-0.42)		(-0.01)
smb		17.156		10.927		10.363
		(1.60)		(1.56)		(1.16)
hml		-2.869		7.497		2.139
		(-0.37)		(1.54)		(0.38)
Adj R2	0.1370	0.1403	0.1170	0.1181	0.0960	0.0919

Panel B. Co-movements in raw returns and market factors

	beta_peer_pc_retc	beta_peer_pc_retp	beta_peer_in_retc	beta_peer_in_retp	beta_peer_cf_retc	beta_peer_cf_retp
Intercept	0.288***	0.219***	0.445***	0.395***	0.472***	0.433***
	(14.62)	(10.53)	(35.89)	(21.27)	(33.99)	(17.75)
factor_ivhv	-0.408***	-0.254*	-0.175***	-0.165**	-0.114*	-0.147*
	(-3.62)	(-1.77)	(-3.03)	(-2.15)	(-1.80)	(-1.71)
factor_vov	-0.282**	-0.292**	-0.019	-0.096	0.027	-0.055
	(-2.38)	(-2.41)	(-0.28)	(-1.07)	(0.29)	(-0.51)
factor_ch	0.061	0.069	0.030	0.041	-0.004	0.002
	(0.88)	(1.01)	(0.90)	(0.91)	(-0.09)	(0.05)
mrp	16.345**	-30.442***	21.762***	-23.063***	17.581***	-22.222***
	(2.53)	(-4.68)	(5.71)	(-5.06)	(4.03)	(-3.92)
smb	29.506**	-7.625	25.577***	-11.730	20.877**	-8.279
	(2.31)	(-0.60)	(4.14)	(-1.33)	(2.54)	(-0.92)
hml	9.046	13.484	14.594***	7.948	17.008***	-1.953
	(1.00)	(1.42)	(2.92)	(1.42)	(2.91)	(-0.26)
Adj R2	0.1098	0.1147	0.1974	0.1077	0.0822	0.0792

Table 3.4 examines the relations between the option return co-movements and the common factors. Since the IV-HV, volatility-of-volatility and cash-to-assets ratio are negative predictors of option returns (Horenstein et al., 2023), the return spread between the top and bottom quintiles of straddles sorted on these variables are negative on average. More negative values of these factors imply a widening of return spreads. The results in Panel A of Table 3.4 (columns (1) to (6)) show that the delta-neutral straddle return co-movements have strong negative relations with the option factors based on IV-HV and volatility-of-volatility. It means that as the common factors in option returns become larger (i.e., more negative), the network-based option return co-movements become stronger. In other words, the degree to which the focal firm's option return is determined by the peers' option return has a positive association with the degree to which option return is determined by IV-HV and volatility-of-volatility. This suggests that the network-based option return co-movements may reflect the similar premium for IV-HV and volatility-of-volatility among connected firms. For example, firms in certain industries may have systematically high or low volatility-of-volatility; when the volatility-of-volatility return spread widens, straddle returns react more strongly to volatility-of-volatility: straddle returns of firms in high (low) volatility-of-volatility industries decrease (increase) together, making the industry-based return co-movements more pronounced. In columns (5) and (6), we find that the common factor based on cash-to-assets ratio has some explanation power for the option return co-movement based on shared analyst coverage.

We also examine the relations between the delta-neutral straddle return co-movements and the stock market common factors. In columns (2), (4) and (6), we include the stock common factors as independent variables. The results show that the stock common factors (the market risk premium, size factor and value factor) do not have a significant relation with the delta-neutral straddle return co-movements. As delta-neutral option returns are independent of the performance of the underlying assets, the co-movements in delta-neutral option returns are not driven by the performance of the stock market.

The results in panel B of Table 3.4 show the relations between the raw option return co-movements and the common factors. The option common factor based on IV-HV can still significantly explain the co-movements in raw call and put returns. The factor based on volatility-of-volatility has relations with the co-movements in raw return based on the production complementarity link, while the factor based on cash-to-assets ratio does not have significant relations with the raw option return co-movements. The strong explanation power of the IV-HV factor relative to other common factors is consistent with Goyal and Saretto (2025). Specifically, they argue that IV-HV can capture the commonality in many other option return predictors, hence IV-HV is especially important in explaining the cross-section of option returns.

It is worth noting that the relations between option return co-movements and common factors can be correlational rather than directional. On the other hand, as Chan et al. (1998) demonstrate, common factors reflect the systematic variation in asset returns, hence being the sources of return co-movement. On the other hand, co-movement can lead to more pronounced common factors. Firms within the same group often share similar characteristics (e.g., value firms tend to be financially distressed and highly leveraged (Chen & Zhang, 1998)). Stronger return co-movement within groups leads to more pronounced differences in returns across groups and therefore larger return spreads when firms are sorted by specific characteristics.

The most noticeable result in panel B of Table 3.4 is that the strength of co-movements in raw option returns is strongly related to the market risk premium, i.e., the stock market excess return. More specifically, the raw call return co-movements intensify when the stock market appreciates, and the raw put return co-movements intensify when the stock market declines. These effects are highly significant for all three economic links. The results highlight the notion that raw option returns depend on the performance of the underlying equity. But why do raw call and put return co-movements have opposite relations with the stock market excess return? First, the return co-movement should become stronger as the difference in return between subsets of options becomes more striking. In bear markets, call options are more likely to expire out-of-the-money or deep out-of-the-money. But option returns in these two situations are the same, making the return difference between subsets of options less pronounced. Similarly, the variation in put option returns across different groups of firms becomes less evident in bull market. Putting all these considerations together, the co-movements in call return should intensify in bull market and the co-movements in put return should intensify in bear market.

Other aggregate factors like investor sentiment or liquidity measures could have influences on return co-movements. In untabulated results, we additionally include the aggregate Amihud illiquidity measure and the market sentiment index (Baker & Wurgler, 2006) in the regressions of the strength of option return co-movements. We find that market liquidity and sentiment are not significantly related to either delta-hedged or raw option return co-movements, and the effects of other common factors are not affected by these variables.

3.3.5. Co-movement in realized volatility risk premium

Delta-neutral straddles provide positive payoffs when the underlying stocks experience large price movements (Vasquez & Xiao, 2024). The expensiveness of the claims (including straddles) that provide hedge against future volatility can be captured by the realized volatility risk premium, which is the difference between implied volatility for the next month and the actual volatility realized over the next month (Lochstoer & Muir, 2022). Given the existence of the option return co-movements, we ask whether there is a commonality in the expensiveness of options among economically linked firms. Specifically, we examine the relation between the realized volatility risk premium of a focal firm and the average realized volatility risk premium of the peers linked to the focal firm.

Table 3.5. Co-movement in realized volatility risk premium

This table shows the co-movements in realized volatility risk premium among economically linked firms by using Fama–MacBeth regressions of realized volatility risk premium of the focal firm *(ivrv)* on the average realized volatility risk premium of its peers linked by production complementarity, industry and shared analyst coverage (*peer_pc_ivrv, peer_in_ivrv, peer_cf_ivrv*). 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.

	ivrv			
	(1)	(2)	(3)	(4)
Intercept	-0.047***	-0.038***	-0.038***	-0.026***
	(-7.94)	(-9.15)	(-9.75)	(-7.32)
peer_pc_ivrv	0.210***			0.114***
	(9.58)			(7.31)
peer_in_ivrv		0.284***		0.178***
		(18.45)		(15.25)
peer_cf_ivrv			0.312***	0.187***
			(18.97)	(12.07)
Avg Adj R2	0.0097	0.0210	0.0308	0.0383

The cross-sectional regression results in Tabe 3.5 show that the realized volatility risk premium of a focal firm has strong and positive relations with the average realized volatility risk premium of the peers linked by production complementarity, industry and shared analyst coverage (columns (1) to (3)). When put together as regressors in column (4), the peers' average realized volatility risk premiums based on production complementarity, industry and shared analyst coverage remain highly significant, suggesting that information from each economic link is not subsumed by information from other links. Our results in Table 3.5 demonstrate that the option on equity of the focal firm tend to be expensive if the options on equity of its peers are also expensive. There is a commonality in the pricing of options among economically linked firms. Our results are consistent with Barberis and Shleifer (2003), Barberis et al. (2005) and Green and Hwang (2009) in that to simplify the processing of information, investors group similar assets into categories and allocate funds to each category rather than to individual assets, causing commonality in prices of assets in each category. The commonality in option pricing can be the reason for the commonality in option returns among linked firms.

3.3.6. Peer option momentum

After showing that option returns comove among related firms, we continue to ask whether there are return predictability spillover effects among linked firms, i.e., whether a predictor of peers' return can also predict the focal firm's return. In line with Lee et al. (2024), Ali and Hirshleifer (2020) and Hoberg and Phillips (2018), we focus on the momentum spillover effect (also referred to as the peer momentum effect), a phenomenon in which past return of peer firms predict future return of the focal firm. The rationale for peer momentum is that investors are inattentive to past return information of related firms hence do not incorporate this information in the price of the focal firms, resulting in the cross-firm return predictability (Ali & Hirshleifer, 2020; Hoberg & Phillips, 2018; Lee et al., 2024).

Table 3.6. Peer option momentum

This table shows the peer option momentum effects among economically linked firms by using Fama–MacBeth regressions of delta-neutral straddle return of the focal firm *(opret)* on the average option return momentum of its peers linked by production complementarity, industry and shared analyst coverage *(peer_pc_opmom, peer_in_opmom, peer_cf_opmom)*, controlling for the option return momentum of the focal firm. The option return momentum refers to the average delta-neutral straddle return from the past 12th month to the past 2nd month. 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.

	opret			
	(1)	(2)	(3)	(4)
Intercept	-0.032*	-0.023	-0.021	-0.026
	(-1.90)	(-1.16)	(-1.04)	(-1.49)
peer_pc_opmom	0.101***			0.097***
	(2.66)			(2.82)
peer_in_opmom		0.084***		0.094***
		(4.17)		(3.47)
peer_cf_opmom			0.067***	0.086***
			(3.21)	(3.13)
opmom	0.064***	0.053***	0.041***	0.044***
	(5.98)	(6.32)	(4.24)	(4.22)
Avg Adj R2	0.0042	0.0032	0.0034	0.0088

In this section, we investigate the relations between peers' past option return and focal firm's future option return. Heston et al. (2023) document that option momentum of a firm (the average past straddle return from lag 2 to lag 12) positively predicts that firm's future option return. We follow Heston et al. (2023) to calculate option momentum of each firm. Then, for each focal firm, we compute the average option momentum of its peers and examine the peer option momentum effect in Table 3.6. In columns (1), (2) and (3), we use production complementarity, industry and shared analyst coverage links, respectively. The results show that the straddle return of the focal firm is positively related to the average option momentum of its peers. The effects are highly significant at the 1% level with the *t-statistics* of 2.66, 4.17 and 3.21 for the peer momentum based on production complementarity, industry and shared analyst coverage, respectively. In the regression, we also control for the option momentum of the focal firm, *opmom*. The focal firm option momentum is positively related to focal firm future option return, consistent with Heston et al. (2023). The peer option momentum effect is highly significant with the presence of focal firm option momentum as control variable, suggesting that the option momentum of peer firms provides incremental information beyond the focal firm's own momentum in predicting the focal firm's future return. In column (4), we include all three types of peer option momentum as independent variables. The result shows that each type of peer option momentum remains highly significant. Thus, the peer option momentum effects based on production complementarity, industry and shared analyst coverage are not subsumed by each other. This is aligned with Lee et al. (2024) and Israelsen (2016) in that the spillover effects through the production complementarity, industry and shared analyst coverage networks can represent distinct sources of information. To conclude, the results in Table 3.6 demonstrate that there is peer option momentum among economically linked firms.

3.3.7. Option return co-movement and the degree of linkage

Conley and Dupor (2003) make a theoretical prediction that the degree of co-movement between two firms depends on the degree of linkage between them. Based on this theoretical prediction, Lee et al. (2024) find that the stock return co-movement based on production complementarity is stronger among firms with stronger production complementarity link.

Particularly, Lee et al. (2024) classify production complementors of each focal firm into three groups (strong, medium and weak complementors) according to the pairwise production complementarity scores with the focal firm and find that the focal firm's stock return shows the strongest co-movement with its strong complementors and the weakest co-movement with its weak complementors. Utilizing the data provided by Lee et al. (2024), we identify the strong, medium and weak complementors of each focal firm ask whether the co-movement in option returns along the production complementarity network is also positively related to the strength of the linkage.

Table 3.7. Option return co-movement and the degree of linkage: evidence from the production complementarity link

This table shows that the co-movements in option returns along the production complementarity network is stronger as the production complementarity link is stronger. Panels A, B and C show the Fama–MacBeth regression results for the co-movements in delta-neutral straddle returns, raw call returns and raw put returns, respectively. In panel A, we regress the focal firm's delta-neutral straddle returns, *opret*, on the average delta-neutral straddle returns of its strong, medium and weak complementors *(peer_pc_strong*, *peer_pc_medium*, and *peer_pc_weak)*, respectively. In panel B, we regress the focal firm's call returns, *retc*, on the average call returns of its strong, medium and weak complementors *(peer_pc_retc_strong*, *peer_pc_retc_medium*, and *peer_pc_retc_weak)*, respectively. In panel C, we regress the focal firm's put returns, *retp*, on the average put returns of its strong, medium and weak complementors *(peer_pc_retp_strong*, *peer_pc_retp_medium*, and *peer_pc_retp_weak)*, respectively. 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. Co-movement in delta-neutral returns with different degrees of linkage

	opret			
	(1)	(2)	(3)	(4)
Intercept	-0.056***	-0.055***	-0.048***	-0.060***
	(-4.48)	(-4.14)	(-3.36)	(-5.02)
peer_pc_strong	0.119***			0.094***
	(9.58)			(7.76)
peer_pc_medium		0.095***		0.068***
		(7.38)		(5.31)
peer_pc_weak			0.066***	0.036***
			(5.81)	(3.25)
Avg Adj R2	0.0089	0.0063	0.0042	0.0151

Panel B. Co-movement in raw call returns with different degrees of linkage

	retc			
	(1)	(2)	(3)	(4)
Intercept	-0.026	-0.028	-0.025	-0.047*
	(-0.95)	(-0.94)	(-0.79)	(-1.82)
peer_ pc_retc_strong	0.236***			0.198***
	(18.28)			(14.78)
peer_ pc_retc_medium		0.150***		0.102***
		(10.80)		(6.62)
peer_ pc_retc_weak			0.100***	0.049***
			(6.47)	(3.41)
Avg Adj R2	0.0196	0.0109	0.0082	0.0289

Panel C. Co-movement in raw put returns with different degrees of linkage

	retp			
	(1)	(2)	(3)	(4)
Intercept	-0.104***	-0.114***	-0.094**	-0.121***
	(-2.92)	(-2.94)	(-2.22)	(-3.75)
peer_ cf_retp_strong	0.188***			0.154***
	(13.33)			(11.50)
peer_ cf_retp_medium		0.110***		0.076***
		(6.35)		(4.64)
peer_ cf_retp_weak			0.065***	0.027*
			(4.84)	(1.85)
Avg Adj R2	0.0150	0.0090	0.0056	0.0210

In Table 3.7, we present the results on option return co-movements across different degrees of production complementarity linkage. Panels A, B and C show the results for the co-movements in delta-neutral straddle returns, raw call returns and raw put returns, respectively. In each panel, we regress the focal firm's option return on the average return of its strong, medium and weak complementors. We find that the strength of option return co-movements decreases as the production complementarity linkage is weaker. For example, in panel A, the delta-neutral return co-movement is weaker when we use the average return from weaker complementors as the independent variable. We observe decreases in the coefficient of the independent variable, t-statistic and adjusted R-squared (from column (1) to column (3)) when focal firm's return is regressed on the average return of weaker complementors. In column (4), when we include the returns of strong, medium and weak complementors as independent variables at the same time, we also find that the effect is strongest for strong complementors and weakest for weak complementors (by comparing the coefficients and the t-statistics). We find similar patterns for raw call and put return co-movements in panel B and C. Thus, consistent with the theoretical prediction, our results in Table 3.7 show that the option return co-movements along the production complementarity network is stronger when the strength of the link is stronger.

3.3.8. Further analysis

Literature suggests that stock return co-movement varies with aggregate market-level uncertainty. Kumar et al. (2013) show that stock return co-movements are more pronounced in market uncertainty because uncertainty exacerbates investors' correlated trading. Following Kumar et al. (2013), we use the Chicago Board of Options Exchange volatility (VIX) index to capture aggregate market uncertainty. We compute the average daily VIX index in the month prior to the option formation. Based on the monthly VIX index, we identify the subsamples of high volatility (VIX above the median) and low volatility (VIX below the median). We then report the results on option return co-movements for each of the subsamples in Table 3.8.

We find that option return co-movements are highly significant in both high and low VIX subsamples. In Table 3.8, columns (1) and (2) refer to the co-movements in delta-neutral returns, columns (3) and (4) refer to the co-movements in raw call returns, and columns (5) and (6) refer to the co-movements in raw put returns. In both high VIX and low VIX subsamples, option return of the focal firm is strongly and positively related to the average option returns of the peers linked by production complementarity, industry and shared analyst coverage, with the coefficients significant at the 1% level. Unlike the stock return co-movement that can become negative in low volatility periods (Kumar et al., 2013), the option return co-movements seem not to be dependent on aggregate market volatility. Thus, our results on the co-movements in delta-neutral option returns and co-movements in raw option returns are robust in different subsamples.

Table 3.8. Option returns co-movements in different market conditions

This table shows that the co-movements in option returns exist in different market conditions. We use the average VIX index in the month before the option formation date to capture the aggregate market volatility and report the option return co-movements in the high volatility (VIX above the median) subsample and low volatility (VIX below the median) subsamples. For the co-movements in delta-neutral returns, we use Fama–MacBeth regressions of delta-neutral straddle returns, *opret*, on peer returns calculated as the average of delta-neutral straddle returns of the peers (*peer_pc*, *peer_in*, and *peer_cf)* linked by production complementarity, industry, and shared analyst coverage, respectively. To assess the co-movements in raw call (put) returns, we regress focal firm's call (put) return, *retc (retp)*, on *peer_pc_retc (peer_pc_retp)*, *peer_in_retc (peer_in_retp)*, *peer_cf_retc (peer_cf_retp)*, which are the average call (put) returns of peers linked by production complementarity, industry and shared analyst coverage, respectively. 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.

	opret		retc		retp	
	High VIX	Low VIX	High VIX	Low VIX	High VIX	Low VIX
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.057***	-0.040***	-0.040**	-0.057**	-0.104***	-0.110***
	(-4.25)	(-3.62)	(-2.20)	(-2.40)	(-3.49)	(-4.01)
peer_pc	0.067***	0.074***				
	(3.60)	(4.13)				
peer_in	0.194***	0.214***				
	(16.87)	(15.03)				
peer_cf	0.249***	0.240***				
	(11.26)	(9.61)				
peer_pc_retc			0.136***	0.091***		
			(7.75)	(4.95)		
peer_in_retc			0.268***	0.265***		
			(18.65)	(17.10)		
peer_cf_retc			0.348***	0.353***		
			(22.28)	(17.29)		
peer_pc_retp					0.083***	0.064***
					(4.64)	(3.26)
peer_in_retp					0.256***	0.219***
					(13.55)	(12.93)
peer_cf_retp					0.265***	0.279***
					(14.29)	(8.92)
Avg Adj R2	0.0542	0.0473	0.0973	0.0915	0.0698	0.0688

The findings on stock return co-movements by Lee et al. (2024), Muslu et al. (2014) and Hoberg and Phillips (2018) suggest that economically connected firms have similar market performance and accounting performance (e.g., return on assets, sales growth, etc.). Yet, our results on delta-neutral straddle return co-movements do not necessarily imply similar patterns in the performance of connected firms. Instead, the straddle return co-movements suggest similar patterns in profits of trading on volatility of connected firms. If both the focal firm and peer experience large increases in realized volatility, they can have high straddle returns at the same time (even when their performances move in opposite directions). We further examine the influence of peers' stock price movements and the focal firm's straddle return in Table 3.9.

Table 3.9. Option return and peer stock price movements

Three panels of this table show that there are co-movements in stock returns and the absolute values of stock returns among firms linked by production complementarity, industry and shared analyst coverage. In each panel, column (1) demonstrates the stock return co-movement by showing the positive relation between the focal firm's stock returns, *ret_stock*, and the average peers' stock returns, *peer_pc_stock, peer_in_stock,* and *peer_cf_stock*. Column (2) demonstrates the co-movement in absolute stock returns by showing the positive relation between the focal firm's absolute stock returns, *ret_stock_abs*, and the average peers' absolute stock returns, *peer_pc_stock_abs, peer_in_stock_abs,* and *peer_cf_stock_abs*. Columns (3) and (4) present results on the regressions of focal firm's delta-neutral straddle returns, *opret*, on the average peers' stock returns an absolute returns. The results show that the focal firm's option returns have a positive relation with the average peers' absolute stock returns but not with the average peers' stock returns. 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. Co-movement based on the production complementarity link

	ret_stock	ret_stock_abs	opret	
	(1)	(2)	(3)	(4)
Intercept	0.005*	0.077***	-0.137***	-0.189***
	(1.78)	(29.96)	(-10.40)	(-10.74)
peer_pc_stock	0.378***		0.207	
	(16.32)		(1.48)	
peer_pc_stock_abs		0.253***		1.321***
		(11.32)		(7.23)
Avg Adj R2	0.0250	0.0131	0.0089	0.0071

Panel B. Co-movement based on industry link

	ret_stock	ret_stock_abs	opret	
	(1)	(2)	(3)	(4)
Intercept	0.005***	0.048***	-0.160***	-0.260***
	(3.45)	(27.97)	(-14.28)	(-19.20)
peer_in_stock	0.553***		0.169	
	(40.17)		(1.42)	
peer_in_stock_abs		0.514***		2.047***
		(38.73)		(18.86)
Avg Adj R2	0.0795	0.0633	0.0214	0.0190

Panel C. Co-movement based on shared analyst coverage link

	ret_stock	ret_stock_abs	opret	
	(1)	(2)	(3)	(4)
Intercept	0.005***	0.052***	-0.145***	-0.252***
	(3.26)	(26.46)	(-12.28)	(-20.03)
peer_pc_stock	0.554***		0.118	
	(38.93)		(1.01)	
peer_pc_stock_abs		0.512***		2.208***
		(37.84)		(20.19)
Avg Adj R2	0.0942	0.0745	0.0222	0.0227

Each panel of Table 3.9 refers to each of the production complementarity, industry and shared analyst coverage links. In the first column of each panel, we show results on stock return co-movements in the period contemporaneous to the lifespan of straddles. Specifically, the focal firm's stock return *ret_stock* is positively related to the average stock return of peers linked by production complementarity *peer_pc_stock*, industry *peer_in_stock*, and shared analyst coverage *peer_pc_stock*, in panels A, B and C, respectively. These results are consistent with Lee et al. (2024), Muslu et al. (2014) and Hoberg and Phillips (2018). Connected firms exhibit similarity in market performance. We further ask whether there is similarity in price volatility of linked firms. In column (2) of panels A, B and C, we regress the absolute price movement (the absolute value of stock return) of the focal firm on the average absolute price movement of the peers and find significantly positive relationships. The results suggest that if the peer firms experience large price movements the focal firm is likely to experience large price movements as well (regardless of the directions). Further, across the three panels, we find that the average stock return of the peers does not have significant relation with the straddle return of the focal firm (columns (3)) while the average absolute price movement of the peers is significantly and positively related to the focal firm's straddle return (columns (4)). Larger absolute price movements of the peers coincide with larger absolute price movements of the focal firm, and hence with higher straddle return of the focal firm. On the other hand, while having a positive association with focal firm's stock return, the average stock return of the peers is not related to the focal firm's straddle return because the focal firm's straddle return is independent of the focal firm's underlying stock performance. Thus, our results suggest that the co-movements in delta-neutral straddle returns are likely to reflect the co-movements in volatilities of linked firms rather than the co-movements in performance of them.

3.4. Conclusion

In this study, we show the co-movements in option returns among economically linked firms. For each focal firm, we identify its peer firms that are either in the same production complementarity networks (Lee et al., 2024), in the same industry (Hoberg & Phillips, 2018) or covered by the same analyst (Ali & Hirshleifer, 2020). We find that option returns of the focal firm and option returns of its peers have a positive association. The results hold for both delta-neutral straddle returns and raw call and put option returns. Given that delta-neutral straddle returns are approximately independent of the underlying stock performance and have no exposure to the market risk premium, our results on delta-neutral return co-movements suggest that the network-based return co-movements can arise beyond the explanation of similar systematic risk exposures.

Further, our study shows that the option common factors can be used to explain the time-varying strength of option return co-movements. The co-movements in option returns strengthen as the options market common factors related to implied-historical volatility difference and volatility-of-volatility widen. The stock market common factors, especially the market risk premium, can well explain the co-movements in raw option returns but cannot explain the co-movements in delta-neutral returns. Our results highlight the notion that raw option returns depend on the underlying asset performance while delta-neutral option returns do not.

Studying the expensiveness of option measured by the realized volatility risk premium (Lochstoer & Muir, 2022), we find that option of a focal firm is likely to be expensive if options of its peer firms are expensive. In other words, there are co-movements in option pricing among economically linked firms. In addition to the option return co-movements, there are also the option momentum spillover effects along the production complementarity, industry and shared analyst coverage networks. Option returns of focal firms can be positively predicted by past returns of their peers. Our study hence contributes to not only the literature on return co-movement but also the literature on option return predictability.

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APPENDICES

Table A1.1. Variable definitions

This table provides definitions of the key variables used in Chapter 1.

	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 $(\Delta * S - C)$ (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 A1.2. 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 A1.3. 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 A1.4. 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 A1.5. 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 A1.6. 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

Table A2.1. Variable definitions

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

	Definition
opret	The option return is the hold-to-maturity return to the delta-neutral one-month straddle that is created from approximately equal positions of call and put equity options. The return is calculated from the payoff at maturity of the call and put positions compared with the initial cost to establish the straddle position.
opmom	The option momentum return, or formation period return, is the average past monthly straddle returns from month *t-2* to month *t-12*.
ID	Information discreteness computed for past option returns in the formation period from the last second month to the last twelfth month. Similar to the ID measure for stock returns Da et al. (2014), our measure is identified by the percentage of small signals whose sign is the opposite of the sign of formation period returns relative to the percentage of small signals whose sign is the same as the sign of formation period returns, using this formula $ID = sign(fpr) \times [\%neg - \%pos]$.
CI	Continuous information is defined as $CI = 1 - ID$. This variable is supposed to capture the strength of option momentum. Its minimum value of 0 indicates the most discrete information.
iv	The implied volatility of straddles is the weighted average of implied volatilities provided by OptionMetrics for the call and put that constitute the straddles and the weights are the same as the proportion of call and put in the straddles.
exvol	The forecast error of implied volatility is the difference between the realized volatility in the next month and the implied volatility for that month.
size	Firm size is firms' market capitalization in 100 billion dollars.
ailliq	Amihud (2002) illiquidity measured over the past 12 months as in Heston et al. (2023)
ivol	Idiosyncratic volatility is the standard deviation of residuals from the asset pricing model as in Ang et al. (2006) and Da et al. (2014).
price	Log underlying stock price as used in Birru and Wang (2016) and Zhan et al. (2022).
asue	The absolute earnings surprises are the average of the absolute value of earnings surprises in the past year, where the earnings surprise is calculated as the realized earnings in the most recent quarter minus the realized earnings in the same quarter of the previous year divided by the standard deviation of earnings in the past eight quarters.
dcoverage	The change in analyst coverage is defined as the average number of analysts covering a firm during the twelve-month formation period in which that firm's continuous information variable is computed, minus the average analyst coverage during the twelve months before that formation period (Da et al., 2014).
numest	The number of analyst coverage is the average number of analysts covering a firm during the twelve-month formation period in which that firm's continuous information variable is computed.
ior	Institutional ownership is the proportion of firm shares held by institutional investors at the beginning of the formation period in which the firm's continuous information variable is computed.
opret1 to opret12	Monthly returns of straddles that are formed in month *t+1* to month *t+12*.

Table A2.2. Ex-post continuous information and option momentum

In this table, we examine the ex-post measure of continuous information to capture the realized information dynamics. Instead of using return information from month *t-12* to month *t-2*, we additionally include the return information in months *t-1* and *t* when computing continuous information. This ex-post continuous information reflects how continuous the arrivals of return information are during the period from month *t-12* to month *t*. We sort straddles based on this ex-post continuous information measure into five quintiles, with quintile (1) representing discrete information and quintile (5) representing continuous information. In each quintile, straddles are then sorted based on past straddle returns, *opmom*, to obtain return differentials between top and bottom *opmom* quintiles. 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.

Ex-post Information	Straddle return						
	(1)	(2)	(3)	(4)	(5)	(5) – (1)	
(1)-discrete	0.4310	0.1030	-0.0855	-0.1990	-0.2860	-0.7170***	(-28.60)
(2)	0.1130	0.0065	-0.0279	-0.0525	-0.1340	-0.2470***	(-22.90)
(3)	-0.0331	-0.1400	0.0236	0.0704	-0.0109	0.0222**	(2.26)
(4)	-0.1220	-0.3140	0.0652	0.2300	0.1110	0.2330***	(17.40)
(5)-continuous	-0.2990	-0.4270	0.0768	0.3330	0.2810	0.5790***	(28.50)
(5) – (1)						1.2958***	(33.78)

Table A2.3. Continuous information and option momentum with and without crashes

In this table, we report the profitability of option momentum in each continuous information quintile in subsamples of months with and without momentum crashes. We classify a month as experiencing a momentum crash if its unconditional option-momentum profitability falls below the 10th percentile of all months in our full sample. The non-crash subsample consists of months without momentum crashes. 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.

Information	Option momentum profitability			
	Non-crash subsample		Crash subsample	
(1)-discrete	0.0246**	(2.25)	-0.1580**	(-2.53)
(2)	0.0624***	(6.17)	-0.1350**	(-2.09)
(3)	0.0750***	(8.44)	-0.1480***	(-3.99)
(4)	0.0940***	(7.31)	-0.1670***	(-2.72)
(5)-continuous	0.1300***	(6.25)	-0.0773	(-1.36)
(5) – (1)	0.1058***	(4.50)	0.0803	(0.95)

Table A2.4. Forecast error of option-implied volatility and option momentum

This table reports results of the Fama–MacBeth regressions of straddle returns, *opret*, on average past straddle returns from the prior 2nd through 12th month, *opmom*, controlling for forecast error of option implied volatility, *exvol*, firm size, *size*, Amihud illiquidity, *ailliq*, stock idiosyncratic volatility, *ivol*. The results in this table show that the option momentum effect disappears when we control for *exvol* but remains highly significant when we control for other variables. 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.

	opret			
	(1)	(2)	(3)	(4)
Intercept	-0.084***	-0.024	-0.022	0.013
	(-4.73)	(-1.13)	(-1.01)	(0.46)
opmom	0.007	0.042***	0.051***	0.052***
	(0.88)	(4.78)	(5.38)	(6.15)
exvol	1.041***			
	(21.81)			
size		0.019**		
		(2.08)		
ailliq			-2.035***	
			(-5.78)	
ivol				-0.122***
				(-4.93)
Avg Adj R^2	0.0618	0.0021	0.0031	0.0068

Table A3.1. Variable definitions

This table provides definitions of the key variables used in Chapter 3.

	Definition
opret	Delta-neutral straddle return is the hold-to-maturity return to the delta-neutral one-month straddle that is created from approximately equal positions of call and put equity options.
deltacall	Delta of the call that constitutes the straddle provided by OptionMetrics.
deltaput	Delta of the put that constitutes the straddle provided by OptionMetrics.
iv	The implied volatility of straddles is the weighted average of implied volatilities provided by OptionMetrics for the call and put that constitute the straddles and the weights are the same as the proportion of call and put in the straddles.
peer_pc	The average of delta-neutral straddle returns of the peers linked by production complementarity.
peer_in	The average of delta-neutral straddle returns of the peers linked by industry.
peer_cf	The average of delta-neutral straddle returns of the peers linked by shared analyst coverage.
ivhv	The difference between implied volatility and historical volatility.
ivol	The focal firm's stock idiosyncratic volatility.
retc	The raw call option return.
peer_pc_retc	The average of raw call option returns of the peers linked by production complementarity.
peer_in_retc	The average of raw call option returns of the peers linked by industry.
peer_cf_retc	The average of raw call option returns of the peers linked by shared analyst coverage.
retp	The raw put option return.
peer_pc_retp	The average of raw put option returns of the peers linked by production complementarity.
peer_in_retp	The average of raw put option returns of the peers linked by industry.
peer_cf_retp	The average of raw put option returns of the peers linked by shared analyst coverage.
factor_ivhv	The option common factor (option return spread) based on implied-historical volatility difference.
factor_vov	The option common factor (option return spread) based on volatility-of-volatility.
factor_ch	The option common factor (option return spread) based on the cash holdings to total assets ratio.
ivrv	Realized volatility risk premium is the difference between implied volatility for the next month and the actual realized volatility over the next month.
peer_pc_ivrv	The average realized volatility risk premium of peers linked by production complementarity.
peer_in_ivrv	The average realized volatility risk premium of peers linked by industry.
peer_cf_ivrv	The average realized volatility risk premium of peers linked by shared analyst coverage.
opmom	The focal firm's option momentum is the average past monthly straddle returns from month *t-2* to month *t-12*.
peer_pc_opmom	The average option momentum of peers linked by production complementarity.
peer_in_opmom	The average option momentum of peers linked by industry.
peer_cf_opmom	The average option momentum of peers linked by shared analyst coverage.

peer_pc_strong	The average delta-neutral straddle returns of the focal firm's strong complementors.
peer_pc_medium	The average delta-neutral straddle returns of the focal firm's medium complementors.
peer_pc_weak	The average delta-neutral straddle returns of the focal firm's weak complementors.
peer_ pc_retc_strong	The average call returns of the focal firm's strong complementors.
peer_ pc_retc_medium	The average call returns of the focal firm's medium complementors.
peer_ pc_retc_weak	The average call returns of the focal firm's weak complementors.
peer_ pc_retp_strong	The average put returns of the focal firm's strong complementors.
peer_ pc_retp_medium	The average put returns of the focal firm's medium complementors.
peer_ pc_retp_weak	The average put returns of the focal firm's weak complementors.
ret_stock	The focal firm's stock return.
ret_stock_abs	The focal firm's stock return in absolute value.
peer_pc_stock	The average stock return of peers linked by production complementarity.
peer_pc_stock_abs	The average absolute stock return of peers linked by production complementarity.
peer_in_stock	The average stock return of peers linked by industry.
peer_in_stock_abs	The average absolute stock return of peers linked by industry.
peer_cf_stock	The average stock return of peers linked by shared analyst coverage.
peer_cf_stock_abs	The average absolute stock return of peers linked by shared analyst coverage.