A Smiling Bear in the Equity Options Market and the Cross-section of Stock Returns

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ABSTRACT

We propose a measure for the convexity of an option-implied volatility curve, *IV convexity*, as a forward-looking measure of excess tail-risk contribution to the perceived variance of underlying equity returns. Using equity options data for individual U.S.-listed stocks during 2000-2013, we find that the average return differential between the lowest and highest *IV convexity* quintile portfolios exceeds 1% per month, which is both economically and statistically significant on a risk-adjusted basis. Our empirical findings indicate that informed options traders anticipating heavier tail risk proactively induce leptokurtic implied distributions of underlying stock returns before equity investors express their tail-risk aversion.

Keywords: Implied volatility, Convexity, Equity options, Stock returns, Predictability

JEL classification: G12; G13; G14

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The non-normality of stock returns has been well-documented in literature (e.g., Merton, 1982; Peters, 1991; Bollerslev, Chou, and Kroner, 1992) as a natural extension of the traditional mean-variance approach to portfolio optimization.[1] According to Scott and Horvath (1980), for example, a rational investor's utility is also a function of higher moments in general, as they tend to have an aversion to negative skewness and high excess kurtosis in the portfolio return. Considerable research has subsequently examined whether the higher moments of stock returns estimated by realized returns are indeed priced in the market.[2] Interestingly, this higher-moment pricing effect is embedded in equity option prices in a forward-looking manner while the *ex-post* higher moments estimated from the realized stock returns can be biased unless the return distribution is stationary and time-invariant.[3] It is noteworthy that the shape of an option-implied volatility curve reveals the *ex-ante* higher-moment implications beyond the standard mean-variance framework, as the curve expresses the degree of abnormality in the market-implied distribution of the underlying stock return as a measure of the deviation between the option-implied distribution and the normal distribution with constant volatility based on the standard Black and Scholes (1973) option-pricing assumption.[4]

Extensive research demonstrates that equity option markets provide informed traders with opportunities to capitalize on their information advantage thanks to several advantages of option trading relative to stock trading, such as reduced trading costs (Cox and Rubinstein, 1985), the lack of restrictions on short selling (Diamond and Verrecchia, 1987) and greater leverage effects (Black, 1975; Manaster and Rendleman, 1982). Recent literature focuses on the relationship between option-implied volatilities and future stock returns by showing an increased interest in

[1] The mean-variance approach is consistent with the maximization of expected utility if either (i) the investors' utility functions are quadratic, or (ii) the assets' returns are jointly normally distributed. However, a quadratic utility function, by construction, exhibits increasing absolute risk aversion, consistent with investors who reduce the dollar amount invested in risky assets as their initial wealth increases. Accordingly, a quadratic utility formulation may be unrealistic for practical purposes; see Arrow (1971) for details.

[2] See Hung, Shackleton, and Xu (2004); Chung, Johnson, and Schill (2006); Dittmar (2002); Doan, Lin, and Zurbruegg (2010); Harvey and Siddique (2000); Kraus and Litzenberger (1976); and Smith (2007); among many others.

[3] Refer to Bali, Hu, and Murray (2015) and Chang, Christoffersen, and Jacobs (2013) among others.

[4] To better explain such a deviation originating from the positively-skewed and platokurtic preference of rational investors, prior studies have attempted to relax the unrealistic normality assumption to capture the negatively-skewed and fat-tailed distribution of stock returns implied by option prices by extending the standard Black and Scholes (1973) model to (i) stochastic volatility models (Duan, 1995; Heston, 1993; Hull and White, 1987; Melino and Turnbull, 1990; 1995; Stein and Stein, 1991; Wiggins, 1987) and (ii) jump-diffusion models (Bates, 1996; Madan, 1996; Merton, 1976).

inter-market inefficiency, leading to a proliferation of studies into the potential lead-lag relationship between options and stock prices. An, Ang, Bali and Cakici (2014) find stocks with large innovations in at-the-money (ATM) call (put) implied volatility positively (negatively) predict future stock returns. Xing, Zhang, and Zhao (2010) propose an option-implied smirk (*IV smirk*) measure that shows its significant predictability for the cross-section of future equity returns. Jin, Livnat, and Zhang (2012) find that options traders have superior abilities to process less anticipated information relative to equity traders by analyzing the slope of option-implied volatility curves. Yan (2011) reports a negative predictive relationship between the slope of the option implied volatility curve (as a proxy of the average size of the jump in the stock price dynamics) and the future stock return by taking the spread between the ATM call and put option-implied volatilities (*IV spread*) as a measure of the slope of the implied volatility curve. Cremers and Weinbaum (2010) argue that future stock returns can be predicted by the deviation from the put-call parity in the equity option market, as stocks with relatively expensive calls compared to otherwise identical puts earn approximately 50 basis points per week more in profit than the stocks with relatively expensive puts.

While considerable research has examined the predictive power of the risk-neutral *skewness* of stock returns captured by the *slope* of the implied volatility curve (i.e., *IV smirk* and *IV spread*, to name a few), whether option-implied *excess kurtosis*, proxied by *IV convexity*, predicts the cross-section of future stock returns has received less attention.[5] Our study attempts to fill this gap. Exploiting the fact that the shape of an option-implied volatility curve contains information about *ex-ante* higher-moment asset pricing implication, we propose a method to decompose the shape of option-implied volatility curves into the slope and convexity components (*IV slope* and *IV convexity* hereafter).[6] Motivated by stochastic volatility (SV) model and stochastic-volatility jump-diffusion (SVJ) model specifications, we assume that *slope* and *convexity* of the option-

[5] There are some notable exceptions from this trend; refer to Bali, Hu, and Murray (2015) and Chang, Christoffersen, and Jacobs (2013) for example. Specifically, we find that the option-implied kurtosis measure proposed by Bali, Hu, and Murray (2015) fails to show any significant predictive power in our setting; see Section III.B for details.

[6] It is also claimed that the options-implied volatility curve is related to the net buying pressure of options traders; see Gârleanu, Pedersen, and Poteshman (2005), Evans, Geczy, Musto, and Reed (2005), Bollen and Whaley (2004). This argument reflects the stylized market fact that the shape of the option-implied volatility curve expresses the option market participants' expected future market situation, as the risk-averse intermediaries who cannot perfectly hedge their option positions in the incomplete capital market induce excess demand on options.

implied volatility curve contain distinct information about future stock return and convey the information about option-implied *skewness* and the *excess kurtosis* of the underlying return distributions, respectively. We confirm our assumption that the slope and convexity carry different information from extensive numerical analyses and develop two testable hypotheses on the impact of option implied kurtosis on future stock returns.

Using equity options data for both individual U.S. listed stocks and the Standard & Poor's 500 (S&P500) index during 2000-2013, we study the cross-sectional predictability of the *IV convexity* measure for future equity returns across quintile portfolios ranked by the curvature of the option-implied volatility curve. We find a significantly negative relationship between *IV convexity* and subsequent stock returns. The average return differential between the lowest and highest *IV convexity* quintile portfolios is over 1% per month, both economically and statistically significant on a risk-adjusted basis. The results are robust across different definitions of the *IV convexity* measure. In addition, time series and cross sectional tests of IV convexity as another risk factor show that other previously known risk factors do not subsume the additional return on the zero-cost portfolio. All in all, the predictive power of our proposed *IV convexity* measure is significant for both the systematic and idiosyncratic components of *IV convexity*, and the results are robust even after controlling for the slope of the option-implied volatility curve and other known predictors based on stock characteristics. Our empirical finding is consistent with earlier studies demonstrating slow information diffusion from options markets to the stock market by providing strong evidence that there exists an asymmetric information transmission from the options market to stock market.[7]

This paper offers several contributions to the existing literature. First, this paper examines whether *IV convexity* exhibits significant predictive power for future stock returns even after controlling for the effect of *IV slope* and other firm-specific characteristics. Although recent evidence shows that the skewness component of the risk-neutral distribution of underlying stock returns captured by option-implied volatility smirk (Xing, Zhang, and Zhao, 2010) and volatility spread between put and call options (Yan, 2011) predicts future equity returns, our research is, to the best of our knowledge, the first study that makes a sharp distinction between the 3rd and 4th

[7] See An, Ang, Bali and Cakici (2014), Chowdhry and Nanda (1990), Easley, O'Hara, and Srinivas (1998), Bali and Hovakimian (2009), and Cremers and Weinbaum (2010) among others.

moments of equity returns implied by option prices. It is also remarkable that our proposed measure of option-implied volatility slope and convexity measures (*IV slope* and *IV convexity)* have an advantage over *IV smirk* measure proposed by Xing, Zhang, and Zhao (2010), which contains mixed information about higher moments and cannot distinguish between the volatility slope and convexity components addressing the 3rd and 4th moment implications in terms of the option-implied stock return distribution. Instead, we decompose *IV smirk* into separate *IV slope* and *IV convexity* measures and empirically verify that both are independently and significantly priced in the cross-section of future stock returns. In addition, *IV spread* measure proposed by Yan (2011) simply captures the effect of the average jump size but not the effect of jump-size volatility in the SVJ model framework. We extend his findings by examining how *IV convexity* explains the cross-section of future stock returns to address the jump-size volatility effect.

On another note, this paper overcomes the potential caveat of ex-post information extracted from past realized returns in the previous studies on the effect of skewness (e.g., Kraus and Litzenberger, 1976; Lim, 1989; Harvey and Siddique, 2000) by estimating an ex-ante measure of skewness (*IV slope*) and excess kurtosis (*IV convexity*) from option price data in a forward-looking manner.[8] Finally, this paper sheds new light on the relationship between the higher moment information extracted from individual equity option prices and the cross-section of future stock returns. Chang, Christoffersen, and Jacobs (2013) investigate how market-implied skewness and kurtosis affect the cross-section of stock returns by looking at the risk-neutral skewness and kurtosis implied by *index option prices* based on Bakshi, Kapadia, and Madan's (2003) proposed framework model. Their approach ignores the idiosyncratic components of option-implied higher moments in stock returns, though Yan (2011) finds that both the systematic and idiosyncratic components of *IV spread* are priced and that the latter dominates the former in capturing the variation of cross-sectional stock returns in the future. In this context, our paper also extends the findings of Chang, Christoffersen, and Jacob (2013) by employing firm-level equity option price data, and further decomposing *IV convexity* into systematic and idiosyncratic components to fully identify both systematic and idiosyncratic relationships between *IV convexity* and the cross-section of future stock returns.

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[8] Note that the ex-post skewness estimated from past returns is an unbiased estimator of the expected skewness only when the moments of stock returns are inter-temporally constant.

The rest of this paper is organized as follows. Section I demonstrates the asset pricing implications of the proposed *IV convexity* measure through numerical analyses to develop our main research questions. Section II describes the data and presents the empirical results for the main hypotheses. Section III provides additional tests as robustness checks and Section IV concludes the paper.

Ⅰ. Asset Pricing Implications

In this section, we demonstrate the asset pricing implications of our proposed *IV convexity* and *IV slope* measures through numerical analyses. An option-implied risk-neutral distribution of the underlying stock return exhibits heavier tails than the normal distribution with the same mean and standard deviation, in the presence of higher moments such as skewness and excess kurtosis.[9] Accordingly, information about these higher moments embedded in the various shapes of implied volatility curves can be examined from various perspectives.

A. Higher Moments and the Shape of the Implied Volatility Curve

Consider a geometric Lèvy process to model the risk-neutral dynamics of the underlying stock price given by

$$\mathrm{S_t} = S_0 e^{X_t}, \tag{1}$$

where X is a Lèvy process whose increments are stationary and independent. In this context, a natural characterization of a probability distribution is specifying its cumulants.[10] To explore the effects of skewness and excess kurtosis on option pricing, we can readily expand the probability distribution function $\mathrm{X_T}$, where T is the option's maturity time via the Gram-Charlier expansion, a method to express a density probability distribution in terms of another (typically Gaussian) probability distribution function using cumulant expansions.[11] Skewness and excess kurtosis determine the degrees of lean and fat tails for the probability distribution function of $\mathrm{X_T}$,

[9] Hereafter, we use *kurtosis* and *excess kurtosis* interchangeably for simplicity, despite their conceptual differences.
[10] The n^{th} cumulant is defined as the n^{th} coefficient of the Taylor expansion of the cumulant generating function, the logarithm of the moment generating function. Intuitively, the first cumulant is the expected value, and the n^{th} cumulant corresponds to the n^{th} central moment for $n=2$ or $n=3$. For $n\geq 4$, the n^{th} cumulant is the n^{th} -degree polynomial in the first n central moments.
[11] See Tanaka, Yamada, and Watanabe (2010) for details.

respectively. This aids in understanding how the skewness and kurtosis of X_T affect the shape of the implied volatility curves.

[Insert Figure 1 about here.]

Figure 1 illustrates the effect of different values of skewness and excess kurtosis on the shape of an implied volatility curve. We can observe that a negatively skewed distribution of X_T, *ceteris paribus*, leads to a steeper volatility smirk, whereas an increase in the excess kurtosis of X_T makes the volatility curve more convex. In this context, we define the implied volatility convexity (*IV convexity*) and the implied volatility slope (*IV slope*) as

$$IV\ Convexity = IV\left(OTM_{put}\right) + IV\left(ITM_{put}\right) - 2 \times IV(ATM), \tag{2}$$

$$IV\ Slope = IV\left(OTM_{put}\right) - IV\left(ITM_{put}\right), \tag{3}$$

where $IV(\cdot)$ denotes the implied volatility as a function of the option's moneyness.[12] Intuitively, *IV convexity* captures the degree of curvature of the implied volatility curve, whereas *IV slope* captures its slope.

[Insert Figure 2 about here.]

Figure 2 confirms the option pricing implication in that the 3rd moment of X_T has linear impact on *IV slope* but little impact on *IV convexity* while 4th moments of X_T has linear impact on *IV convexity* but no impact on *IV slope* of the implied volatility curve. This distinct impact of 3rd and 4th moment to *IV slope* and *IV convexity* provides us the unique opportunity to examine the effect of higher moments in the distribution of future stock price embedded in option prices on the predictability of future stock prices.

B. Analytical Interpretation

Although a stock return with normal distribution is extensively postulated in finance, it has long been disputed by empirical findings (e.g., Peters, 1991; Bollerslev, Chou, and Kroner, 1992) that

[12] In the absence of arbitrage opportunities, put-call parity implies that the option-implied volatilities of European call and put options should be identical when they have the same strike price and expiration date. In other words, both *IV Convexity* and *IV Slope* can be defined in terms of the implied volatilities of call options.

the empirical distribution of stock returns tends to have fatter tails than those implied by the normal distribution. Earlier studies suggest *stochastic volatility* and *jump diffusion* models to capture the investors' positively-skewed and platokurtic preferences. In this context, the 3rd and 4th moments of the model-implied return distributions are worthy of investigation.

For a more in-depth exploration of the relationship between option pricing and the option-implied volatility curve, we first investigate Heston's (1993) stochastic volatility (SV) model. Specifically, we assume that the risk-neutral dynamics of the stock price follows a system of stochastic differential equations given by

$$dS_t = (r - q)S_t dt + \sqrt{\upsilon_t} S_t dW_t^{(1)}, \tag{4}$$

$$d\upsilon_t = \kappa(\theta - \upsilon_t)dt + \sigma_\upsilon \sqrt{\upsilon_t} dW_t^{(2)}, \tag{5}$$

where $\mathrm{E}[dW_t^{(1)}\, dW_t^{(2)}] = \rho \mathrm{dt}$. Here, S_t denotes the stock price at time t, r is the annualized risk-free rate under the continuous compounding rule, q is the annualized continuous dividend yield, υ_t is the time-varying variance process whose evolution follows the square-root process with a long-run variance of θ, a speed of mean reversion κ, and a volatility of the variance process σ_υ. In addition, $W_t^{(1)}$ and $W_t^{(2)}$ are two independent Brownian motions under the risk-neutral measure, and ρ represents the instantaneous correlation between the two Brownian motions.

[Insert Figure 3 about here.]

Based on our numerical experiments, Figure 3 demonstrates that *IV slope* reflects the leverage effect measured by the correlation coefficient (ρ), while *IV convexity* represents the degree of a large contribution of extreme events to the variance, i.e., tail risk, driven by the volatility of variance risk (σ_υ). Put simply, *IV convexity* contains the information about the volatility of stochastic volatility (σ_υ) and can be interpreted as a simple measure of the perceived kurtosis that addresses the option-implied tail risk in the distribution of underlying stock returns; a similar intuition is also illustrated in Figures 1-3 of Heston (1993).

On another note, *IV convexity* can be viewed as a component of variance risk premium (VRP), as documented by Bakshi, Kapadia, and Madan (2003), Carr and Wu (2009), Bollerslev, Tauchen, and Zhou (2010), and Drechsler and Yaron (2011), among others. According to Carr and Wu (2009), VRP consists of two components: (i) the correlation between the variance and the stock return and (ii) the volatility of the variance. In the SV model framework, the first component is captured by the correlation coefficient (ρ), while the second component is addressed by the volatility of stochastic volatility (σ_v). Nevertheless, recent researches into VRP have focused on the aggregate effect of VRP on stock returns, but do not separately investigate how the two VRP components have different impacts on stock returns. Thus, it is interesting to investigate the implications of *IV slope* and *IV convexity* on VRP in the context of Carr and Wu (2009). Specifically, our study aims to investigate the impact of the second component of VRP by analyzing the information delivered by the *IV convexity* measure.

We next consider the impact of jumps in the dynamics of the underlying asset price. For example, Bakshi, Cao, and Chen (1997) show that jump components are necessary to explain the observed shapes of implied volatility curves in practice. In the presence of jump risk, the option-implied risk-neutral distribution of a stock price return is a function of the average jump size and jump volatility. To illustrate the implications of jump components on the shape of the option-implied volatility curve, we consider the following stochastic-volatility jump-diffusion (SVJ) model under the risk-neutral pricing measure given by

$$dS_t = (r - q - \lambda\, \mu_J)S_t dt + \sqrt{\upsilon_t} S_t dW_t^{(1)} + J S_t dN_t, \tag{6}$$

$$d\upsilon_t = \kappa(\theta - \upsilon_t)dt + \sigma_v \sqrt{\upsilon_t} dW_t^{(2)}, \tag{7}$$

where $\mathrm{E}[dW_t^{(1)}\, dW_t^{(2)}] = \rho \mathrm{dt}$, N_t is an independent Poisson process with intensity $\lambda > 0$, and J is the relative jump size, where $\log(1+J) \sim N(\log(1+\mu_J) - 0.5\sigma_J^2, \sigma_J^2)$. The SVJ model can be taken as an extension of the SV model with the addition of log-normal (Merton-type) jumps in the underlying asset price dynamics.[13]

[Insert Figure 4 about here.]

As we can see from Figure 4, our numerical analysis illustrates that *IV slope* is mainly driven by the average jump size (μ_J), whereas the jump size volatility (σ_J) contributes mainly to *IV convexity*. From this perspective, Yan (2011) argues that the implied-volatility spread between ATM call and put options contain information about the perceived jump risk by investigating the relationship between the implied-volatility spread and the cross-section of stock returns. Strictly speaking, in the SVJ model framework, implied-volatility spread measure of Yan (2011) simply captures the effect of μ_J but ignores the information from σ_J. In other words, the implied-volatility spread measure fails to provide any evidence in terms of whether the implied jump size volatility σ_J, can predict future stock returns. Therefore, this study extends his finding by looking at the predictability of the *IV convexity* measure, which contains the information from σ_J, and examining how *IV convexity* affects the cross-section of future stock returns accordingly.

C. Hypothesis Development

We have seen that the convexity of an option-implied volatility curve is a forward-looking measure of the perceived likelihood of extreme movements in the underlying equity price originating from the stochastic volatility and/or jump risk under the risk-neutral measure. Additionally, option prices can provide ex-ante information about the anticipated stochastic volatility and jump-diffusion due to its forward-looking nature. In this regard, the *IV slope and IV convexity* measures can be employed as proxies for the 3rd and 4th moments in the option-implied distribution of stock returns, respectively.

Hence, the overall goal of this study is to determine if a measure of option-implied volatility convexity can show significant cross-sectional predictive power for future equity returns.

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[13] Note that the SVJ model given by (6)-(7) can be interpreted as a variation of the Bates (1996) model. Duffie, Pan, and Singleton (2000) provide an illustrative example to examine the implications of the SVJ model for options valuation.

This is summarized in the hypotheses as follows:

- Hypothesis 1: *If options traders have no information advantage to stock investors about the prediction for excess tail risk contributions to the perceived variance of the underlying equity returns, IV convexity cannot predict future stock returns with statistical significance.*

- Hypothesis 2: *If there is a slow and one-way information transmission from the options market to the stock market, informed options traders can anticipate the excess tail risk contribution to the perceived variance of the underlying equity returns. The option investors then proactively induce leptokurtic implied distributions of stock returns before equity investors express their tail-risk aversion. Hence, IV convexity will show its predictive power for future stock price returns with a negative relationship.*

If we reject Hypothesis 1 and observe negative relationship between IV convexity and future stock return with statistical significance, it would empirically support the existing literature demonstrating the information transmission between the options and stock markets in that informed options traders anticipating heavy tail risks proactively induce leptokurtic implied distributions before equity investors express their tail risk aversion in the stock market.

Ⅱ. Empirical Analysis

This section introduces the data set and methodology to estimate option-implied convexity in a cross-sectional manner. We then test whether *IV convexity*, a proxy for the option-implied volatility of stochastic volatility (σ_v) and the jump size volatility (σ_J), has strong predictive power for future stock returns with statistical significance. Additionally, we compare the impact of the option implied volatility slope with that of our *IV convexity* measure on stock returns.

A. Data

We obtain the U.S. equity and index option data from OptionMetrics on a daily basis from January 2000 through December 2013. As the raw data include individual equity options in the American style, OptionMetrics applies the binomial tree model of Cox, Ross, and Rubinstein

(1979) to estimate the options-implied volatility curve to account for the possibility of an early exercise with discrete dividend payments. Employing a kernel smoothing technique, OptionMetrics offers an option-implied volatility surface across different option deltas and time-to-maturities. Specifically, we obtain the fitted implied volatilities on a grid of fixed time-to-maturities, (30 days, 60 days, 90 days, 180 days, and 360 days) and option deltas (0.2, 0.25, …, 0.8 for calls and -0.8, -0.75, … , -0.2 for puts), respectively. Following An, Ang, Bali and Cakici (2014) and Yan (2011), we then select the options with 30-day time-to-maturity on the last trading day of each month to examine the predictability of *IV convexity* for future stock returns.

[Insert Table I about here.]

Table I shows the summary statistics of the fitted implied volatility and fixed deltas of the individual equity options with one month (30 days), two month(60 days), three month(91 days) and six month(182days) time-to-maturity chosen at the end of each month. We can clearly observe a positive convexity in the option-implied volatility curve as a function of the option's delta in that the implied volatilities from in-the-money (ITM) (calls for delta of 0.55~0.80, puts for delta of -0.80~-0.55) options and OTM (calls for delta of 0.20~0.45, puts for delta of -0.45~-0.20) options are greater on average than those near the ATM options (calls for delta of 0.50, puts for delta of -0.50).[14]

We obtain daily and monthly individual common stock (shrcd in 10 or 11) returns from the Center for Research in Security Prices (CRSP) for stocks traded on the NYSE (exchcd=1), Amex (exchcd=2), and NASDAQ (exchcd=3). Stocks with a price less than three dollars per share are excluded to weed out very small or illiquid stocks and the potential extreme skewness effect (Loughran and Ritter (1996)). Accounting data is obtained from Compustat. We obtain both daily and monthly data for each factor from Kenneth R. French's Website.[15]

B. Variables and Portfolio Formation

We demonstrate that *IV convexity* has a positive relationship with the volatility of stochastic volatility (σ_v) and jump volatility (σ_J) in previous section. That is, *IV convexity* can be

[14] Note that the convexity of the implied volatility curve becomes less pronounced as the time-to maturity increases.
[15] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

interpreted as a simple measure of the perceived kurtosis of the option-implied distribution of the stock returns driven by the volatility of stochastic volatility and jump size volatility. As expected, it is hard to directly calibrate the volatility of stochastic volatility (σ_v) and jump size volatility (σ_J) for each underlying stock from the cross-sectional perspective on a daily basis. We thus overcome this computational difficulty by adopting *IV convexity* as a simple proxy for the volatility of stochastic volatility (σ_v) and jump size volatility (σ_J) to investigate how the ex-ante 4th moment in the option-implied distribution of the stock returns affects the cross-section of future stock returns. Accordingly, we define our measure of *IV convexity* as

$$IV\ convexity = \mathrm{IV}_{\mathrm{put}}(\Delta = -0.2) + \mathrm{IV}_{\mathrm{put}}(\Delta = -0.8) - 2 \times \mathrm{IV}_{\mathrm{call}}(\Delta = 0.5), \tag{8}$$

Specifically, we use the implied volatilities of OTM and ITM put and ATM call options to capture the convexity of the implied volatility curve. The rationale is that those who sensitively respond to the forthcoming tail risk would buy put options either as a protection against the potential decrease in the stock return for hedging purposes or as a leverage to grab a quick profit for speculative purposes to capitalize on private information. Therefore, those investors would have an incentive to trade OTM and/or ITM put options rather than call options. Based on this line of reasoning, we choose OTM and ITM puts for calculating the *IV convexity* measure. As a benchmark of the option-implied volatility curve, motivated by Xing, Zhang, and Zhao (2010), we use the implied volatility of an ATM call as a representative value for the implied volatility level, as the ATM call is generally the most frequently traded option best reflecting market participants' sentiment regarding the firm's future status and condition.

As alternative measures related to the option-implied volatility curve, options implied volatility level (*IV level*), *IV slope*, *IV smirk*, and *IV spread* are defined as

$$IV\ level = 0.5[\mathrm{IV}_{\mathrm{put}}(\Delta = -0.5) + \mathrm{IV}_{\mathrm{call}}(\Delta = 0.5)], \tag{9}$$

$$IV\ slope = \mathrm{IV}_{\mathrm{put}}(\Delta = -0.2) - \mathrm{IV}_{\mathrm{put}}(\Delta = -0.8), \tag{10}$$

$$IV\ smirk = \mathrm{IV}_{\mathrm{put}}(\Delta = -0.2) - \mathrm{IV}_{\mathrm{call}}(\Delta = 0.5), \tag{11}$$

$$IV\ spread = \mathrm{IV}_{\mathrm{put}}(\Delta = -0.5) - \mathrm{IV}_{\mathrm{call}}(\Delta = 0.5). \tag{12}$$

The *IV spread* measure proposed by Yan (2011) considers only the contribution of 3^{rd} moments of stock distributions. The *IV smirk* measure proposed by Xing, Zhang and Zhao (2010) contains both 3rd and 4^{th} moments in a mixed manner, which makes it impossible to distinguish individual contributions of them.[16] In contrast to *IV spread* and *IV smirk*, our proposed measures or *IV slope* and *IV convexity* respectively proxy the contribution of 3^{rd} and 4^{th} moments of stock return distribution. This decomposition enables us to investigate whether the *IV slope* and *IV convexity* actually have distinct impacts on a cross-section of future stock returns thus to check whether *IV convexity* carries extra predictability of future stock returns controlling for return predictability of 3^{rd} moment of stock return distribution, which is already identified by Yan (2011).

At the end of each month, we compute the cross-sectional *IV level*, *IV slope*, *IV convexity*, *IV smirk*, and *IV spread* measures from 30-day time-to-maturity options. We define a firm's size (Size) as the natural logarithm of the market capitalization (prc×shrout×1000), which is computed at the end of each month using CRSP data. When computing book-to-market ratio (BTM), we match the yearly Book value of Equity or BE [book value of common equity (CEQ) plus deferred taxes and investment tax credit (txditc)] for all fiscal years ending in June at year t to returns starting in July of year t-1, and dividing this BE by the market capitalization at month t-1. Hence, the book-to-market ratio is computed on a monthly basis. Market betas (β) are estimated with rolling regressions using the previous 36 monthly returns available up to month t-1 (a minimum of 12 months) given by

$$(\mathrm{R_i} - \mathrm{R_f})_k = \alpha_i + \beta_i(\mathrm{MKT} - \mathrm{R_f})_k + \varepsilon_{i,k}, \tag{13}$$

where $t - 36 \leq k \leq t - 1$ on a monthly basis. Following Jegadeesh and Titman (1993), we compute momentum (MOM) using cumulative returns over the past six months skipping one month between the portfolio formation period and the computation period to exclude the reversal effect. Momentum is also rebalanced every month and assumed to be held for the next one

[16] Note that our proposed measures of *IV slope* and *IV convexity* have a relationship with *IV smirk* in the following way: *IV smirk* = (*IV slope* + *IV convexity*) / 2

month. Short-term reversal (REV) is estimated based on the past one-month return as in Jegadeesh (1990) and Lehmann (1990).

Motivated by Amihud (2002) and Hasbrouck(2009), we define illiquidity (ILLIQ) as the average of the absolute value of the stock return divided by the trading volume of the stock in thousand USD using the past one-year's daily data up to month t.

Following Harvey and Siddique (2000), we regress daily excess returns of individual stocks on the daily market excess return and the daily squared market excess return using a moving-window approach with a window size of one year. Specifically, we re-estimate the regression model at each month-end, where the regression specification is given by

$$(\mathrm{R_i} - \mathrm{R_f})_k = \alpha_i + \beta_{1,i}(\mathrm{MKT} - \mathrm{R_f})_k + \beta_{2,i}(\mathrm{MKT} - \mathrm{R_f})^2{}_k + \varepsilon_{i,k}, \tag{14}$$

where $t - 365 \leq k \leq t - 1$ on a daily basis. In this context, the co-skewness (Coskew) of a stock is defined as the coefficient of the squared market excess return. We require at least 225 trading days in a year to reduce the impact of infrequent trading on the co-skewness estimates.

Following Ang, Hodrick, Xing, and Zhang (2006), we compute idiosyncratic volatility using daily returns. The daily excess returns of individual stocks over the last 30 days are regressed on Fama and French's (1993, 1996) three factors daily and momentum factors every month, where the regression specification is given by

$$(\mathrm{R_i} - \mathrm{R_f})_k = \alpha_i + \beta_{1i}(\mathrm{MKT} - \mathrm{R_f})_k + \beta_{2i}\mathrm{SMB_k} + \beta_{3i}\mathrm{HML_k} + \beta_{4i}\mathrm{WML_k} + \varepsilon_k, \tag{15}$$

where $t - 30 \leq k \leq t - 1$ on a daily basis. Idiosyncratic volatility is computed as the standard deviation of the regression residuals in every month. To reduce the impact of infrequent trading on idiosyncratic volatility estimates, a minimum of 15 trading days in a month for which CRSP reports both a daily return and non-zero trading volume is required.

We estimate systematic volatility using the method suggested by Duan and Wei (2009): $v_{sys}^2 = \beta^2 v_{\mathrm{M}}^2 / v^2$ for every month. We also computed idiosyncratic implied variance as $v_{idio}^2 = v^2 -$

$\beta^2 v_M^2$ on a monthly basis, where v_M is the implied volatility of the S&P500 index option following Dennis, Mayhew, and Stivers (2006).

The impact of the volatility of stochastic volatility and the jump size volatility on the return dynamics of the underlying stock would be either systematic or idiosyncratic. As there are two types of options data, equity options and index options, we can disentangle *IV convexity* into systematic and the idiosyncratic components. We run the time series regression each month using the S&P 500 index options with 30-day time-to maturity as a benchmark for the market along with individual equity options with daily frequency to decompose *IV convexity* into the systematic and the idiosyncratic components as follows:

$$IV\ convexity_{i,\mathrm{k}} = \alpha_{\mathrm{i}} + \beta_{\mathrm{i}} \times IV\ convexity_{S\&P500,\mathrm{k}} + \varepsilon_{\mathrm{i,k}}, \quad (16)$$

where $\mathrm{t} - 30 \leq \mathrm{k} \leq \mathrm{t} - 1$ on a daily basis. We define the fitted values and residual terms as *the systematic component of IV convexity* ($convexity_{sys}$) and *the idiosyncratic component of IV convexity* ($convexity_{idio}$), respectively. When constructing a single sorted *IV convexity* portfolio, we sort all stocks at the end of each month based on the *IV convexity* and match with the subsequent monthly stock returns. The *IV convexity* portfolios are rebalanced every month.

To investigate whether the anomaly of *IV convexity* persists even after controlling for other systematic risk factors, we double sort all stocks following Fama and French (1993). At the end of each month, we first sort all stocks into 5 portfolios based on the level of systematic factors (i.e., firm size, book-to-market ratio, market β, momentum, reversal etc.) and then sub-sort them into five groups based on the *IV convexity*. These constructed portfolios are matched with subsequent monthly stock returns. This process is repeated every month.

C. Portfolio Characteristics Sorted by IV convexity

C.1. Predicting Cross-sectional Stock Returns

We report our empirical results regarding the predictive power of *IV convexity* for the cross-section of future stock returns.

[Insert Table II about here.]

Panel A of Table II shows the descriptive statistics for each implied volatility measure computed at the end of each month using 30-day time-to-maturity options. As for the average values for each of variable, *IV level* has 0.4739, *IV slope* for 0.0423, *IV spread* for 0.009, *IV smirk* for 0.0687, and *IV convexity* for 0.0942, respectively. The standard deviation of *IV convexity* is 0.2624 and 0.1682 for $convexity_{sys}$, 0.2015 for $convexity_{idio}$, respectively. It seems that the $convexity_{idio}$ measure better captures the variation in *IV convexity* than the $convexity_{sys}$ measure.

Panel A of Table II also presents descriptive statistics for the alternative convexity measure using various OTM put deltas. The alternative *IV convexity* measures are computed by

$$\text{p}\Delta_1\text{\_c50\_p}\Delta_2 = \text{IV}_{\text{put}}(\Delta_1) + \text{IV}_{\text{put}}(\Delta_2) - 2 \times \text{IV}_{\text{call}}(0.5), \quad (17)$$

where $-0.45 \leq \Delta_1 \leq -0.25$ (for the range of OTM puts) and $-0.75 \leq \Delta_2 \leq -0.55$ (for the range of ITM puts), respectively. For example, applying Δ_1=-0.25 for OTM put and Δ_2=-0.75 for ITM put, we calculate

$$\text{p25\_c50\_p75} = \text{IV}_{\text{put}}(-0.25) + \text{IV}_{\text{put}}(-0.75) - 2 \times \text{IV}_{\text{call}}(0.5). \quad (18)$$

Similarly, p45_p50_p55 is defined as $\text{IV}_{\text{put}}(-0.45) + \text{IV}_{\text{put}}(-0.55) - 2 \times \text{IV}_{\text{call}}(0.5)$. It is natural that the *IV convexity* measure computed using deep out-of-the-money (DOTM) and deep in-the-money (DITM) options have higher options convexity values compared to measurements using OTM and ITM options. For example, *IV convexity* of p25_c50_p75 is 0.065, which is larger than the value of p45_p50_p55, 0.018.

Panel B of Table II reports the descriptive statistics of the quintile portfolios sorted by firm characteristic variables (Size, BTM, Market β, MOM, REV, ILLIQ and Coskew). While the mean and median of SIZE are 19.4607 and 19.3757, respectively, its quintile average is monotonically increasing from 16.7256 to 22.4613. On the other hand, BTM has a right-skewed distribution, with a mean of 0.9186 and median of 0.5472, whereas its quintile average varies from 0.1467 to 2.6192.

To examine the relationship between *IV convexity* and future stock returns, we form five portfolios according to the *IV convexity* value at the last trading day of each month. Quintile 1 is composed of stocks with the lowest *IV convexity* while Quintile 5 is composed of stocks with the highest *IV convexity*. These portfolios are equally weighted, rebalanced every month, and assumed to be held for the subsequent one-month period.

[Insert Table III about here.]

Table III reports the means and standard deviations of the five *IV convexity* quintile portfolios and average monthly portfolio returns over the entire sample period. Specifically, Panel A shows the descriptive statistics for kurtosis along with the average monthly returns of both equal-weighted (EW) and value-weighted (VW) portfolios sorted by *IV convexity, IV spread, and IV smirk,* where the last two measures are defined and estimated as in Yan (2011) and Xing, Zhang, and Zhao (2010), respectively.

As shown, the average EW portfolio return monotonically decreases from 0.0208 for the lowest quintile portfolio Q1 to 0.0074 for the highest quintile portfolio Q5. The average monthly return of the arbitrage portfolio buying the lowest *IV convexity* portfolio Q1 and selling highest *IV convexity* portfolio Q5 is significantly positive (0.0134 with t-statistics of 7.87). The average VW portfolio returns exhibit a similar decreasing pattern from Q1 (0.0136) to Q5 (0.0023), and the return of zero-investment portfolio (Q1-Q5) is significantly positive (0.0113 with t-statistics of 5.08).

In addition, the EW portfolios sorted by *IV spread* show that their average returns decrease monotonically from 0.0145 for quintile portfolio Q1 to 0.0013 for quintile portfolio Q5, where the average return difference between Q1 and Q5 amounts to 0.0131 with t-statistics of 7.31 and similar patterns are observed with VW portfolios sorted by *IV spread*. These results certainly confirm Yan's (2011) empirical finding in that low *IV spread* stocks outperform high *IV spread* stocks. In a similar vein, we find that the average returns of quintile portfolios sorted by *IV smirk* are decreasing in *IV smirk*, and the returns of zero-investment portfolios (Q1-Q5) are all positive and statistically significant for both the EW and VW portfolios, consistent with Xing, Zhang and

Zhao (2010) in that there exists a negative predictive relationship between *IV smirk* and future stock return.

Panel B reports descriptive statistics for average portfolio returns using alternative *IV convexities* estimated with various delta points. The decreasing patterns in portfolio returns are still observed for the alternative *IV convexity* and arbitrage portfolio returns by buying the low *IV convexity* quintile portfolio and selling the high *IV convexity* quintile portfolio, which are significantly positive for both the EW and VW portfolio returns. This result confirms that the negative relationship between *IV convexity* and stock returns are robust and consistent whatever OTM put (ITM put) we use to compute convexity. These results support *Hypothesis 2*, indicating that information transmission between the options and stock markets: informed options traders anticipating heavy tail risks proactively induce leptokurtic implied distributions before equity investors express their tail risk aversion in the stock market.

[Insert Figure 5 about here.]

Panel A of Figure 5 shows the monthly average *IV convexity* value for each quintile portfolio, while Panel B plots the monthly average return of the arbitrage portfolio formed by taking long position in the lowest quintile and short position in the highest quintile portfolios (Q1-Q5). The time-varying average monthly returns of the long-short portfolio are mostly positive, confirming the results reported in Table 2.

C.2. Controlling Systematic Risks

Moreover, we investigate whether the positive arbitrage portfolio returns (Q1-Q5) are compensations for taking systematic risk. If the positive arbitrage portfolio returns are still significant after controlling for systematic risk factors, we can argue that the decreasing pattern in the portfolio return in *IV convexity* may not be driven by systematic risks and can be recognized as an abnormal phenomenon. In this context, we test whether systematic risk factors crowd out the negative relationship between *IV convexity* and stock returns. We begin this task by looking at two-way cuts on systematic risk and *IV convexity*, and then we conduct time-series tests by running risk factor-model [e.g., the CAPM and Fama and French (1993) factor model] regressions with the standard equity risk factors; i.e., Market β, SMB, HML, and MOM.

C.2.1. Double Sorting by Systematic risk and IV convexity

To examine whether the relationship between *IV convexity* and stock returns disappear after controlling for the systematic risk factors, we double-sort all stocks following Fama and French (1992). All stocks are sorted into five quintiles by ranking on systematic risk and then sorting within each quintile into five quintiles according to *IV convexity*. Fama and French (1993) suggest that firm size, book-to-market ratio, and Market β are systematic risk components of stock returns, so we adopt these three firm characteristic risks as systematic risks.

[Insert Table IV about here.]

Table IV reports the average monthly returns of the 25 (5 × 5) portfolios sorted first by firm characteristic risks (firm size, book-to-market ratio, and Market β) and then by *IV convexity* and average monthly returns of the long-short arbitrage portfolios (Q1-Q5).

We can observe that the average monthly portfolio returns generally decline as the average firm-size increases. As for the results from double-sorting using firm-size and *IV convexity*, we find that the returns of the *IV convexity* quintile portfolios are still decreasing in *IV convexity* in most size quintiles, and the return of all zero-investment portfolios (Q1-Q5) in size quintiles are all positive and statistically significant. Particularly, the positive difference in the smallest quintile is largest (0.0187) compared to the other size quintile portfolios.

The two-way cuts on book-to-market and *IV convexity* show that the higher book-to-market portfolio gets more returns compared to the lower book-to-market portfolios in each *IV convexity* quintile. The decreasing patterns in *IV convexity* portfolio returns remain even after controlling the systematic compensation drawn from the book-to-market factor. Note that the overall zero-cost portfolios formed by long Q1 and short Q5 are also positive and statistically significant: 0.0097 (t-statistic = 4.82) for B1 (BTM quintile 1), 0.0121 (t-statistic = 5.76) for B2, 0.0108 (t-statistic = 5.42) for B3, 0.0134 (t-statistic = 5.67) for B4, and 0.0177 (t-statistic = 5.19) for B5.

When sorting the 25 portfolios first by Market β and then by *IV convexity*, the negative relationship between *IV convexity* and stock return persists, implying that this decreasing pattern cannot be explained by Market β. Note that the average monthly portfolio returns generally increase as the average Market β rises.

We also consider the other four systematic risk factors (i) the momentum effect documented by Jegadeesh and Titman (1993), (ii) the short-term reversal suggested by Jegadeesh (1990) and Lehmann (1990), (iii) the illiquidity proposed by Amihud (2002) and (iv) co-skewness suggested by Harvey and Siddique (2000) to examine whether the decreasing pattern of portfolio returns in *IV convexity* disappears when controlling these systematic risk factors. Stocks are first sorted into five groups based on their momentum (or reversal, illiquidity, co-skewness) measures and then sorted by *IV convexity* forming 25 ($= 5 \times 5$) portfolios.

[Insert Table V about here.]

Table V presents the returns of 25 portfolios sorted by momentum (or Reversal, Illiquidity, Co-skewness) and *IV convexity*. When we look at the momentum patterns in the momentum-*IV convexity* portfolios, winner portfolios consistently achieve more abnormal returns than loser portfolios except for the lowest momentum-lowest *IV convexity* quintiles, which could be caused by using a different sample datasets compared to that in Jegadeesh and Titman (1993). While Jegadeesh and Titman (1993) use only stocks traded on the NYSE (exchcd=1) and Amex (exchcd=2), we add stocks traded on the NASDAQ (exchcd=3). For the holding period strategies, Jagadeesh and Titman (1993) adopt 3-, 6-, 9-, and 12-month holding periods, while this study assumes that portfolios are held for one month.

Even after controlling momentum as a systematic risk, we observe that the portfolio return differential between the lowest and highest *IV convexity* in each momentum quintile remains significantly positive, indicating that *IV convexity* contains economically meaningful information that cannot be explained by the momentum factor.

For the reversal-*IV convexity* double sorted portfolio case, there is a clear reversal patterns in most cases when using a reversal strategy (i.e., the past winner earns higher returns in the next month compared to past loser), though there are some distortions in the lowest reversal-highest *IV convexity* quintiles. The Q1-Q5 strategy of buying and selling stocks based on *IV convexity* in each reversal portfolio and holding them for one month still earns significantly positive returns. This implies that the same results still hold even after controlling for reversal effects.

We further incorporate the Amihud (2002) measure of illiquidity to address the role of the liquidity premium in asset pricing. Amihud (2002) finds that the expected market illiquidity has positive and highly significant effect on the expected stock returns, as investors in the equity market require additional compensation for taking liquidity risk. We examine whether Amihud's (2002) market illiquidity measure (ILLIQ) explains the higher return on the lowest *IV convexity* stock portfolio (Q1) relative to the *highest IV convexity* stock portfolio (Q5). The double-sorted quintile portfolios by ILLIQ and *IV convexity* exhibit analogous patterns in that their average returns tend to decrease in *IV convexity*. The zero-investment portfolios (Q1-Q5) based on the ILLIQ quintiles demonstrate their significantly positive average returns across different ILLIQ quintiles. This finding implies that a significantly negative *IV convexity* premium remains even after we control for the illiquidity premium effect.

Next, we consider conditional skewness, as Harvey and Siddique (2000) find that conditional skewness (*Coskew*) can explain the cross-sectional variation of expected returns even after controlling factors based on size and book-to-market value. To examine whether this *Coskew* factor captures the higher returns of the lowest *IV convexity* stocks relative to the highest *IV convexity* stocks, we constructed 25 portfolios sorted first by *Coskew* and then by *IV convexity*. For the *Coskew -IV convexity* double sorted portfolios, there is a clear decreasing pattern in *IV convexity* within each *Coskew* sorted quintile portfolio. The returns of zero-cost *IV convexity* portfolios (Q1-Q5) within each *Coskew* quintile portfolio are all positive and statistically significant: 0.0130 (t-statistic of 4.60) for C1 (*Coskew* quintile 1), 0.0090 (t-statistic of 3.83) for C2, 0.0040 (t-statistics 2.39) for C3, 0.0076 (t-statistics 4.18) for C4, and 0.0127 (t-statistics 5.07) for C5, respectively. The implication is that a negative IV convexity premium remains significantly even after we control for the *Coskew* premium effect.

In summary, we conclude that the negative relationship between *IV convexity* and stock return consistently persists even after controlling for various kinds of systematic risks identified in prior researches. Therefore, we argue that *IV convexity* is not caused by systematic risk components and can be considered a significantly priced risk factor.

C.2.2. Controlling for IV slope

As demonstrated in the theoretical development, we focus on the role of the four parameters (ρ, σ_v, μ_J, σ_J) suggested in the SV and SVJ models as an extension to the standard Black-Scholes (1973) option pricing model, as they are deeply related to the shape of options implied volatility curve. Specifically, *IV slope* is associated with ρ and μ_J, which are associated with the skewness of the distribution of stock returns, whereas *IV convexity* has a positive relationship with σ_v and σ_J, which play major role in the risk-neutral kurtosis of stock returns.

Although we numerically verify that the impact of *IV slope* on the distribution of stock returns is different from those of *IV convexity* on the distribution of stock returns, it is still unclear whether the *IV convexity* really affects the stock return differently from *IV slope*. To answer this question, we examine whether the negative relationship between *IV convexity* and stock returns persists after controlling for the effect of the option-implied volatility slope on stock returns suggested by other researchers. For this purpose, we consider the following three measures for the slope of the option-implied volatility curve: (i) *IV slope* following our definition, (ii) *IV spread* suggested by Yan (2011), (iii) *IV smirk* proposed by Xing, Zhang, and Zhao (2010).

[Insert Table VI about here.]

Table VI presents the average monthly returns of 25 portfolios sorted first by *IV slope*, *IV spread,* and *IV smirk* and then sorted by *IV convexity* within each *IV slope*, *IV spread,* and *IV smirk* sorted quintile portfolio, respectively.

The first five columns show the results of our *IV slope-IV convexity* double sorted portfolio returns. We can observe a decreasing pattern with respect to *IV convexity* in each *IV slope* quintile, and the Q1-Q5 strategy based on *IV convexity* in each *IV slope* portfolio and holding them for one month returns significantly positive profits across the different specifications.

As for *IV spread*, following Yan (2011), the *IV convexity* strategy that buys the lowest quintile portfolio and sells the highest quintile portfolio within each *IV spread* portfolio yields significantly positive returns in all cases, suggesting that *IV spread* does not capture the *IV convexity* effect.

It is noteworthy that *IV convexity* arbitrage portfolios (Q1-Q5) in the S1 and S5 *IV smirk* portfolios produce significantly positive returns, while the portfolio returns lose their statistical significance for the S2, S3, and S4 *IV smirk* quintiles. As the *IV smirk* measure contains mixed information of *IV slope* and *IV convexity*, it is natural to observe that *IV smirk* explains a negative *IV convexity* premium to some extent. However, *IV smirk* cannot fully capture the negative relationship between *IV convexity* and future stock returns in the S1 and S5 portfolios.

All in all, these findings support the proposition that the negative relationship of *IV convexity* to future stock returns still holds after considering the impact of *IV slope* and *IV spread* on stock returns. This implies that the impact of *IV convexity* on the distribution of stock returns does not come from *IV slope* and *IV spread* and that *IV convexity* is an important factor in determining the fat-tailed distribution characteristics of future stock returns

C.3. Systematic and Idiosyncratic Components of IV convexity

The variance of stock returns are composed of two components: systematic and idiosyncratic volatility. Only systematic risk (Market β) should be priced in equilibrium while idiosyncratic risk cannot capture the cross-sectional variation in stock returns. However, in the real world, investors cannot perfectly diversify away the idiosyncratic risks, so some researchers argue that idiosyncratic risk can also play important role in explaining the cross-sectional variation in stock returns. In this context, we try to decompose the volatility of stochastic volatility (σ_v) and jump size volatility (σ_J) into systematic and idiosyncratic components to further investigate the source of the negative relationship between *IV convexity* and cross-section stock returns. Importantly, the fact that there are two types of option data, equity options and index options, allows us to decompose *IV convexity* into the systematic and idiosyncratic components. By analyzing the two components of *IV convexity*, we can check whether the volatility of stochastic volatility and/or the jump risk shock determines the fat-tailed property of stock returns, and if these are driven by the market and/or individual firms' properties.

[Insert Table VII about here.]

Panel A of Table VII provides the descriptive statistics for the average portfolio returns sorted by systematic components and idiosyncratic components of *IV convexity*. It shows that the average portfolio return monotonically decreases from Q1 to Q5 and that the return differential between Q1 and Q5 is significantly positive. It is worth noting that the negative pattern is robust even if we decompose *IV convexity* into the systematic and idiosyncratic components. That is, $convexity_{sys}$ and $convexity_{idio}$ reveal decreasing patterns in the portfolio returns as the *IV convexity* portfolio increases. The difference between the lowest and the highest quintile portfolios sorted by $convexity_{sys}$ and $convexity_{idio}$ are significantly positive with t-statistics of 6.56 and 5.72, respectively. This implies that both components have predictive power for future portfolio returns and are significantly priced.

Panel B of Table VII reports the average monthly portfolio returns of the 25 quintile portfolios formed by sorting stocks based on $convexity_{\mathrm{sys}}$ (or $convexity_{\mathrm{idio}}$) first, and then sub-sorted by *IV convexity* in each $convexity_{\mathrm{sys}}$ (or $convexity_{\mathrm{idio}}$) quintile. This will allow us to figure out how the systematic or idiosyncratic components contribute to *IV convexity*. In other words, if the decreasing patterns of returns in *IV convexity* portfolio become less clearly observed under the control of $convexity_{\mathrm{sys}}$ (or $convexity_{\mathrm{idio}}$), this can be interpreted as a component of $convexity_{\mathrm{sys}}$ (or $convexity_{\mathrm{idio}}$) and can mostly explain the cross-sectional variation of return on *IV convexity* compared to the other component of $convexity_{\mathrm{sys}}$ (or $convexity_{\mathrm{idio}}$).

As for the results from the sample sorted first by $convexity_{\mathrm{sys}}$ and then by *IV convexity*, the decreasing patterns generally persist for the $convexity_{\mathrm{sys}}$ quintiles, though there are some distortions in the 1st and 3rd $convexity_{\mathrm{sys}}$ quintiles for the highest *IV convexity* quintiles. Note that the arbitrage portfolio's returns (Q1-Q5) in each $convexity_{\mathrm{sys}}$ quintile portfolio still remain large and statistically significant. As for the $convexity_{\mathrm{idio}}$- *IV convexity* double sorted portfolios shown in the right-hand side of Table VII, the negative relationship between *IV convexity* and average portfolio return exists, though the order of portfolio returns are not perfectly preserved in the 3rd and 5th $convexity_{\mathrm{idio}}$ case. Additionally, the long-short *IV convexity* portfolio returns in the $convexity_{\mathrm{idio}}$ quintile portfolio (Q1-Q5) are significantly positive with a t-statistic higher than two.

Thus, these results provide evidence that neither component can fully capture and explain all cross-section variations of returns on *IV convexity*, but both components ($convexity_{\mathrm{sys}}$, $convexity_{\mathrm{idio}}$) have decreasing patterns of portfolio returns, and are needed to capture the cross-sectional variations of returns.

C.4. Time-Series Analysis

In a perfectly and completely well-functioning financial market, the mean-variance efficiency of the market portfolio should hold as argued in the capital asset pricing model (CAPM), and Market β should be the only risk factor that captures the cross-sectional variation in expected returns. However, as many investors cannot hold perfectly diversified portfolios in practice, CAPM may not be valid in reality, the biggest drawback for this theory. Fama and French (1996) found that CAPM's measure of systematic risk is unreliable and instead, firm size and book-to-market ratio are more dependable, arguing that the three-factor model in Fama and French (1993) can capture the cross-sectional variations in returns that are not fully captured by the CAPM model. The Fama and French (1993) model has three factors: (i) $\mathrm{R_m} - \mathrm{R_f}$ (the excess return on the market), (ii) SMB (the difference in returns between small stocks and big stocks) and (iii) HML (the difference in returns between high book-to-market stocks and low book-to-market stocks).

To test whether the existing risk factor models can absorb the observed negative relationship between *IV convexity* and future stock returns, we conduct a time-series test based on CAPM and the Fama-French three factor model, respectively. Along with the Fama-French three factor model (FF3), we also use an extended four-factor model (Carhart, 1997) that includes a momentum factor (UMD) suggested by Jegadeesh and Titman (1993) (FF4).

[Insert Table VIII about here.]

Table VIII reports the coefficient estimates of CAPM, FF3, and FF4 time-series regressions for monthly excess returns on five portfolios sorted by *IV convexity* (or systematic and idiosyncratic components of *IV convexity*). The left-most six columns are the results using a portfolio sorted by *IV convexity*. When running regressions using CAPM, FF3, and FF4, we still observe the estimated intercepts in the Q1~Q3 *IV convexity* portfolio ($\hat{\alpha}_{Q1}, \hat{\alpha}_{Q2}, \hat{\alpha}_{Q3}$), which are statistically significant and have negative patterns with respect to portfolios formed by *IV convexity*. In addition, the differences in the intercept between the lowest and highest *IV convexity*, $\hat{\alpha}_{Q5} - \hat{\alpha}_{Q1}$, are 0.0132 (t-statistic = 7.72) for CAPM, 0.0134 (t-statistic = 7.75) for FF3, and 0.0136 (t-statistic = 7.61) for FF4. Adopting Gibbons, Ross, and Shanken (1989), we test the null hypothesis that all estimated intercepts simultaneously are zero ($\hat{\alpha}_{Q1} = \cdots = \hat{\alpha}_{Q5} = 0$), and this is rejected with a p-value < 0.001 in the CAPM, FF3, and FF4 model specifications. These results imply that the widely-accepted existing factors ($\mathrm{R_m} - R_f$, SMB, HML, UMD) cannot fully capture and explain the negative portfolio return patterns sorted by *IV convexity*. We argue that the existing systematic risk factors do not contain cross-sectional *IV convexity*, thus this is another risk factor that can capture the cross-sectional variations in returns not explained by existing models (CAPM, FF3, and FF4).

When we conduct time-series test using portfolios sorted by decomposed components of *IV convexity* ($convexity_{\mathrm{sys}}$ $convexity_{\mathrm{idio}}$) to see which components are not explained by existing risk factors, most of the estimated intercepts are significantly positive, indicating that the CAPM, FF3, and FF4 models leaves some portion of unexplained returns for the $convexity_{\mathrm{sys}}$, $convexity_{\mathrm{idio}}$ portfolios in Q1~Q3(Q4).

The joint tests from Gibbons, Ross, and Shanken (1989) examining whether the model explains the average portfolio returns sorted by each component of *convexity* ($convexity_{\mathrm{sys}}$, $convexity_{\mathrm{idio}}$) are strongly rejected with p-value < 0.001 for the CAPM, FF3, and FF4 models. Therefore, regardless of whether *IV convexity* is invoked by the market (systematic) or by idiosyncratic risk, both components of *IV convexity* ($convexity_{\mathrm{sys}}$, $convexity_{\mathrm{idio}}$) are not explained by existing systematic risk factors. Thus, we infer that it is hard to explain the negative return patterns shown in Tables 3-8 with existing traditional risk-based factor models. These results provide strong evidence for the information transmission in the context of *Hypothesis2*.

D. Short-selling constraints and information asymmetry

It is well-documented that options market provides informed traders with better opportunities to capitalize on their informational advantage owing to the reduction of trading expense, no restrictions on short selling and greater leverage effects. We conjecture that these properties account for the cross-sectional prediction power of the *IV convexity* measure, as informed traders have incentive to participate in the options market rather than in the stock market. Accordingly, we first hypothesize that the decreasing pattern of the *IV convexity* portfolio returns becomes more pronounced for the firms with more restrictive short-selling constraints. Secondly, we infer that informed traders have more opportunities to get higher profit from the stocks with more severe disparity of information possessed by informed traders. Subsequently, the decreasing pattern of the *IV convexity* portfolio returns will become more pronounced for the stocks with stronger information asymmetry.

In this context, we employ the measures of analyst coverage and analyst forecast dispersion as proxies for information asymmetry along with the share of institutional ownership as a proxy for the short-selling constraints. As proposed by Diether, Malloy, and Scherbina (2002), analyst forecast dispersion is measured by the scaled standard deviation of I/B/E/S analysts' current fiscal quarterly earnings per share forecasts. Stronger information asymmetry is implied by less numbered analyst coverage and greater analyst forecast dispersion. As the measure of short-sale constraint, following Campbell, Hilscher, and Szilagyi (2008) and Nagel (2005), we calculate the share of institutional ownership by summing the stock holdings of all reporting institutions for each stock on a quarterly basis. Nagel (2005) refers that short-sale constraints are most likely to bind among the stocks with high individual (i.e., low institutional) ownership, so the stocks with less institutional ownership suffer from more binding short-sale constraints.

[Insert Table IX about here.]

Table IX reports the average monthly returns of double-sorted portfolios, first sorted by the previous quarterly percentage of shares outstanding held by institutions obtained from the Thomson Financial Institutional Holdings (13F) database, previous quarter's analyst coverage obtained from I/B/E/S, previous quarter's analyst forecast dispersion obtained from I/B/E/S, respectively and then sub-sorted according to *IV convexity* within each quintile portfolio on a monthly basis.

In the left panel, we observe that the decreasing pattern in the average monthly portfolio returns appears to be more pronounced for the stocks with institutional investors owning a small fraction of the firm's share. Furthermore, we find that the *IV convexity* zero-cost portfolio within lowest institutional ownership portfolio earns greater positive return than that within the highest institutional ownership portfolio. The *IV convexity* anomaly appears to be stronger when less sophisticated investors (i.e., more institutional investors) own a large fraction of a firm's shares. This result confirms the hypothesis that the decreasing patterns of the *IV convexity* portfolio returns become more pronounced for the stocks with stronger short-selling constraints.

The next five columns show how the degree of information asymmetry affects the *IV convexity* anomaly effect. We find that the decreasing pattern of the *IV convexity* quintile portfolio returns becomes stronger for in lower analyst coverage quintiles, albeit some distortion in AC4 and AC5 quintiles. The last pair of columns show the results based on the analyst forecast dispersion as a proxy for information asymmetry measure. We find that the *IV convexity* anomaly effect becomes stronger for high analyst forecast dispersion firms, and the returns of zero-investment *IV convexity* portfolios (Q1-Q5) within the lowest AD quintile portfolio return is 0.0081, while that of the highest AD quintile portfolio return amounts to 0.0162 on a monthly basis.

These results imply that the stocks with strong information asymmetry and with severe short-sale constraints induce the informed traders mainly trade in the options market rather than in the stock market. This finding confirms our *Hypothesis 2* in the sense that there is a slow one-way information transmission from the options market to the stock market.

Ⅲ. Robustness Checks

We address additional aspects of *IV slope* and *IV convexity* measurements for robustness. We first conduct a Fama-Macbeth regression analysis with various control variables, and then investigate a number of alternative *IV convexity* measures to check the robustness of our results.

A. Fama-Macbeth Regression

The time-series test results indicate that the existing factor models may not be able to perfectly capture the return predictability of *IV convexity*. As *IV convexity* can be a candidate risk factor that can explain stock returns, we conduct Fama-Macbeth (1973) cross-sectional regressions at the firm level to investigate whether *IV convexity* is another risk factor beyond others suggested in previous literature.

We consider Market β [estimated following Fama and French (1992)], size (*ln_mv*), book-to-market (*btm*), momentum (*MOM*), reversal (*REV*), illiquidity (*ILLIQ*), options volatility slope (*IV spread* and *IV smirk*), idiosyncratic risk (*idio_risk*), implied volatility level (*IV level*), systematic volatility (v_{sys}^2), and idiosyncratic implied variance (v_{idio}^2)[17] as common measures of risks that explain stock returns. We run the monthly cross-sectional regression of individual stock returns of the subsequent month on *IV convexity* and other known measures of risks presented above.

[Insert Table X about here.]

Panel A of Table X reports the averages of the monthly Fama-Macbeth (1973) cross-sectional regression coefficient estimates for individual stock returns with Market β and other widely accepted risk factors as a control variable along with the Newey-West adjusted t-statistics for the time-series average of coefficients with a lag of 3.

The column of Model 1 shows the results with Market β and other stock fundamentals including firm-size (*ln_mv*) and book-to-market ratio (*btm*) as control variables. We observe that the coefficient on *IV convexity* is significantly negative, and this result confirms our previous finding in the portfolio formation approach. When we include both *IV convexity* and *IV smirk* (or *IV spread*), as shown in Models 2 and 3, the coefficients on *IV convexity* are still significantly negative, indicating that *IV convexity* has a strong explanatory power for stock returns that *IV smirk* and *IV spread* cannot fully capture. The significantly negative coefficients on *log (MV)* confirm the existence of size effects shown in earlier studies, whereas the coefficients on *btm* are significantly positive, supporting the existence of a value premium.

[17] We do not include the co-skewness factor in the Fama-Macbeth (1973) regression. Harvey and Siddique (2000) argue that co-skewness is related to the momentum effect, as the low momentum portfolio returns tend to have higher skewness than high momentum portfolio returns. Thus, we exclude co-skewness from the Fama-Macbeth regression specification to avoid the multi-collinearity problem with the momentum factor.

Model 4 to Model 6 represent the Fama-Macbeth regression result using Market β, *ln_mv*, *btm*, *MOM*, *REV*, *ILLIQ*, and idiosyncratic risk. These variables are widely accepted stock characteristics that can capture the cross-sectional variation in stock returns. However, the result is surprising in that the coefficients on Market β are insignificant, while *ln_mv* and *btm* have significantly negative and positive coefficients, respectively. The estimated coefficients on MOM and ILLIQ have positive signs without statistical significance, whereas REV has significantly negative coefficients. Moreover, the estimated coefficient on idiosyncratic risk suggested by Ang, Hodrick, Xing, and Zhang (2006) is significantly negative. In an ideal asset pricing model that fully captures the cross-sectional variation in stock return, idiosyncratic risk should not be significantly priced.[18] Fu (2009) finds a significantly positive relationship between idiosyncratic risk and stock returns, and Bali and Cakici (2008) show no significant negative relationship, but insignificant positive relationships when they form equal-weighted portfolios. However, the statistical significance of the estimated coefficient on the idiosyncratic risk in Model 4 to Model 6 in Panel A of Table X implies that idiosyncratic risk is negatively priced and there may exist other risk factors besides Market β, *ln_mv*, *btm*, *MOM*, *REV*, and *ILLIQ*.

It is noteworthy that *IV convexity* has a significantly negative coefficient, with the value and significance level of the coefficients on idiosyncratic risk in Model 4. We conjecture that *IV convexity* can be a significant risk factor that explains some part of the cross-sectional variation in returns that cannot be fully explained by Market β, *ln_mv*, *btm*, *MOM*, *REV*, *ILLIQ* or idiosyncratic risk. The statistical significance of *IV convexity* remains, after including both *IV smirk* and *IV spread* Models 5 and 6, respectively.

When alternative ex-ante volatility measures such as implied volatility level (*IV level*), systematic volatility (v_{sys}^2), and idiosyncratic implied variance (v_{idio}^2), are included, as in Models 7-12, the sign and significance for the *IV convexity* coefficients remain unchanged. They still have significantly negative coefficients, confirming that investors seem to require a risk premium

[18] The relationship between idiosyncratic risk and stock returns are inconclusive, though this is somewhat controversial among researchers. Ang, Hodrick, Xing, and Zhang (2006) show that stocks with low idiosyncratic risk earn higher average returns compared to high idiosyncratic risk portfolios, and the arbitrage portfolio for long high idiosyncratic risk and short low idiosyncratic risk earns significantly negative returns. However, other researchers argue that this relationship does not persist when using different sample periods and equal-weighted returns. Note that Ang, Hodrick, Xing, and Zhang (2006) employed value-weighted returns for their research.

for *IV convexity*. All in all, it can be inferred that there is no evidence that existing risk factors suggested by prior research can explain the negative return patterns in *IV convexity*, and it is possible that *IV convexity* is a priced risk factor that can capture the cross-sectional variations in returns not explained by existing models.

Finally, we conduct additional analyses with $convexity_{\mathrm{sys}}$ and $convexity_{\mathrm{idio}}$ to investigate whether the systematic and idiosyncratic components of *IV convexity* are priced. As reported in Panel B of Table X, the univariate regressions of $convexity_{\mathrm{sys}}$ and $convexity_{\mathrm{idio}}$ in Models 1 and 2 show that the estimated coefficients on $convexity_{\mathrm{sys}}$ and $convexity_{\mathrm{idio}}$ are significantly negative (-0.022 and -0.011 with *t*-statistics of -7.20 and -4.29, respectively), confirming our previous findings from the portfolio formation approach in Section II.C.3.

As shown in Models 4-6, the coefficients on the $convexity_{\mathrm{sys}}$ and $convexity_{\mathrm{idio}}$ maintain their statistical significance even after controlling for Market β, *ln_mv*, *btm*, *MOM*, *REV*, and idiosyncratic risk. In Model 4, $convexity_{\mathrm{sys}}$ has a significantly negative average coefficient. Moreover, Model 5 shows the similar results by adding the $convexity_{\mathrm{idio}}$ factor, and both systematic and idiosyncratic parts of *IV convexity* keep their statistical significance in Model 6. Our findings suggest that not only $convexity_{\mathrm{sys}}$ but $convexity_{\mathrm{idio}}$ are a significantly priced risk factor, even after we control for idiosyncratic risk.

The statistical significance of both $convexity_{\mathrm{sys}}$ and $convexity_{\mathrm{idio}}$ is intact even after including alternative ex-ante volatility measures such as implied volatility level (*IV level*), systematic volatility (v_{sys}^2), and idiosyncratic implied variance (v_{idio}^2), in Models 7 and 12, respectively. We still observe the same results, confirming that the cross-sectional predictive power of *IV convexity* is statistically significant for both the systematic and idiosyncratic components of *IV convexity*.

B. Alternative Measures of Option-implied Volatility Convexity

In this section, we explore alternative measures of options-implied volatility convexity than ours. We define alternative option-implied volatility convexity measures given by

$$convexity_{cp} = \frac{[\mathrm{IV}_{\mathrm{call}}(0.2)+\mathrm{IV}_{\mathrm{put}}(-0.8)]}{2} + \frac{[\mathrm{IV}_{\mathrm{call}}(0.8)+\mathrm{IV}_{\mathrm{put}}(-0.2)]}{2} - [\mathrm{IV}_{\mathrm{call}}(0.5) + \mathrm{IV}_{\mathrm{put}}(-0.5)] \quad (19)$$

$$convexity_{Bali} = \mathrm{IV}_{\mathrm{call}}(0.25) + \mathrm{IV}_{\mathrm{put}}(-0.25) - \mathrm{IV}_{\mathrm{call}}(0.5) - \mathrm{IV}_{\mathrm{put}}(-0.5) \quad (20)$$

$$convexity_{put} = \mathrm{IV}_{\mathrm{put}}(-0.2) + \mathrm{IV}_{\mathrm{call}}(0.2) - 2 \times \mathrm{IV}_{\mathrm{put}}(-0.5) \quad (21)$$

$$convexity_{call} = \mathrm{IV}_{\mathrm{call}}(0.2) + \mathrm{IV}_{\mathrm{call}}(0.8) - 2 \times \mathrm{IV}_{\mathrm{call}}(0.5). \quad (22)$$

Note that $convexity_{cp}$ incorporates comprehensive implied volatility information from call and put options, whereas our proposed *IV convexity* is constructed by deep OTM put, deep ITM put, and ATM call options. Motivated by Bali, Hu and Murray (2015), we define $convexity_{Bali}$ as the sum of OTM call and OTM put implied volatilities less the sum of the ATM call and ATM put implied volatilities. Finally, we construct a put-based *IV convexity* measure, $convexity_{put}$ and a call-based measure, $convexity_{call}$.

[Insert Table XI about here.]

Table XI reports the descriptive statistics of the average portfolio returns sorted by alternative measures of option-implied volatility convexity. Though there are slight distortions in the $convexity_{cp}$ and $convexity_{put}$ quintiles, the portfolio returns still generally display a decreasing pattern with alternative measures of option-implied volatility convexity. Further, the returns of the arbitrage portfolio (Q1-Q5) in $convexity_{cp}$ and $convexity_{put}$ quintile portfolios remain positive with statistical significance (0.0087 for $convexity_{cp}$ with t-statistic = 5.10, and 0.0091 for $convexity_{put}$ with t-statistic = 6.09). This result confirms that the negative relationship between *IV convexity* and future stock returns are robust and consistent across different definitions of option-implied volatility convexity.

It is remarkable that the arbitrage portfolio (Q1-Q5) return is positive but insignificant, when the portfolio is constructed withthe $convexity_{Bali}$ and $convexity_{call}$ measures. This is consistent with the demand-based option pricing argument of Gârleanu, Pedersen, and Poteshman (2009) in that the pessimistic perception of the stock's performance from investors' aversion to the anticipated excess kurtosis is reflected more in the put option prices than in the call option prices.

C. Performance Evaluation based on Sharpe Ratios

Considering the risk-return trade-off, we evaluate the performance of each portfolio using two different versions of Sharpe ratios. The standard Sharpe ratio (SR) is defined as

$$SR = \frac{\mu - r}{\sigma}, \tag{23}$$

which can be interpreted as the market price of risk under the standard mean-variance framework. In the context of non-normality in asset return distributions, however, investors prefer higher moments within the expected utility function. To overcome the shortcomings of the standard Sharpe ratio, Zakamouline and Koekebakker (2009) propose a Generalized Sharpe Ratio (GSR) as the ultimate generalization by accounting for all moments of distribution.[19] Assuming negative exponential utility functions with zero initial wealth, we can numerically solve an optimal capital allocation problem by maximizing the expected utility function given by

$$\mathrm{E}\left[U^*\left(\widetilde{W}\right)\right] = \max_{a} E[-e^{-\lambda a(x-r_f)}], \tag{24}$$

and the GSR is computed in a non-parametric way using[20]

$$\mathrm{GSR} = \sqrt{-2\log(-E[U^*(\widetilde{W})])}. \tag{25}$$

[Insert Table XII about here.]

Panel A of Table XII shows the Sharpe ratios for single-sorted portfolios based on *IV convexity* along with alternative measures of option-implied convexity. Although there are some minor distortions in $convexity_{cp}$ quintiles, similar decreasing patterns of SR and GSR occur in quintile portfolios based on *IV convexity*, $convexity_{cp}$ and $convexity_{put}$. Moreover, the arbitrage portfolios (Q1-Q5) based on *IV convexity*, $convexity_{cp}$ and $convexity_{put}$ show positive SR and GSR (over 0.3). This result implies that one can enjoy profit from taking excess tail risk contributions to the perceived variance from the zero-cost portfolios based on *IV*

[19] The generalized Sharpe ratio is originally introduced by Hodges (1998).
[20] It can be shown that the GSR reduces to the standard Sharpe ratio when we assume normally distributed asset returns.

convexity. On the other hand, when we construct portfolios based on $convexity_{Bali}$ and $convexity_{call}$, the decreasing SR and GSR patterns are substantially distorted.

Panel B of Table XII presents the SR and GSR of double-sorted quintile portfolios formed based on *IV slope* (as well as *IV spread* and *IV smirk*) first and then sub-sorted into five groups based on *IV convexity*. The decreasing patterns in *IV convexity* portfolios' SR and GSR persist even after controlling for *IV slope (IV spread)*, and the SR and GSR of the arbitrage portfolios (Q1-Q5) are higher than 0.19. However, when we control for *IV smirk* as suggested by Xing, Zhang, and Zhao (2010), *IV convexity* arbitrage portfolios' (Q1-Q5) SR and GSR in the S2, S3 and S4 *IV smirk* portfolios become less than 0.09, confirming the results in Panel B in Table IV.

D. Performance persistence

We turn to examine whether the effect of information asymmetry disappears as the forecasting horizon increases by investigating the long-short arbitrage strategy based on *IV convexity* portfolios.

[Insert Table XIII about here.]

Table XIII reports the average equal-weighted returns of the quintile portfolios formed on *IV convexity* for various forecasting horizons up to 12 months. Specifically, we take monthly returns of N month after the portfolio formation time and denote r_{N} for the N-month ahead non-overlapping monthly portfolio return where N=1, 2, …, 12. The results show that the decreasing patterns of the average monthly returns from Q1 to Q5 persist and yields significantly positive returns until 6 months from the portfolio formation by *IV convexity*. Interestingly, the risk-adjusted returns implied by Fama-French 3 and 4 factor models (α_{FF3}, α_{FF4}) are positive with statistical significance only up to 3-month forecasting horizon.

The decreasing patterns become less pronounced and the arbitrage portfolio (Q1-Q5) return decreases from 0.0134 (t-statistic = 7.87) for r_1 to 0.038 (t-statistic = 3.31) for r_6 on a monthly basis as the forecasting horizon increases. The decreasing patterns in the *IV convexity* portfolio returns from Q1 to Q5 become distorted and the portfolio return on *IV convexity* becomes insignificant afterwards. We observe similar results from the risk-adjusted returns after controlling for Fama-French 3 and 4 factors.

[Insert Figure 6 about here.]

Figure 6 plots the average monthly returns and the risk-adjusted returns implied by Fama-French 3 and 4 factor models of the long-short *IV convexity* portfolios for various forecasting horizons based on Table XII results along with their 95% and 99% confidence intervals. We observe that the average monthly returns of Q1-Q5 portfolio and the risk-adjusted returns implied by Fama-French 3 and 4 factor models (α_{FF3}, α_{FF4}) dramatically decrease (from 1.134 to 0.0031 for Q1-Q5, 0.018 to 0.0025 for α_{FF3}, and 0.012 to 0.0026 for α_{FF4}) during the first two months after the portfolio formation time. Thereafter, the trading strategy based on *IV convexity* does not generate economically meaningful profits. The wide confidence intervals indicate that there is quite little chance to get positive profits based on the *IV convexity* information in a long run.

Our finding implies that the arbitrage profits based on the *IV convexity* information can be realized in the first few months only, because the arbitrage opportunity from the information asymmetry disappears as the forecasting horizon increases.

E. Sub-period analysis

Next, we examine whether the stock return predictability of *IV convexity* depends on the state of the economy. We determine states of the economy based on the Chicago FED National Activity Index (CFNAI)[21] and the National Bureau of Economic Research (NBER) recession dummy taking the value of one if the U.S. economy is in recession as determined by the NBER.

[Insert Table XIV about here.]

Table XIV shows the average monthly returns of the Q1-Q5 portfolios sorted by *IV convexity* based on the CFIAN and the NBER recession dummy, respectively.

[21] The CFNAI, the weighted average of 85 monthly indicators of national economic activity, is a monthly index designed to assess overall economic activity and related inflationary pressure. It is constructed to have an average value of zero and a standard deviation of one. A positive index reading corresponds to growth above the trend and a negative index reading corresponds to growth below the trend. Its time-series data is available from the following URL: https://www.chicagofed.org/research/data/cfnai/historical-data.

In the left panel, we divide the entire sample period into the expansion and contraction periods by taking the median value of the CFNAI as the threshold level. As shown, the decreasing patterns of the portfolio returns sorted by *IV convexity* are consistently observed in both periods. Furthermore, we find that the Q1-Q5 zero-cost portfolio formed on *IV convexity* earns significantly positive return in each sub-period. Interestingly, the values of average portfolio returns of each quintile in the contraction period are higherthan those in the expansion period. The return of zero-investment *IV convexity* portfolios (Q1-Q5) is 0.0074 with the t-statistics of 4.92 for the expansion period, whereas the return becomes 0.0194 with the t-statistics of 6.65 for the contraction period. Overall, the trading strategy based on *IV convexity* seemingly earns more pay-off in the contraction period than in expansion period, as investors tend to overreact to bad news and the inter-market information asymmetry exacerbates in the recession state. In the right panel, we take the NBER business cycle dummy variable to classify the entire period into the expansion and contraction periods.[22] It is notable that similar results are observed, as both sub-periods show the decreasing patterns in *IV convexity* portfolios along with strictly positive returns in zero-cost portfolios with statistical significance. The decreasing patterns in the *IV convexity* portfolios are more pronounced in the contraction period than those in expansion periods, and the magnitude of the zero-investment (Q1-Q5) portfolio return in the contraction period is larger than that in the expansion period.[23]

Ⅳ. Conclusion

This study finds empirical evidence that *IV convexity*, our proposed measure for the convexity of an option-implied volatility curve, has a negative predictive relationship with the cross-section of future stock returns, even after controlling for the slope of an option-implied volatility curve discussed in recent literature. We demonstrate that the *IV convexity* measure, as a proxy of both the volatility of stochastic volatility and the volatility of stock jump size, reflects informed options traders' anticipation of the excess tail-risk contribution to the perceived variance of the underlying equity returns. Consistent with earlier studies, our empirical findings indicate that options traders have an information advantage over stock traders in that informed traders

[22] NBER recession dummy variables are obtained from the following URL: https://research.stlouisfed.org/fred2/series/USREC.

[23] We should carefully interpret the statistical significance of the zero-investment (Q1-Q5) portfolio in each sub-period based on the NBER business cycle dummy, as the expansion period outnumbers the contraction period.

anticipating heavier tail risk proactively choose the options market to capitalize on their private information. The average portfolio returns sorted by *IV convexity* monotonically decrease from 0.0208 for quintile portfolio 1 (Q1) to 0.0074 for quintile portfolio 5 (Q5) on a monthly basis, implying that the average monthly return on the arbitrage portfolio buying Q1 and selling Q5 is significantly positive. It is interesting that this pattern persists after decomposing *IV convexity* into systematic and idiosyncratic components, as the results still reveal decreasing patterns in the portfolio returns as the portfolio-specific *IV convexity* increases with statistical significance. In addition, the negative relationship between *IV convexity* and future stock returns is robust after controlling for the various kinds of systematic risks suggested in earlier studies. Furthermore, the negative relationship between *IV convexity* and future stock returns remains after considering the impact of our *IV slope* and other well-documented option-implied volatility skewness measures. This consistency implies that *IV convexity* can be an important measure to capture the fat-tailed characteristics of stock return distributions in a forward-looking manner, as this behavior leads to the leptokurtic implied distributions of underlying stock returns before equity investors show their kurtosis risk aversion. Thus, we argue that *IV convexity* should be considered as a significantly priced factor in the short run.

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Table I. Descriptive Statistics: Option implied volatilities and Macro economic variables

This table reports the summary statistics of the fitted implied volatilities and fixed deltas of the individual equity options with one month (30 days), two month(60 days), three month(91 days) and six month(182days) to expiration at the end of month obtained from OptionMetrics. DS measures the degree of accuracy in the fitting process at each point and computed by the weighted average standard deviations. The sample period covers Jan 2000 to Dec 2013.

								Call						
Maturity	delta	20	25	30	35	40	45	50	55	60	65	70	75	80
	Mean	0.4942	0.4817	0.4739	0.4696	0.4677	0.4676	0.4694	0.4730	0.4779	0.4841	0.4917	0.5019	0.5157
30 days	stdev	0.2774	0.2764	0.2755	0.2746	0.2735	0.2724	0.2722	0.2732	0.2744	0.2763	0.2783	0.2808	0.2840
	DS	0.0502	0.0397	0.0306	0.0244	0.0208	0.0190	0.0182	0.0181	0.0190	0.0213	0.0258	0.0334	0.0436
	Mean	0.4748	0.4671	0.4626	0.4607	0.4606	0.4619	0.4644	0.4683	0.4734	0.4795	0.4868	0.4961	0.5081
60 days	stdev	0.2670	0.2660	0.2651	0.2645	0.2639	0.2635	0.2637	0.2649	0.2664	0.2681	0.2699	0.2719	0.2742
	DS	0.0328	0.0264	0.0206	0.0166	0.0145	0.0135	0.0133	0.0135	0.0144	0.0162	0.0196	0.0252	0.0329
	Mean	0.4562	0.4518	0.4498	0.4497	0.4510	0.4533	0.4566	0.4609	0.4660	0.4720	0.4792	0.4879	0.4989
91 days	stdev	0.2552	0.2537	0.2526	0.2519	0.2517	0.2518	0.2525	0.2537	0.2550	0.2566	0.2586	0.2607	0.2630
	DS	0.0269	0.0220	0.0178	0.0151	0.0135	0.0128	0.0127	0.0130	0.0138	0.0153	0.0181	0.0229	0.0298
	Mean	0.4398	0.4385	0.4384	0.4394	0.4414	0.4442	0.4477	0.4521	0.4574	0.4634	0.4704	0.4783	0.4874
182 days	stdev	0.4398	0.4385	0.4384	0.4394	0.4414	0.4442	0.4477	0.4521	0.4574	0.4634	0.4704	0.4783	0.4874
	DS	0.0178	0.0159	0.0141	0.0129	0.0122	0.012	0.0121	0.0126	0.0134	0.0146	0.0166	0.0198	0.0241

								Put						
Maturity	delta	-80	-75	-70	-65	-60	-55	-50	-45	-40	-35	-30	-25	-20
	Mean	0.4958	0.4855	0.4788	0.4755	0.4745	0.4755	0.4784	0.4831	0.4893	0.4970	0.5067	0.5199	0.5381
30 days	stdev	0.2976	0.2919	0.2876	0.2846	0.2821	0.2803	0.2796	0.2797	0.2803	0.2813	0.2823	0.2836	0.2844
	DS	0.0452	0.0369	0.0289	0.0231	0.0197	0.0181	0.0178	0.0183	0.0198	0.0228	0.0285	0.0382	0.0514
	Mean	0.4805	0.4741	0.4700	0.4684	0.4687	0.4705	0.4738	0.4785	0.4845	0.4918	0.5008	0.5123	0.5279
60 days	stdev	0.2843	0.2801	0.2765	0.2741	0.2723	0.2713	0.2709	0.2713	0.2723	0.2736	0.2751	0.2767	0.2778
	DS	0.0315	0.0261	0.0208	0.0168	0.0144	0.0133	0.013	0.0134	0.0145	0.0166	0.0207	0.0278	0.0379
	Mean	0.4667	0.4627	0.4606	0.4602	0.4613	0.4636	0.4671	0.4717	0.4775	0.4845	0.4930	0.5038	0.5178
91 days	stdev	0.2729	0.2691	0.2658	0.2631	0.2613	0.2602	0.2599	0.2603	0.2611	0.2623	0.2641	0.2660	0.2679
	DS	0.0275	0.0228	0.0185	0.0154	0.0136	0.0127	0.0126	0.0129	0.0138	0.0156	0.0189	0.0247	0.0334
	Mean	0.4521	0.4508	0.4505	0.4513	0.4530	0.4556	0.4592	0.4638	0.4695	0.4763	0.4843	0.4940	0.5060
182 days	stdev	0.2565	0.2541	0.2519	0.2502	0.2488	0.2480	0.2477	0.2480	0.2490	0.2505	0.2523	0.2547	0.2574
	DS	0.0191	0.0167	0.0146	0.0131	0.0122	0.0119	0.0120	0.0125	0.0134	0.0149	0.0174	0.0214	0.0270

Table II. Descriptive Statistics

Panel A reports the descriptive statistics of options implied volatility, skew and convexity of the equity options with one month (30 days) to expiration at the end of month. $\mathrm{IV_{put}}(\Delta_{\mathrm{put}})$ and $\mathrm{IV_{call}}(\Delta_{\mathrm{call}})$ refer to fitted implied volatilities with one month(30days) to expiration and $\Delta_{call,put}$ are options deltas. Options implied volatility is defined by $IV\ level = 0.5[\mathrm{IV_{put}}(-0.5) + \mathrm{IV_{call}}(0.5)]$ and Options volatility slopes are computed with $IV\ slope = \mathrm{IV_{put}}(-0.2) - \mathrm{IV_{put}}(-0.8)$, $IV\ spread = \mathrm{IV_{put}}(-0.5) - \mathrm{IV_{call}}(0.5)$, and $IV\ smirk = \mathrm{IV_{put}}(-0.2) - \mathrm{IV_{call}}(-0.5)$, respectively, following our definition of options volatility slope, Yan (2011) and Xing, Zhang and Zhao (2010). Option implied convexity is calculated by $IV\ convexity = \mathrm{IV_{put}}(-0.2) + \mathrm{IV_{put}}(-0.8) - 2 \times \mathrm{IV_{call}}(0.5)$. Using daily options implied convexity of equity options and S&P500 index option, we conduct time series regressions in each month to decompose options implied convexity into the systematic and idiosyncratic components given by:

$$IV\ convexity_{i,\mathrm{k}} = \alpha_{\mathrm{i}} + \beta_{\mathrm{i}} \times IV\ convexity_{S\&P500,\mathrm{k}} + \varepsilon_{\mathrm{i,k}}, \quad \text{where } \mathrm{t} - 30 \leq \mathrm{k} \leq \mathrm{t} - 1$$

On a daily basis. The fitted values and residual terms are the systematic components ($convexity_{sys}$) of options implied convexity and the idiosyncratic components ($convexity_{idio}$) of options implied convexity, respectively. We select the observations at the end of each month. Alternative *IV convexity* are defined by $\mathrm{p}\Delta_1\_\mathrm{c50}\_\mathrm{p}\Delta_2 = \mathrm{IV_{put}}(\Delta_1) + \mathrm{IV_{put}}(\Delta_2) - 2 \times \mathrm{IV_{call}}(0.5)$, where $-0.45 \leq \Delta_1 \leq -0.2$ and $-0.80 \leq \Delta_2 \leq -0.55$. Panel B shows the descriptive statistics of firm characteristic variables. Size (ln_mv) is computed at the end of each month and we define size as natural logarithm of the market capitalization. When computing book-to-market ratio(BTM), we match the yearly BE (book value of common equity (CEQ) plus deferred taxes and investment tax credit (txditc)) for all fiscal years ending at year t-1 to returns starting in July of year t and this BE is divided by market capitalization at month t-1.

Beta (β) is estimated from time-series regressions of raw stock excess returns on the Rm-Rf by month-by-month rolling over past three year (36 months) returns (a minimum of 12 months). Momentum (MOM) is computed based on past cumulative returns over the past six months skipping one month between the portfolio formation period and the computation period to exclude the reversal effect following Jegadeesh and Titman (1993). Reversal (REV) is computed based on past one-month return following Jegadeesh (1990) and Lehmann (1990). Illiquidity (ILLIQ) is the average of the absolute value of stock return divided by the trading volume of the stock in thousand USD calculated using the past one-year's daily data up to month t following Amihud (2002) and Hasbrouck(2009). Following Harvey and Siddique (2000), daily excess returns of individual stocks are regressed on the daily market excess return and the daily squared market excess return using the last one year data month by month given by:

$$(\mathrm{R_i} - \mathrm{R_f})_k = \alpha_{\mathrm{i}} + \beta_{1,\mathrm{i}}(\mathrm{MKT} - \mathrm{R_f})_{\mathrm{k}} + \beta_{2,\mathrm{i}}(\mathrm{MKT} - \mathrm{R_f})^2{}_k + \varepsilon_{\mathrm{i,k}}, \quad \text{where } \mathrm{t} - 365 \leq \mathrm{k} \leq \mathrm{t} - 1$$

on a daily basis. The co-skewness of a stock is the coefficient of the squared market excess return. To reduce the impact of infrequent trading on co-skewness estimates, a minimum of 255 trading days in a month daily return are required.

Panel A. Option Implied Volatility, Option Implied Volatility Slope and Option Implied Volatility Convexity

	Implied Volatility	Implied Slope			Implied Convexity						Alternative Convexity Measures				
					Daily			Monthly							
	IV level	*IV slope*	*IV spread*	*IV smirk*	IV convexity	$convexity_{sys}$	$convexity_{idio}$	IV convexity	$convexity_{sys}$	$convexity_{idio}$	p25_c50_p75	p30_c50_p70	p35_c50_p65	p40_c50_p60	p45_c50_p55
Mean	0.4739	0.0423	0.0090	0.0687	0.0942	0.0942	0.0000	0.0952	0.0933	0.0019	0.0650	0.0450	0.0320	0.0230	0.0180
Stdev	0.2689	0.1614	0.1235	0.1413	0.2624	0.1682	0.2015	0.2774	0.1703	0.2235	0.2130	0.1990	0.1900	0.1840	0.1830
Median	0.4088	0.0422	0.0045	0.0516	0.0595	0.0668	-0.0049	0.0590	0.0655	-0.0053	0.0390	0.0270	0.0190	0.0140	0.0100

Panel B. Firm Characteristic Variables

	Size			BTM			Beta (β)			MOM			REV			ILLIQ($\times 10^6$)			Coskew		
Quintile	Mean	Median	Stdev	Mean	Median	Stdev	Mean	Median	Stdev	Mean	Median	Stdev	Mean	Median	Stdev	Mean	Median	Stdev	Mean	Median	Stdev
Q1	16.7256	16.8167	0.8923	0.1467	0.1434	0.0836	-0.0413	0.0865	0.5902	-0.2788	-0.2536	0.1693	-0.1499	-0.1231	0.1080	0.0008	0.0004	0.0010	-18.9451	-13.5341	17.1791
Q2	18.2541	18.2806	0.5998	0.3559	0.3389	0.1028	0.5764	0.5891	0.2163	-0.0699	-0.0611	0.1123	-0.0424	-0.0322	0.0534	0.0062	0.0034	0.0074	-6.3591	-5.0588	5.0064
Q3	19.3495	19.3875	0.5814	0.5771	0.5547	0.1597	0.9689	0.9783	0.2222	0.0454	0.0484	0.1086	0.0073	0.0102	0.0457	0.0310	0.0157	0.0367	-0.9856	-0.6643	2.2680
Q4	20.5129	20.5177	0.5699	0.8946	0.8553	0.2919	1.4901	1.4735	0.2625	0.1763	0.1711	0.1316	0.0603	0.0561	0.0549	0.1789	0.0862	0.2302	4.2063	3.2719	3.3457
Q5	22.4613	22.2198	1.1355	2.6192	1.6282	4.8822	2.8661	2.5030	1.2970	0.6099	0.4474	0.7128	0.2181	0.1623	0.2263	3.6874	1.3916	11.3552	15.3192	11.9180	13.5290
All	19.4607	19.3757	2.1054	0.9186	0.5472	2.3613	1.1720	0.9808	1.1860	0.0966	0.0461	0.4515	0.0187	0.0080	0.1701	0.7808	0.0183	5.2832	-1.3516	-0.5745	15.2483

Table III. Average returns sorted by option-implied volatility convexity

Panel A reports descriptive statistics of the kurtosis and equal-weighted and value-weighted average portfolio monthly returns sorted by *IV convexity (IV spread and IV smirk)*. We estimate *IV convexity, IV spread* and *IV smirk* following our definition of *IV convexity*, Yan (2011) and Xing, Zhang and Zhao (2010), respectively. On the last trading day of every each month, all firms are assigned to one of five portfolio groups based on *IV convexity* (*IV spread and IV smirk*) and we assume stocks are held for the next one-month-period. This process is repeated for every month. Panel B reports descriptive statistics of the equal-weighted and value-weighted average portfolio monthly returns sorted by alternative *IV convexity*. Alternative *IV convexity* are defined by $p\Delta_1\_c50\_p\Delta_2 = IV_{put}(\Delta_1) + IV_{put}(\Delta_2) - 2 \times IV_{call}(0.5)$, where $-0.45 \leq \Delta_1 \leq -0.2$ and $-0.80 \leq \Delta_2 \leq -0.55$. Value-weighted portfolio returns are weighted by the lag of market capitalization of the underlying stocks. Monthly stock returns are obtained from Center for Research in Security Prices (CRSP) with stocks traded on the NYSE (exchcd=1), Amex (exchcd=2) and NASDAQ (exchcd=3). We use only common shares (shrcd in 10, 11). The sample excludes stocks with a price less than three dollars. "Q1-Q5" denotes an arbitrage portfolio that buys a low option-implied convexity portfolio (Q1) and sells a high *IV convexity* portfolio (Q5). The sample period covers Jan 2000 to Dec 2013. Numbers in parentheses indicate t-statistics.

Panel A. *IV convexity* (*IV spread* and *IV smirk*) and Equal-weighted (Value-weighted) portfolio return

	IV convexity						*IV spread*					*IV smirk*				
Quintile	Avg # firms	Mean	Stdev	Avg kurtosis of return	EW Ret	VW Ret	Avg # firms	Mean	Stdev	EW Ret	VW Ret	Avg # firms	Mean	Stdev	EW Ret	VW Ret
Q1 (Low)	432	-0.1364	0.2822	4.0509	0.0208	0.0136	425	-0.0834	0.1491	0.0145	0.0109	418	-0.0519	0.1462	0.0136	0.0112
Q2	423	0.0156	0.0317	4.0434	0.0124	0.0061	434	-0.0094	0.0131	0.0102	0.0067	422	0.0292	0.0176	0.0099	0.0066
Q3	415	0.0637	0.0394	4.1244	0.0098	0.0051	425	0.0040	0.0109	0.0081	0.0044	417	0.0527	0.0202	0.0073	0.0035
Q4	404	0.1333	0.0672	4.1822	0.0090	0.0025	396	0.0189	0.0173	0.0066	0.0040	410	0.0845	0.0286	0.0066	0.0033
Q5 (High)	389	0.3980	0.3539	4.2857	0.0074	0.0023	384	0.1096	0.1844	0.0013	-0.0004	396	0.2182	0.1863	0.0034	0.0019
Q1-Q5					0.0134	0.0113				0.0131	0.0113				0.0102	0.0094
					(7.87)	(5.08)				(7.31)	(3.91)				(5.05)	(3.64)

Panel B. Alternative measure of *IV convexity* and Equal-weighted (Value-weighted) portfolio return

	p25_c50_p75			p30_c50_p70			p35_c50_p65			p40_c50_p60			p45_c50_p55		
Quintile	Mean	EW Ret	VW Ret	Mean	EW Ret	VW Ret	Mean	EW Ret	VW Ret	Mean	EW Ret	VW Ret	Mean	EW Ret	VW Ret
Q1 (Low)	-0.1304	0.0202	0.0136	-0.1364	0.0199	0.0106	-0.1385	0.0199	0.0109	-0.1388	0.0198	0.0106	-0.1395	0.0204	0.0116
Q2	0.0010	0.0120	0.0058	-0.0079	0.0123	0.0064	-0.0130	0.0124	0.0061	-0.0155	0.0124	0.0063	-0.0163	0.0122	0.0069
Q3	0.0421	0.0095	0.0052	0.0292	0.0096	0.0049	0.0206	0.0095	0.0056	0.0147	0.0096	0.0057	0.0110	0.0090	0.0052
Q4	0.0977	0.0093	0.0023	0.0755	0.0089	0.0031	0.0604	0.0085	0.0034	0.0498	0.009	0.0032	0.0428	0.0088	0.0034
Q5 (High)	0.3120	0.008	0.0029	0.2644	0.0084	0.0035	0.2313	0.0088	0.0019	0.2092	0.0083	0.0008	0.1967	0.0086	0.0012
Q1-Q5		0.0122	0.0106		0.0115	0.0071		0.0111	0.009		0.0115	0.0098		0.0118	0.0104
		(7.74)	(4.85)		(7.32)	(3.36)		(7.11)	(3.89)		(7.03)	(4.07)		(6.79)	(3.87)

Table IV. Average returns of portfolios sorted by firm-size, book-to-market ratio, market beta, and option-implied volatility convexity

This table reports the average monthly returns of twenty five double-sorted portfolios, first sorted by firm characteristic variables (firm size, book-to-market ratio, market beta) and *IV convexity* on a monthly basis, and then sub-sorted according to *IV convexity* within each quintile portfolio into one of the five portfolios on a monthly basis. Using CRSP data, we compute market capitalization (Size) is computed at the end of each month and we define size as the natural logarithm of the market capitalization. When computing book-to-market ratio(BTM), we match the yearly BE (book value of common equity (CEQ) plus deferred taxes and investment tax credit (txditc)) for all fiscal years ending at year t-1 to returns starting in July of year t and this BE is divided by market capitalization(Size) at month t-1. Market betas (Beta) are estimated using a rolling regression with the previous 36 monthly returns available up to month t-1 given by

$$(R_i - R_f)_k = \alpha_i + \beta_i (MKT - R_f)_k + \varepsilon_{i,k}, \quad \text{where } t-36 \leq k \leq t-1$$

on a monthly basis. We require at least 12-month returns when estimating market beta. Stocks are assumed to be held for one month, and portfolio returns are equally-weighted. Monthly stock returns are obtained from the Center for Research in Security Prices (CRSP) with stocks traded on the NYSE (exchcd=1), Amex (exchcd=2) and NASDAQ (exchcd=3). We use only common shares (shrcd in 10, 11). Stocks with a price less than three dollars are excluded from the sample. "Q1-Q5" denotes an arbitrage portfolio that buys a low *IV convexity* portfolio and sells a high *IV convexity* portfolio in each characteristic portfolio. The sample covers Jan 2000 to Dec 2013. Numbers in parentheses indicates t-statistics.

Avg Return															
IV convexity Quintiles	Size Quintiles					BTM Quintiles					Beta Quintiles				
	S1(Small)	S2	S3	S4	S5(Large)	B1(Low)	B2	B3	B4	B5(High)	beta1(Low)	beta2	beta3	beta4	beta5(High)
Q1 (Low *IV convexity*)	0.0255	0.0164	0.0112	0.0122	0.0093	0.0106	0.0148	0.0171	0.0225	0.0337	0.0157	0.0189	0.0189	0.0213	0.0263
Q2	0.0205	0.0118	0.0111	0.0093	0.0064	0.0035	0.0089	0.0121	0.0153	0.0274	0.0100	0.0118	0.0125	0.0132	0.0148
Q3	0.0160	0.0111	0.0080	0.0109	0.0071	0.0063	0.0080	0.0106	0.0134	0.0195	0.0096	0.0121	0.0099	0.0109	0.0102
Q4	0.0139	0.0097	0.0081	0.0081	0.0057	0.0033	0.0060	0.0082	0.0126	0.0189	0.0084	0.0109	0.0109	0.0098	0.0084
Q5 (High *IV convexity*)	0.0068	0.0034	0.0064	0.0065	0.0034	0.0009	0.0028	0.0063	0.0091	0.0160	0.0076	0.0083	0.0072	0.0089	0.0050
Q1-Q5	0.0187	0.0130	0.0048	0.0057	0.0059	0.0097	0.0121	0.0108	0.0134	0.0177	0.0081	0.0106	0.0118	0.0124	0.0213
	(6.49)	(5.86)	(2.26)	(3.23)	(3.97)	(4.82)	(5.76)	(5.42)	(5.67)	(5.19)	(4.73)	(6.15)	(6.13)	(5.13)	(6.32)

Avg # of firms															
IV convexity Quintiles	Size Quintiles					BTM Quintiles					Beta Quintiles				
	S1(Small)	S2	S3	S4	S5(Large)	B1(Low)	B2	B3	B4	B5(High)	beta1(Low)	beta2	beta3	beta4	beta5(High)
Q1 (Low *IV convexity*)	82	82	82	82	82	75	75	75	75	75	76	77	76	75	70
Q2	83	83	83	83	83	76	76	76	76	76	79	79	79	78	76
Q3	83	83	83	83	83	76	76	76	76	76	79	79	79	78	76
Q4	83	83	83	83	83	76	76	76	76	76	78	79	79	78	76
Q5 (High *IV convexity*)	82	82	82	82	82	75	75	75	75	75	76	77	77	76	73

Table V. Average returns of portfolios sorted by MOM (REV, ILLIQ, Coskew, *IV slope, IV spread, IV smirk*), and option-implied volatility convexity

This table reports the average monthly returns of a double-sorted quintile portfolio formed based on momentum (reversal, illiquidity, co-skewness) and *IV convexity*. Momentum (MOM) is computed based on the past six months skipping one month between the portfolio formation period and the computation period to exclude the reversal effect following Jegadeesh and Titman (1993). Reversal (REV) is computed based on previous one-month return following Jegadeesh(1990) and Lehmann(1990). Illiquidity (ILLIQ) is the average of the absolute value of stock return divided by the trading volume of the stock in thousand USD calculated using the past one-year's daily data up to month t following Amihud (2002) and Hasbrouck(2009).Following Harvey and Siddique (2000), we regress daily excess returns of individual stocks on the daily market excess return and the daily squared market excess return month by month using the last one year data as below:

$$(R_i - R_f)_k = \alpha_i + \beta_{1,i}(MKT - R_f)_k + \beta_{2,i}(MKT - R_f)^2_k + \varepsilon_{i,k}, \quad \text{where } t - 365 \leq k \leq t - 1$$

on a daily basis. The co-skewness of a stock is the coefficient of the squared market excess return. Daily stock returns are obtained from the Center for Research in Security Prices (CRSP). To reduce the impact of infrequent trading on co-skewness estimates, a minimum of 255 trading days in a month for which CRSP reports daily return are required. Monthly stock returns are obtained from the Center for Research in Security Prices (CRSP). The sample covers Jan 2000 to Dec 2013 with stocks traded on the NYSE (exchcd=1), Amex (exchcd=2) and NASDAQ (exchcd=3). For each month, stocks are sorted into five groups based on momentum (reversal, liquidity, co-skewness) and then subsorted within each quintile portfolio into one of the five portfolios according to *IV convexity*. Stocks are assumed to be held for one month, and portfolio returns are equally-weighted. We use only common shares (shrcd in 10, 11). Stocks with a price less than three dollars are excluded from the sample. "Q1-Q5" denotes an arbitrage portfolio that buys a low *IV convexity* portfolio and sells a high *IV convexity* portfolio in each momentum (reversal, illiquidity, coskew) portfolio. Numbers in parentheses indicate t-statistics.

	Avg Return																			
IV convexity Quintiles	MOM Quintiles					REV Quintiles					ILLIQ Quintiles					Coskew Quintiles				
	M1(Loser)	M2	M3	M4	M5(Winner)	R1(Low)	R2	R3	R4	R5(High)	I1(Low)	I2	I3	I4	I5(High)	C1(Low)	C2	C3	C4	C5(High)
Q1 (Low *IV convexity*)	0.0225	0.0157	0.0130	0.0147	0.0273	0.0237	0.0170	0.0160	0.0136	0.0134	0.0108	0.0157	0.0165	0.0222	0.0302	0.0128	0.0169	0.0131	0.0132	0.0140
Q2	0.0107	0.0094	0.0103	0.0100	0.0185	0.0160	0.0132	0.0096	0.0092	0.0083	0.0081	0.0104	0.0135	0.0158	0.0231	0.0115	0.0111	0.0116	0.0085	0.0082
Q3	0.0025	0.0060	0.0078	0.0087	0.0183	0.0123	0.0119	0.0098	0.0075	0.0065	0.0064	0.0100	0.0101	0.0127	0.0174	0.0098	0.0099	0.0087	0.0098	0.0057
Q4	-0.0012	0.0071	0.0070	0.0086	0.0177	0.0084	0.0092	0.0087	0.0066	0.0068	0.0053	0.0083	0.0110	0.0116	0.0162	0.0056	0.0086	0.0092	0.0074	0.0037
Q5 (High *IV convexity*)	-0.0029	0.0036	0.0072	0.0082	0.0166	0.0061	0.0095	0.0070	0.0055	0.0013	0.0051	0.0097	0.0072	0.0069	0.0109	-0.0003	0.0079	0.0091	0.0056	0.0013
Q1-Q5	0.0254	0.0121	0.0058	0.0066	0.0108	0.0176	0.0076	0.0089	0.0081	0.0122	0.0057	0.0060	0.0093	0.0153	0.0193	0.0130	0.0090	0.0040	0.0076	0.0127
	(8.36)	(5.92)	(3.76)	(4.51)	(5.39)	(6.99)	(3.64)	(4.69)	(4.49)	(5.73)	(2.88)	(3.01)	(4.28)	(6.12)	(6.39)	(4.60)	(3.83]	(2.39)	(4.18)	(5.07)

	Avg # of firms																			
IV convexity Quintiles	MOM Quintiles					REV Quintiles					ILLIQ Quintiles					Coskew Quintiles				
	M1(Loser)	M2	M3	M4	M5(Winner)	R1(Low)	R2	R3	R4	R5(High)	I1(Low)	I2	I3	I4	I5(High)	C1(Low)	C2	C3	C4	C5(High)
Q1 (Low *IV convexity*)	80	80	80	80	79	77	79	79	79	78	83	81	83	83	78	73	75	75	75	74
Q2	80	80	80	80	80	80	80	80	80	80	87	81	82	83	77	76	77	77	77	76
Q3	80	80	80	80	80	80	80	80	81	80	85	80	82	81	74	76	77	77	77	76
Q4	80	80	80	80	80	79	80	80	80	80	82	80	80	80	73	76	77	77	77	76
Q5 (High *IV convexity*)	80	80	80	79	78	78	79	79	79	78	74	74	75	75	74	74	76	76	76	75

Table VI. Average returns of portfolios sorted by option-implied volatility slope (spread, smirk) and option implied volatility convexity

This table reports the average monthly returns of a double-sorted quintile portfolio formed based on *IV slope (IV spread, IV smirk)* and *IV convexity*. Portfolios are sorted in five groups at the end of each month based on *IV slope (IV spread, IV smirk)* first and then sub-sorted into five groups based on *IV convexity*. Options volatility slopes are computed by $IV\ slope = \mathrm{IV}_{\mathrm{put}}(-0.2) - \mathrm{IV}_{\mathrm{put}}(-0.8)$, $IV\ spread = \mathrm{IV}_{\mathrm{put}}(-0.5) - \mathrm{IV}_{\mathrm{call}}(0.5)$, and $IV\ smirk = \mathrm{IV}_{\mathrm{put}}(-0.2) - \mathrm{IV}_{\mathrm{call}}(-0.5)$, respectively, following our definition of options volatility slope, Yan(2011) and Xing, Zhang and Zhao(2010). Stocks are held for one month, and portfolio returns are equal-weighted. Monthly stock returns are obtained from the Center for Research in Security Prices (CRSP) with stocks traded on the NYSE (exchcd=1), Amex (exchcd=2) and NASDAQ (exc hcd=3). We use only common shares (shrcd in 10, 11). Stocks with a price less than three dollars are excluded from the sample. "Q1-Q5" denotes an arbitrage portfolio that buys a low *IV convexity* portfolio and sells a high *IV convexity* portfolio in each *IV slope (IV spread, IV smirk)* portfolio. The sample period covers Jan 2000 to Dec 2013. Numbers in parentheses indicate t-statistics.

	Avg Return														
IV convexity Quintiles	*IV slope* Quintiles					*IV spread* Quintiles					*IV smirk* Quintiles				
	S1(Low)	S2	S3	S4	S5(High)	S1(Low)	S2	S3	S4	S5(High)	S1(Low)	S2	S3	S4	S5(High)
Q1 (Low *IV convexity*)	0.0267	0.027	0.0178	0.0160	0.0151	0.0320	0.0163	0.0123	0.0138	0.0130	0.0314	0.0143	0.0104	0.0098	0.0125
Q2	0.0165	0.0164	0.0115	0.0111	0.0136	0.0228	0.0132	0.0092	0.0085	0.0122	0.0224	0.0126	0.0084	0.0085	0.0093
Q3	0.0126	0.0101	0.0079	0.0089	0.0123	0.0189	0.0102	0.0073	0.0067	0.0091	0.0198	0.0118	0.0084	0.0081	0.0087
Q4	0.0079	0.007	0.0081	0.0070	0.0089	0.0150	0.0111	0.0091	0.0074	0.0059	0.0191	0.0101	0.0078	0.0089	0.0059
Q5 (High *IV convexity*)	0.0039	0.0085	0.0066	0.0113	0.0087	0.0167	0.0104	0.0078	0.0076	0.0028	0.0200	0.0132	0.0077	0.0078	0.0029
Q1-Q5	0.0227	0.0185	0.0112	0.0047	0.0064	0.0153	0.0059	0.0045	0.0063	0.0102	0.0114	0.0011	0.0026	0.0020	0.0096
	(6.84)	(6.30)	(4.59)	(2.14)	(2.52)	(5.21)	(3.22)	(2.61)	(3.17)	(3.77)	(3.90)	(0.62)	(1.24)	(0.93)	(3.75)

	Avg # of firms														
Curvature Quintiles	*IV slope* Quintiles					*IV spread* Quintiles					*IV smirk* Quintiles				
	S1(Low)	S2	S3	S4	S5(High)	S1(Low)	S2	S3	S4	S5(High)	S1(Low)	S2	S3	S4	S5(High)
Q1(Low *IV convexity*)	82	85	86	88	86	85	88	85	82	80	85	87	86	86	82
Q2	80	82	86	87	86	87	85	83	77	75	88	86	86	84	80
Q3	79	83	86	86	84	85	87	85	78	76	86	85	84	82	79
Q4	77	81	83	84	80	86	89	87	79	76	83	83	82	80	77
Q5(High *IV convexity*)	77	79	80	80	77	82	86	85	79	77	76	80	80	78	77

Table VII. Average portfolio returns sorted by systematic and idiosyncratic components of *IV convexity* and *IV convexity*

Panel A report the descriptive statistics of the average portfolio returns sorted by systematic components ($convexity_{sys}$) and idiosyncratic components ($convexity_{idio}$) of *IV convexity*. Using daily *IV convexity* of equity options and S&P500 index option, we conduct time series regressions in each month to decompose *IV convexity* into the systematic and idiosyncratic components given by:

$$IV\ convexity_{i,\mathrm{k}} = \alpha_{\mathrm{i}} + \beta_{\mathrm{i}} \times IV\ convexity_{S\&P500,\mathrm{k}} + \varepsilon_{\mathrm{i,k}}, \qquad \text{where } \mathrm{t} - 30 \leq \mathrm{k} \leq \mathrm{t} - 1$$

on a daily basis. The fitted values and residual terms are the systematic components ($convexity_{sys}$) and the idiosyncratic components $convexity_{idio}$) of *IV convexity* (, respectively. On the last trading day of every each month, all firms are assigned into one of five portfolio groups based on *IV convexity*, $convexity_{sys}$($convexity_{idio}$) and we assume stocks are held for the next one-month-period. This process is repeated in every month. Panel B reports the average monthly returns of a double-sorted quintile portfolio using systematic components of *IV convexity* ($convexity_{\mathrm{sys}}$) and idiosyncratic components of *IV convexity* ($convexity_{\mathrm{idio}}$). Portfolios are sorted into five groups at the end of each month based on $convexity_{\mathrm{sys}}$ (or $convexity_{\mathrm{idio}}$) first, and then sub-sorted into five groups based on *IV convexity*. Stocks are held for one month, and portfolio returns are equal-weighted. Stocks are assumed to be held for one month, and portfolio returns are equally-weighted. Monthly stock returns are obtained from the Center for Research in Security Prices (CRSP) with stocks traded on the NYSE (exchcd=1), Amex (exchcd=2) and NASDAQ (exchcd=3). We use only common shares (shrcd in 10, 11) of which stock price exceeds three dollars are excluded from the sample. "Q1-Q5" denotes an arbitrage portfolio that buys a low *IV convexity* portfolio and sells a high *IV convexity* portfolio in each $convexity_{\mathrm{sys}}$ (or $convexity_{\mathrm{idio}}$) portfolio. The sample period covers Jan 2000 to Dec 2013. Numbers in parentheses indicate t-statistics.

Panel A. Option implied convexity and averaged portfolio return

	$convexity_{sys}$				$convexity_{idio}$			
Quintile	Avg # of firms	Mean	Stdev	Avg Ret	Avg # of firms	Mean	Stdev	Avg Ret
Q1 (Low *IV convexity*)	423	-0.0434	0.1517	0.0199	420	-0.2113	0.2402	0.0174
Q2	426	0.0373	0.0199	0.0111	419	-0.0518	0.0383	0.0117
Q3	420	0.0682	0.0260	0.0100	413	-0.0039	0.0330	0.0116
Q4	410	0.1145	0.0425	0.0094	408	0.0470	0.0483	0.0101
Q5 (High *IV convexity*)	385	0.2773	0.2113	0.0089	403	0.2379	0.2781	0.0087
Q1-Q5				0.0110				0.0086
				(6.56)				(5.72)

Panel B. Double sorted quintile portfolio using $convexity_{\mathrm{sys}}$ and $convexity_{\mathrm{idio}}$

	$convexity_{\mathrm{sys}}$									
IV convexity Quintiles	Avg Return					Avg # of firms				
	$c_{sys}1$	$c_{sys}2$	$c_{sys}3$	$c_{sys}4$	$c_{sys}5$	$c_{sys}1$	$c_{sys}2$	$c_{sys}3$	$c_{sys}4$	$c_{sys}5$
Q1 (Low *IV convexity*)	0.0319	0.0158	0.0156	0.0143	0.0155	553	775	776	762	665
Q2	0.0224	0.0122	0.0091	0.0091	0.0095	691	676	736	741	644
Q3	0.0188	0.0090	0.0079	0.0101	0.0094	677	646	713	713	604
Q4	0.0131	0.0102	0.0088	0.0077	0.0070	702	696	726	709	561
Q5 (High *IV convexity*)	0.0140	0.0086	0.0090	0.0059	0.0029	686	766	767	721	478
Q1-Q5	0.0179	0.0072	0.0066	0.0084	0.0126					
	(5.93)	(3.49)	(3.24)	(4.07)	(5.45)					

	$convexity_{\mathrm{idio}}$									
IV convexity Quintiles	Avg Return					Avg # of firms				
	$c_{idio}1$	$c_{idio}2$	$c_{idio}3$	$c_{idio}4$	$c_{idio}5$	$c_{idio}1$	$c_{idio}2$	$c_{idio}3$	$c_{idio}4$	$c_{idio}5$
Q1 (Low *IV convexity*)	0.0152	0.0145	0.0130	0.0111	0.0049	631	767	713	741	737
Q2	0.0129	0.0107	0.0105	0.0081	0.0044	783	753	659	732	790
Q3	0.0115	0.0093	0.0079	0.0075	0.0059	801	753	696	755	754
Q4	0.0101	0.0064	0.0095	0.0068	0.0007	755	754	730	745	709
Q5 (High *IV convexity*)	0.0049	0.0065	0.0079	0.0057	-0.0033	605	672	686	663	590
Q1-Q5	0.0102	0.0080	0.0051	0.0053	0.0082					
	(3.16)	(3.66)	(2.63)	(2.71)	(3.30)					

Table VIII. Time series tests of 3- and 4- factor models using options implied volatility convexity quintiles

This table presents the coefficient estimates of CAPM, Fama-French three (four)-factor models for monthly excess returns on *IV convexity* quintiles portfolios. Fama-French factors [$R_M - R_f$], small market capitalization minus big (SMB), and high book-to-market ratio minus low (HML), and momentum factor (UMD)] are obtained from Kenneth French's website. *IV convexity* quintiles are formed as in Table IV. The sample period covers Jan 2000 to Dec 2013 with stocks traded on the NYSE (exchcd=1), Amex (exchcd=2) and NASDAQ (exchcd=3). Stocks with a price less than three dollars are excluded from the sample, and Newey-west (1987) adjusted t-statistics are reported in square brackets. The last row in each model labeled "Joint test p-value" reports a Gibbons, Ross and Shanken (1989) results that tests the null hypothesis that all intercept are jointly zero or $\hat{\alpha}_{Q1} = \cdots = \hat{\alpha}_{Q5} = 0$.

Model	Factor sensitivities	*IV convexity*						$convexity_{sys}$						$convexity_{idio}$					
		Q1	Q2	Q3	Q4	Q5	Q1-Q5	Q1	Q2	Q3	Q4	Q5	Q1-Q5	Q1	Q2	Q3	Q4	Q5	Q1-Q5
CAPM	Alpha	0.0146	0.0069	0.0042	0.0032	0.0014	0.0132	0.0138	0.0056	0.0043	0.0035	0.0031	0.0107	0.0113	0.0061	0.0061	0.0044	0.0026	0.0087
		(5.60)	(4.75)	(2.88)	(2.04)	(0.66)	(7.72)	(5.51)	(3.96)	(2.83)	(2.05)	(1.53)	(6.39)	(4.70)	(3.92)	(4.41)	(2.88)	(1.20)	(5.62)
	MKTRF	1.4472	1.2075	1.2505	1.3057	1.383	0.0642	1.4207	1.2283	1.2811	1.3393	1.3338	0.087	1.4086	1.2623	1.2307	1.2831	1.411	-0.0024
		(23.11)	(31.82)	(36.13)	(34.53)	(27.20)	(1.38)	(25.71)	(33.44)	(35.29)	(30.46)	(27.65)	(2.06)	(25.73)	(30.01)	(33.77)	(35.37)	(29.21)	(-0.06)
	$\overline{Adj}\ R^2$	0.792	0.8968	0.9065	0.9007	0.85	0.0126	0.0126	0.9057	0.9003	0.8858	0.8494	0.0295	0.0295	0.8932	0.9128	0.9017	0.8442	<0.0001
	Joint test: p-value			(0.00)						(0.00)						(0.00)			
FF3	Alpha	0.0124	0.0048	0.0023	0.0011	-0.001	0.0134	0.0118	0.0039	0.0024	0.0011	0.0004	0.0114	0.0087	0.0038	0.0042	0.0025	0.0005	0.0082
		(5.87)	(4.52)	(2.34)	(1.03)	(-0.64)	(7.75)	(6.00)	(3.69)	(2.47)	(0.90)	(0.26)	(7.48)	(4.60)	(3.62)	(4.12)	(2.49)	(0.31)	(5.36)
	MKTRF	1.3027	1.1149	1.1512	1.2026	1.265	0.0377	1.2767	1.1361	1.1724	1.2278	1.2313	0.0454	1.2713	1.1624	1.1475	1.1776	1.2796	-0.0083
		(23.58)	(37.48)	(44.49)	(40.90)	(28.50)	(0.85)	(28.30)	(38.33)	(46.30)	(34.29)	(29.01)	(1.38)	(25.92)	(36.13)	(38.38)	(43.02)	(29.43)	(-0.20)
	SMB	0.6328	0.4493	0.4557	0.4824	0.552	0.0808	0.6199	0.4238	0.4955	0.5324	0.5111	0.1088	0.63	0.4786	0.4016	0.4772	0.5825	0.0475
		(5.33)	(8.39)	(9.74)	(8.46)	(5.76)	(1.44)	(5.55)	(8.44)	(11.93)	(7.58)	(5.01)	(2.41)	(5.85)	(8.64)	(7.18)	(9.60)	(5.91)	(0.91)
	HML	0.0211	0.1346	0.0717	0.1006	0.1138	-0.0927	-0.0094	0.0685	0.069	0.1377	0.1863	-0.1957	0.0995	0.1277	0.1146	0.0573	0.0386	0.0609
		(0.23)	(2.71)	(1.70)	(2.44)	(1.67)	(-1.27)	(-0.12)	(1.42)	(1.73)	(2.51)	(2.70)	(-3.48)	(1.19)	(2.39)	(2.65)	(1.31)	(0.61)	(0.84)
	$\overline{Adj}\ R^2$	0.8685	0.9541	0.9642	0.9585	0.9133	0.0491	0.0491	0.9572	0.9654	0.9508	0.9063	0.1781	0.1781	0.9527	0.9576	0.9625	0.9159	<0.0001
	Joint test: p-value			(0.00)						(0.00)						(0.00)			
FF4	Alpha	0.0132	0.005	0.0024	0.0014	-0.0003	0.0136	0.0126	0.004	0.0026	0.0015	0.0011	0.0115	0.0094	0.0042	0.0044	0.0028	0.0011	0.0083
		(7.33)	(5.10)	(2.48)	(1.54)	(-0.29)	(7.61)	(7.55)	(3.94)	(2.90)	(1.48)	(0.90)	(7.32)	(5.85)	(4.63)	(4.58)	(2.93)	(0.88)	(5.32)
	MKTRF	1.1125	1.058	1.1264	1.1304	1.1112	0.0013	1.105	1.1005	1.12	1.1355	1.0804	0.0246	1.1044	1.0793	1.0974	1.1272	1.138	-0.0336
		(18.13)	(34.90)	(37.00)	(38.48)	(27.91)	(0.02)	(19.37)	(34.59)	(42.41)	(34.70)	(29.53)	(0.54)	(20.55)	(40.32)	(35.53)	(36.75)	(25.76)	(-0.69)
	SMB	0.7588	0.487	0.4722	0.5302	0.6539	0.1049	0.7336	0.4474	0.5302	0.5935	0.611	0.1226	0.7406	0.5336	0.4348	0.5106	0.6763	0.0643
		(7.28)	(11.09)	(9.97)	(11.01)	(8.59)	(1.51)	(7.50)	(9.27)	(13.78)	(10.08)	(7.54)	(2.09)	(7.64)	(12.92)	(8.60)	(11.41)	(8.01)	(1.04)
	HML	-0.0143	0.124	0.0671	0.0871	0.0852	-0.0995	-0.0413	0.0619	0.0592	0.1206	0.1582	-0.1995	0.0684	0.1122	0.1053	0.048	0.0123	0.0561
		(-0.22)	(3.02)	(1.64)	(2.52)	(1.86)	(-1.36)	(-0.68)	(1.35)	(1.78)	(3.06)	(3.89)	(-3.30)	(1.20)	(3.10)	(2.89)	(1.22)	(0.23)	(0.80)
	UMD	-0.3321	-0.0994	-0.0433	-0.1261	-0.2686	-0.0635	-0.2999	-0.0622	-0.0915	-0.1612	-0.2635	-0.0364	-0.2916	-0.1452	-0.0875	-0.088	-0.2474	-0.0441
		(-4.35)	(-4.37)	(-1.77)	(-7.22)	(-11.29)	(-0.97)	(-3.96)	(-2.40)	(-4.13)	(-7.41)	(-9.08)	(-0.61)	(-4.59)	(-5.23)	(-3.86)	(-4.63)	(-6.43)	(-0.84)
	$\overline{Adj}\ R^2$	0.9232	0.9619	0.9654	0.9694	0.9553	0.0675	0.0675	0.96	0.9713	0.9675	0.9497	0.1813	0.9324	0.9681	0.9635	0.9679	0.9499	0.0025
	Joint test: p-value			(0.00)						(0.00)						(0.00)			

Table IX. Short-selling constraints and information asymmetry

This table reports the average monthly returns of twenty five double-sorted portfolios, first sorted by the previous quarterly percentage of shares outstanding held by institutions (from the Thomson Financial Institutional Holdings (13F) database), previous quarter's analyst coverage (from I/B/E/S), previous quarter's analyst forecast dispersion (from I/B/E/S) and then sub-sorted according to *IV convexity* within each quintile portfolio into one of the five portfolios on a monthly basis. Following Campbell et al. (2008) and Nagel (2005), we calculate the share of institutional ownership by summing the stock holdings of all reporting institutions for each stock in each quarter. Analyst forecast dispersion is measured as the scaled standard deviation of I/B/E/S analysts' current fiscal year earnings per share forecasts by the method in Diether et al. (2002).
Stocks are assumed to be held for one month, and portfolio returns are equally-weighted. Monthly stock returns are obtained from the Center for Research in Security Prices (CRSP) with stocks traded on the NYSE (exchcd=1), Amex (exchcd=2) and NASDAQ (exchcd=3). We use only common shares (shrcd in 10, 11) of which price exceeds. three dollars. "Q1-Q5" denotes an arbitrage portfolio that buys a low *IV convexity* portfolio and sells a high *IV convexity* portfolio in each characteristic portfolio. The sample covers Jan 2000 to Dec 2013. Numbers in parentheses indicates t-statistics.

Mean Return															
IV Convexity Quintiles	F-13 filings(Institutional Holdings)					Analyst Coverage					Analyst Forecast Dispersion				
	F1 (Low)	F2	F3	F4	F5 (High)	AC1 (Low)	AC2	AC3	AC4	AC5 (High)	AD1 (Low)	AD2	AD3	AD4	AD5 (High)
Q1 (Low)	0.0228	0.0215	0.0210	0.0195	0.0150	0.0230	0.0228	0.0195	0.0169	0.0177	0.0225	0.0207	0.0215	0.0190	0.0151
Q2	0.0150	0.0141	0.0132	0.0117	0.0084	0.0156	0.0151	0.0122	0.0107	0.0094	0.0161	0.0139	0.0118	0.0115	0.0089
Q3	0.0103	0.0083	0.0103	0.0112	0.0075	0.0129	0.0115	0.0102	0.0098	0.0084	0.0140	0.0108	0.0087	0.0091	0.0014
Q4	0.0088	0.0124	0.0117	0.0101	0.0066	0.0118	0.0122	0.0098	0.0087	0.0081	0.0144	0.0126	0.0095	0.0088	0.0035
Q5 (High)	0.0064	0.0096	0.0086	0.0124	0.0085	0.0086	0.0087	0.0086	0.0078	0.0063	0.0145	0.0121	0.0099	0.0061	-0.0011
Q1-Q5	0.0164	0.0120	0.0124	0.0071	0.0065	0.0145	0.0141	0.0109	0.0091	0.0114	0.0081	0.0086	0.0116	0.0129	0.0162
	(5.18)	(4.44)	(5.78)	(3.38)	(3.34)	(4.93)	(5.02)	(4.36)	(4.60)	(5.21)	(3.76)	(4.46)	(4.87)	(5.34)	(5.46)

Avg # of firms															
IV Convexity Quintiles	F-13 filings (Institutional Holdings)					Analyst Coverage					Analyst Forecast Dispersion				
	F1 (Low)	F2	F3	F4	F5 (High)	AC1 (Low)	AC2	AC3	AC4	AC5 (High)	AD1 (Low)	AD2	AD3	AD4	AD5 (High)
Q1 (Low)	49	51	52	51	51	60	70	74	73	76	71	71	70	67	61
Q2	49	54	54	53	55	58	71	76	75	78	75	74	73	71	64
Q3	49	54	54	53	54	59	71	75	74	78	75	74	73	70	64
Q4	48	53	53	52	54	57	69	74	74	78	73	73	71	68	61
Q5 (High)	46	51	51	49	51	56	66	70	71	75	70	69	67	63	55

Table X. Fama-MacBeth regressions

Panel A reports the averages of month-by–month Fama and Macbeth (1973) cross-sectional regression coefficient estimates for individual stock returns on *IV convexity* and control variables. Panel B shows the averages of month-by–month Fama and Macbeth (1973) cross-sectional regression coefficient estimates for individual stock returns on $convexity_{\mathrm{sys}}$ and $convexity_{\mathrm{idio}}$ and control variables. The cross-section of expected stock returns is regressed on control variables. Control variables include market β estimated following Fama and French (1992), size (*ln_mv*), book-to-market (*btm*), momentum (MOM), reversal (REV), illiquidity (ILLIQ), *IV slope (IV spread, IV spread)*, idiosyncratic risk (*idio_risk*), implied volatility level (*IV level*), systematic volatility (v_{sys}^2), idiosyncratic implied variance (v_{isio}^2). Market β is estimated from time-series regressions of raw stock excess returns on the Rm-Rf by month-by-month rolling over the past three year (36 months) returns (a minimum of 12 months). Following Ang, Hodrick, Xing, and Zhang (2006), daily excess returns of individual stocks are regressed on the four Fama-French (1993, 1996) factors daily in every month as:

$$(\mathrm{R_i} - \mathrm{R_f})_k = \alpha_i + \beta_{1i}(\mathrm{MKT} \; - \mathrm{R_f})_k + \beta_{2i}\mathrm{SMB_k} + \beta_{3i}\mathrm{HML_k} + \beta_{4i}\mathrm{WML_k} + \varepsilon_k, \quad \text{where } t - 30 \le k \le \; t - 1$$

on a daily basis. The idiosyncratic volatility of a stock is computed as the standard deviation of the regression residuals. Daily stock returns are obtained from the Center for Research in Security Prices (CRSP). Momentum (MOM) is computed based on the past six months skipping one month between the portfolio formation period and the computation period to exclude the reversal effect following Jegadeesh and Titman (1993). Reversal (REV) is computed based on past one-month return following Jegadeesh (1990) and Lehmann (1990). Illiquidity (ILLIQ) is defined as the absolute monthly stock return divided by the dollar trading volume in the stock (in $thousands) following Amihud (2002). Systematic volatility is estimated by the method suggested by Duan and Wei (2009) as $v_{\mathrm{sys}}^2 = \beta^2 v_m^2 / v^2$. Idiosyncratic implied variance as $v_{idio}^2 = v^2 - \beta^2 v_M^2$, where $\mathrm{v_m}$ is the implied volatility of S&P500 index option, is also computed following Dennis, Mayhey and Stivers (2006). The daily factor data are downloaded from Kenneth R. French's web site. To reduce the impact of infrequent trading on idiosyncratic volatility estimates, a minimum of 15 trading days in a month for which CRSP reports both a daily return and non-zero trading volume are required. The sample period covers Jan 2000 to Dec 2013 with stocks traded on the NYSE (exchcd=1), Amex (exchcd=2) and NASDAQ (exchcd=3) and stocks with a price less than three dollars are excluded from the sample. Newey-west adjusted t-statistics for the time-series average of coefficients using lag3 are reported. Numbers in parentheses indicate t -statistics.

Panel A. *IV convexity*

Variable	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL6	MODEL 7	MODEL 8	MODEL 9	MODEL 10	MODEL 11	MODEL 12
IV	**-0.015*** **	**-0.011*** **	**-0.013*** **	**-0.015*** **	**-0.011*** **	**-0.012*** **	**-0.015*** **	**-0.011*** **	**-0.012*** **	**-0.015*** **	**-0.011*** **	**-0.012*** **
convexity	**(-6.60)**	**(-3.86)**	**(-4.12)**	**(-6.70)**	**(-4.20)**	**(-3.80)**	**(-6.61)**	**(-4.14)**	**(-3.82)**	**(-6.59)**	**(-4.46)**	**(-4.15)**
IV		-0.018**			-0.017**			-0.017**			-0.017**	
Spread		(-2.22)			(-2.12)			(-1.98)			(-2.13)	
IV			-0.007			-0.009			-0.011			-0.010
Smirk			(-0.98)			(-1.26)			(-1.41)			(-1.30)
Beta	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001
	(0.33)	(0.34)	(0.34)	(0.20)	(0.22)	(0.22)	(0.25)	(0.25)	(0.27)	(0.41)	(0.45)	(0.45)
Log(MV)	-0.002**	-0.002**	-0.002**	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(-2.39)	(-2.37)	(-2.30)	(-2.86)	(-2.82)	(-2.75)	(-3.26)	(-3.19)	(-3.11)	(-2.85)	(-2.82)	(-2.71)
Btm	0.004**	0.004**	0.004**	0.004**	0.004**	0.004**	0.003**	0.003**	0.003**	0.004**	0.003**	0.004**
	(2.14)	(2.13)	(2.15)	(2.24)	(2.23)	(2.27)	(2.15)	(2.15)	(2.18)	(2.18)	(2.17)	(2.22)
MOM				0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
				(0.15)	(0.15)	(0.18)	(0.28)	(0.29)	(0.31)	(0.21)	(0.22)	(0.24)
REV				-0.017***	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***
				(-3.47)	(-3.47)	(-3.45)	(-3.48)	(-3.49)	(-3.46)	(-3.43)	(-3.43)	(-3.42)
ILLIQ				-0.007	-0.006	-0.007	0.002	0.001	0.001	0.001	0.001	0.000
				(-0.37)	(-0.34)	(-0.36)	(0.09)	(0.07)	(0.07)	(0.04)	(0.06)	(0.02)
idio_risk				-0.110**	-0.108*	-0.104*						
				(-2.00)	(-1.96)	(-1.90)						
IV							-0.007	-0.007	-0.007			
level							(-1.05)	(-0.95)	(-1.01)			
v_{sys}^2										-0.002	-0.002	-0.002
										(-1.52)	(-1.61)	(-1.58)
v_{isio}^2										-0.008*	-0.008*	-0.008*
										(-1.82)	(-1.79)	(-1.81)
$\overline{Adj}\ R^2$	0.050	0.051	0.051	0.064	0.065	0.065	0.068	0.068	0.068	0.067	0.067	0.068

Panel B. $convexity_{\text{sys}}$ and $convexity_{\text{idio}}$

Variable	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5	MODEL 6	MODEL 7	MODEL 8	MODEL 9	MODEL10	MODEL11	MODEL12
$\boldsymbol{convexity_{\text{sys}}}$	**-0.022*** **		**-0.022*** **	**-0.021*** **		**-0.021*** **	**-0.022*** **		**-0.022*** **	**-0.022*** **		**-0.022*** **
	(-7.20)		**(-7.23)**	**(-7.64)**		**(-7.60)**	**(-8.06)**		**(-8.00)**	**(-8.01)**		**(-7.99)**
$\boldsymbol{convexity_{\text{idio}}}$		**-0.011*** **	**-0.012*** **		**-0.011*** **	**-0.012*** **		**-0.011*** **	**-0.012*** **		**-0.011*** **	**-0.012*** **
		(-4.29)	**(-4.68)**		**(-4.29)**	**(-4.69)**		**(-3.99)**	**(-4.42)**		**(-4.04)**	**(-4.48)**
Beta	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001
	(0.33)	(0.34)	(0.33)	(0.22)	(0.22)	(0.22)	(0.25)	(0.24)	(0.26)	(0.44)	(0.45)	(0.43)
ln_mv	-0.002**	-0.002**	-0.002**	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(-2.47)	(-2.30)	(-2.47)	(-3.00)	(-2.75)	(-3.00)	(-3.39)	(-3.08)	(-3.43)	(-2.96)	(-2.69)	(-2.99)
Btm	0.004**	0.004**	0.004**	0.004**	0.004**	0.004**	0.003**	0.003**	0.003**	0.004**	0.003**	0.004**
	(2.15)	(2.06)	(2.14)	(2.26)	(2.18)	(2.25)	(2.15)	(2.09)	(2.15)	(2.18)	(2.11)	(2.18)
MOM				0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
				(0.15)	(0.19)	(0.16)	(0.27)	(0.34)	(0.29)	(0.19)	(0.27)	(0.21)
REV				-0.017***	-0.018***	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***
				(-3.42)	(-3.53)	(-3.47)	(-3.41)	(-3.54)	(-3.48)	(-3.36)	(-3.49)	(-3.42)
ILLIQ				-0.010	-0.005	-0.011	-0.002	0.003	-0.002	-0.003	0.003	-0.003
				(-0.55)	(-0.25)	(-0.60)	(-0.09)	(0.19)	(-0.13)	(-0.16)	(0.16)	(-0.18)
idio_risk				-0.116**	-0.111**	-0.112**						
				(-2.10)	(-2.00)	(-2.04)						
IV level							-0.007	-0.006	-0.008			
							(-1.04)	(-0.92)	(-1.09)			
v_{sys}^2										-0.002	-0.002*	-0.002
										(-1.58)	(-1.66)	(-1.56)
v_{isio}^2										-0.008*	-0.008*	-0.008*
										(-1.80)	(-1.74)	(-1.84)
$\overline{Adj}\ R^2$	0.050	0.050	0.051	0.064	0.064	0.065	0.068	0.068	0.069	0.067	0.067	0.068

Table XI . Alternative Measures of Options implied Convexity

This table reports the descriptive statistics of the average portfolio returns sorted by alternative measures of option implied convexity. $convexity_{cp}$ is an unbiased pure kurtosis measure without loss of information and is calculated by;

$$IV\ convexity_{cp} = \frac{[\mathrm{IV}_{\mathrm{call}}(0.8)+\mathrm{IV}_{\mathrm{put}}(-0.2)]}{2} + \frac{[\mathrm{IV}_{\mathrm{call}}(0.2)+\mathrm{IV}_{\mathrm{put}}(-0.8)]}{2} - [\mathrm{IV}_{\mathrm{call}}(0.5) + \mathrm{IV}_{\mathrm{put}}(-0.5)].$$

Alternative option implied convexities are calculated by;

$$IV\ convexity_{Bali} = \mathrm{IV}_{\mathrm{call}}(0.25) + \mathrm{IV}_{\mathrm{put}}(-0.25) - \mathrm{IV}_{\mathrm{call}}(0.5) - \mathrm{IV}_{\mathrm{put}}(-0.5)$$
$$IV\ convexity_{put} = \mathrm{IV}_{\mathrm{put}}(-0.2) + \mathrm{IV}_{\mathrm{call}}(0.2) - 2 \times \mathrm{IV}_{\mathrm{put}}(-0.5)$$
$$IV\ convexity_{call} = \mathrm{IV}_{\mathrm{call}}(0.2) + \mathrm{IV}_{\mathrm{call}}(0.8) - 2 \times \mathrm{IV}_{\mathrm{call}}(0.5).$$

On the last trading day of each month, all firms are assigned to one of five portfolio groups based on alternative options implied convexity assuming that stocks are held for the next one-month-period. This process is repeated in every month. Monthly stock returns are obtained from the Center for Research in Security Prices (CRSP) with stocks traded on the NYSE (exchcd=1), Amex (exchcd=2), and NASDAQ (exchcd=3). We use only common shares (shrcd in 10, 11). Stocks with a price less than three dollars are excluded from the sample. "Q1-Q5" denotes an arbitrage portfolio that buys a low options implied convexity portfolio (Q1) and sells a high options implied convexity portfolio (Q5). The sample covers Jan 2000 to Dec 2013. Numbers in parentheses indicate t-statistics.

	$IV\ convexity_{cp}$			$IV\ convexity_{Bali}$			IV $convexity_{put}$			IV $convexity_{call}$		
Quintile	Mean	Stdev	Avg Return	Mean	Stdev	Avg Ret	Mean	Stdev	Avg Return	Mean	Stdev	Avg Return
Q1 (Low)	-0.0407	0.1191	0.0190	-0.0517	0.1324	0.0138	-0.0571	0.1627	0.0177	-0.0562	0.1588	0.0154
Q2	0.0227	0.0134	0.0110	0.0056	0.0070	0.0155	0.0166	0.0130	0.0140	0.0139	0.0138	0.0125
Q3	0.0501	0.0200	0.0098	0.0245	0.0096	0.0082	0.0470	0.0213	0.0095	0.0434	0.0229	0.0093
Q4	0.0923	0.0350	0.0096	0.0584	0.0229	0.0095	0.0955	0.0413	0.0099	0.0904	0.0416	0.0097
Q5 (High)	0.2350	0.1566	0.0103	0.2238	0.2183	0.0127	0.2747	0.2034	0.0086	0.2533	0.1893	0.0128
Q1-Q5			0.0087			0.0011			0.0091			0.0026
			(5.10)			(0.86)			(6.09)			(1.76)

Table XII. Alternative Measures of Portfolio Performance: Sharpe Ratio (SR) and Generalized Sharpe Ratio (GSR)

Panel A reports the Sharpe ratio for single-sorted portfolios formed based on *IV convexity* or alternative measures of option implied convexity. *IV convexity* is estimated following our definition of *IV convexity* and alternative measures of option implied convexities are computed as in Table XI. Panel B presents the Sharp ratio of double-sorted quintile portfolios formed based on *IV slope (IV spread, IV smirk)* first and then sub-sorted into five groups based on *IV convexity*. Options volatility slopes are computed by $IV\ slope = \mathrm{IV_{put}}(-0.2) - \mathrm{IV_{put}}(-0.8)$, *IV spread*$= \mathrm{IV_{put}}(-0.5) - \mathrm{IV_{call}}(0.5)$, and *IV smirk*$= \mathrm{IV_{put}}(-0.2) - \mathrm{IV_{call}}(-0.5)$, respectively, following our definition of options volatility slope, Yan (2011) and Xing, Zhang and Zhao (2010). Sharpe ratios are estimated by standard Sharpe ratio (SR) and Generalized Sharpe ratio (GSR) suggested by Zakamouline and Koekebakker (2009). SR is defined as $\frac{\mu-r}{\sigma}$ and GSR is computed as $\sqrt{-2\log(-E[U^*(\widetilde{W})])}$, where $\mathrm{E}[U^*(\widetilde{W})] = \max_a E[-e^{-\lambda a(x-r_f}]$. Monthly stock returns are obtained from the Center for Research in Security Prices (CRSP) with stocks traded on the NYSE (exchcd=1), Amex (exchcd=2) and NASDAQ (exchcd=3). We use only common shares (shrcd in 10, 11). Stocks with a price less than three dollars are excluded from the sample. "Q1-Q5" denotes an arbitrage portfolio that buys a low *IV convexity* portfolio and sells a high *IV convexity* portfolio. The sample covers Jan 2000 to Dec 2013.

Panel A. Sharpe ratio for single-sorted portfolios: *IV convexity* (alternative convexity)

	Sharpe Ratio									
	SR					GSR				
Quintile	*IV convexity*	$convexity_{cp}$	$convexity_{Bali}$	$convexity_{put}$	$convexity_{call}$	*IV_convexity*	$convexity_{cp}$	$convexity_{Bali}$	$convexity_{put}$	$convexity_{call}$
Q1 (Low)	0.2526	0.2294	0.1715	0.2160	0.1866	0.2575	0.2325	0.1717	0.2170	0.1868
Q2	0.1815	0.1545	0.2118	0.1976	0.1723	0.1799	0.1533	0.2113	0.1973	0.1717
Q3	0.1334	0.1334	0.1088	0.1314	0.1248	0.1322	0.1321	0.1080	0.1303	0.1237
Q4	0.1150	0.1220	0.1200	0.1277	0.1239	0.1139	0.1210	0.1192	0.1266	0.1228
Q5 (High)	0.0826	0.1298	0.1672	0.1025	0.1716	0.0823	0.1289	0.1659	0.1019	0.1706
Q1-Q5	0.6087	0.3950	0.0667	0.4711	0.1362	0.7598	0.4018	0.0669	0.4829	0.1362

Panel B. Sharp ratio of double-sorted quintile portfolios: *IV slope (IV spread, IV smirk)* first and then on *IV convexity*

	SR															GSR														
	IV slope Quintiles					*IV spread* Quintiles					*IV smirk* Quintiles					*IV slope* Quintiles					*IV spread* Quintiles					*IV smirk* Quintiles				
	S1(Low)	S2	S3	S4	S5(High)	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5
Q1 (Low)	0.27	0.31	0.24	0.20	0.17	0.33	0.21	0.17	0.18	0.15	0.33	0.19	0.13	0.11	0.15	0.28	0.33	0.24	0.20	0.17	0.35	0.21	0.17	0.18	0.15	0.34	0.19	0.13	0.11	0.15
Q2	0.21	0.24	0.19	0.16	0.16	0.26	0.20	0.13	0.11	0.14	0.25	0.20	0.11	0.10	0.11	0.21	0.24	0.18	0.16	0.16	0.27	0.20	0.13	0.11	0.14	0.26	0.19	0.11	0.10	0.11
Q3	0.15	0.15	0.12	0.12	0.15	0.23	0.15	0.10	0.08	0.10	0.24	0.20	0.12	0.10	0.10	0.15	0.15	0.12	0.12	0.15	0.23	0.15	0.10	0.08	0.10	0.24	0.19	0.11	0.10	0.10
Q4	0.09	0.09	0.11	0.08	0.10	0.19	0.15	0.12	0.09	0.06	0.26	0.15	0.11	0.11	0.06	0.08	0.09	0.11	0.08	0.10	0.19	0.15	0.12	0.09	0.06	0.26	0.15	0.11	0.11	0.06
Q5 (High)	0.03	0.10	0.08	0.14	0.11	0.21	0.14	0.10	0.09	0.01	0.24	0.17	0.09	0.09	0.02	0.03	0.10	0.07	0.14	0.11	0.21	0.14	0.10	0.09	0.01	0.25	0.17	0.09	0.09	0.02
Q1-Q5	0.53	0.49	0.35	0.17	0.19	0.40	0.25	0.20	0.25	0.29	0.30	0.05	0.10	0.07	0.29	0.60	0.63	0.44	0.17	0.20	0.43	0.26	0.19	0.25	0.29	0.31	0.05	0.1	0.07	0.29

Table XIII. Different forecasting horizons

This table reports the average equal-weighted monthly returns and risk-adjusted returns (using Fama-French 3 and 4 factor models) of the quintile portfolios formed on *IV convexity* for various forecasting horizons. We sort stocks every month based on *IV convexity* into five quintiles and form an equal-weighted portfolio that buys a low *IV convexity* portfolio and sells a high *IV convexity* portfolio. We denote by r_t the t-month ahead non-overlapping monthly portfolio return. The sample covers Jan 2000 to Dec 2013. Numbers in parentheses indicate t-statistics.

	r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}	r_{11}	r_{12}
Q1 (Low)	0.0208	0.0083	0.0100	0.0102	0.0108	0.0113	0.0097	0.0115	0.0117	0.0115	0.0122	0.0125
Q2	0.0124	0.0094	0.0092	0.0088	0.0085	0.0089	0.0096	0.0092	0.0098	0.0097	0.0112	0.0116
Q3	0.0098	0.0076	0.0079	0.0079	0.0092	0.008	0.0096	0.0079	0.0092	0.0095	0.0098	0.0105
Q4	0.009	0.0086	0.0071	0.0088	0.0092	0.0094	0.0088	0.0088	0.009	0.0096	0.0113	0.0098
Q5 (High)	0.0074	0.0052	0.0061	0.0073	0.0076	0.0075	0.0096	0.0088	0.0088	0.0102	0.0108	0.0111
Q1-Q5	0.0134	0.0031	0.0038	0.0028	0.0032	0.0038	0.0001	0.0026	0.0029	0.0013	0.0014	0.0014
	(7.87)	(2.36)	(2.70)	(1.24)	(2.64)	(3.31)	(0.09)	(2.11)	(2.57)	(0.89)	(1.19)	(1.00)
α_{FF3}	0.0118	0.0025	0.0032	0.0014	0.0018	0.0030	-0.0011	0.0017	0.0018	-0.0003	0.0004	0.0002
	(6.90)	(2.31)	(2.22)	(1.13)	(1.66)	(2.92)	(-0.83)	(1.52)	(1.58)	(-0.25)	(0.34)	(0.17)
α_{FF4}	0.012	0.0026	0.0033	0.0015	0.0017	0.0028	-0.0013	0.0016	0.0018	-0.0002	0.0003	0.0001
	(6.80)	(2.40)	(2.26)	(1.17)	(1.53)	(2.73)	(-1.02)	(1.39)	(1.62)	(-0.16)	(0.22)	(0.11)

Table XIV. Subsample robustness checks

This table reports the average equal-weighted returns of the quintile portfolios formed on *IV convexity* for various subsamples. We check the robustness of our results by dividing the entire sample period into the expansion and contraction sub-periods (i) by taking the median value of the Chicago Fed National Activity Index (CFNAI) as a threshold and (ii) by using the NBER Business cycle dummy variable, which takes one for the contraction period and 0 otherwise. On the last trading day of each month, we sort stocks based on *IV convexity* into five quintiles and form an equal-weighted portfolio that buys a low *IV convexity* portfolio and sells a high *IV convexity* portfolio. We assume stocks are held for the next one-month-period. This process is repeated for every month. The sample covers Jan 2000 to Dec 2013.

	Chicago Fed National Activity Index (CFNAI)						NBER Business Cycle Dummy					
	Expansion period (84 months)			Contraction periods (84 months)			Expansion periods (142 months)			Contraction periods (26 months)		
Quintile	Mean	Stdev	Avg Ret	Mean	Stdev	Avg Ret	Mean	Stdev	Avg Ret	Mean	Stdev	Avg Ret
Q1 (Low)	-0.1256	0.2701	0.0127	-0.1478	0.2939	0.0288	-0.1394	0.2897	0.0142	-0.1584	0.2685	0.0103
Q2	0.0144	0.0252	0.0101	0.0167	0.0371	0.0146	0.015	0.0288	0.0119	0.0181	0.0459	0.0016
Q3	0.0593	0.027	0.0085	0.068	0.0483	0.0111	0.0618	0.0342	0.01	0.0756	0.061	-0.0019
Q4	0.126	0.0473	0.0071	0.1406	0.0815	0.0108	0.1301	0.0576	0.0091	0.1537	0.1044	-0.0063
Q5 (High)	0.3738	0.3319	0.0053	0.4221	0.3729	0.0094	0.3915	0.3441	0.0046	0.4863	0.4582	-0.0133
Q1-Q5			0.0074			0.0194			0.0096			0.0236
			(4.92)			(6.65)			(5.88)			(3.87)

Figure 1. Shape of the Implied Volatility Curves

This figure illustrates the effect of different values of skewness and excess kurtosis of underlying asset returns on the shape of the implied volatility curve. The base parameters are consistent with those of Figure 1 and $(S_0, T, r) = (100, 0.5, 0.05)$.

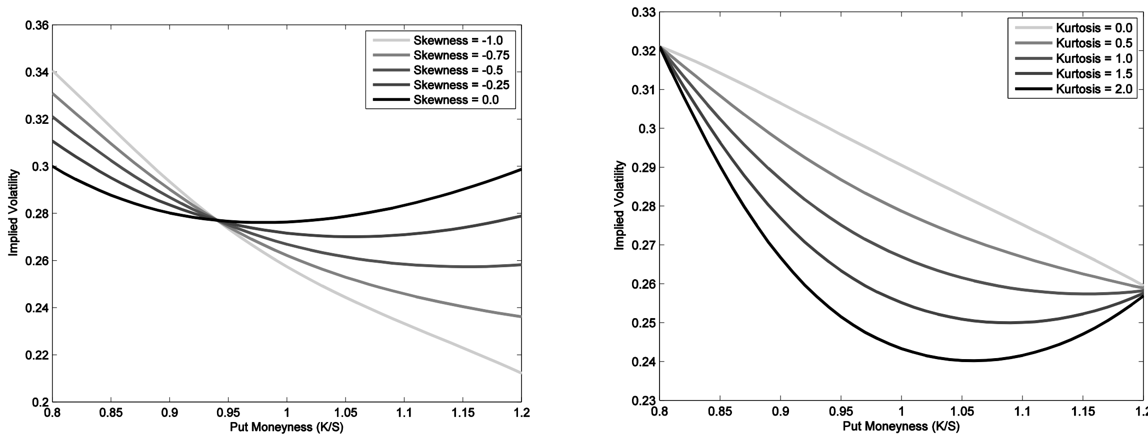

Figure 2. Higher Moments of Underlying Asset Return, *IV slope* and *IV convexity*

This figure shows the effect of skewness and excess kurtosis of underlying asset returns on *IV slope* and *IV convexity*. The base parameters are consistent with those of Figure 1 and 2. We take 0.8, 1.0 and 1.2 as the moneyness (K/S) points for *IV slope* and *IV convexity*, respectively.

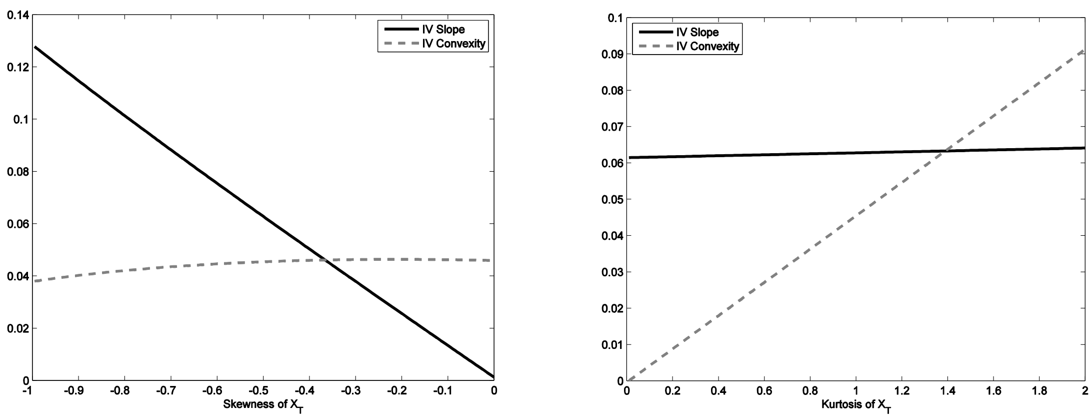

Figure 3. Impact of ρ and σ_v on *IV slope* and *IV convexity* in the SV Model

This figure shows the effect of ρ and σ_v on *IV slope* and *IV convexity* in the SV model given by (4)-(5). The base parameter set $(S, v_0, \kappa, \theta, \sigma_v, \rho, T, r, q) = (100, 0.01, 2.0, 0.01, 0.1, 0.0, 0.5, 0.0, 0.0)$ is taken from Heston (1993).

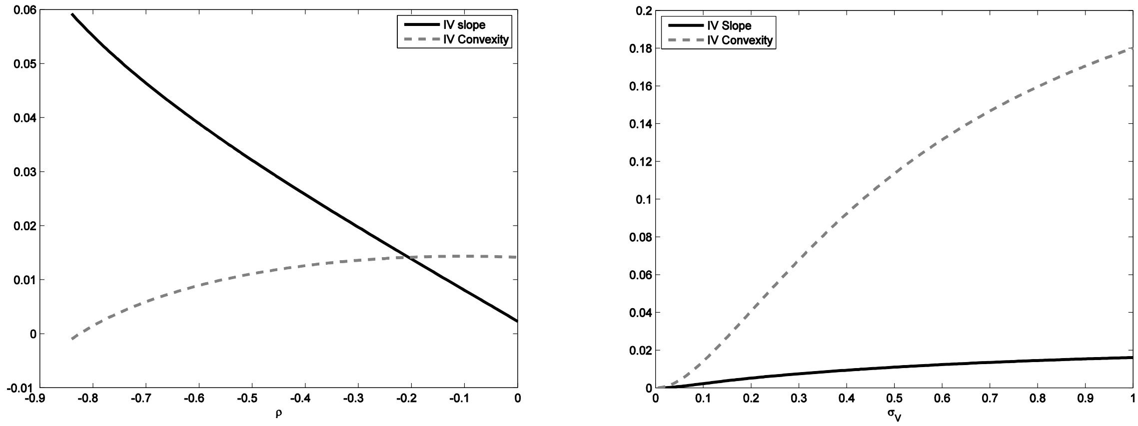

Figure 4. The Impacts of μ_J and σ_J on *IV slope* and *IV convexity* in the SVJ Model

This figure shows the effect of μ_J and σ_J on *IV slope* and *IV convexity* in the SVJ model given by (6)-(7). The base parameter set $(S, v_0, \kappa, \theta, \sigma_v, \rho, \lambda, \mu_J, \sigma_J, T, r, q) = (100, 0.094^2, 3.99, 0.014, 0.27, -0.79, 0.11, -0.12, 0.15, 0.5, 0.0319, 0.0)$ is taken from Duffie, Pan and Singleton (2000).

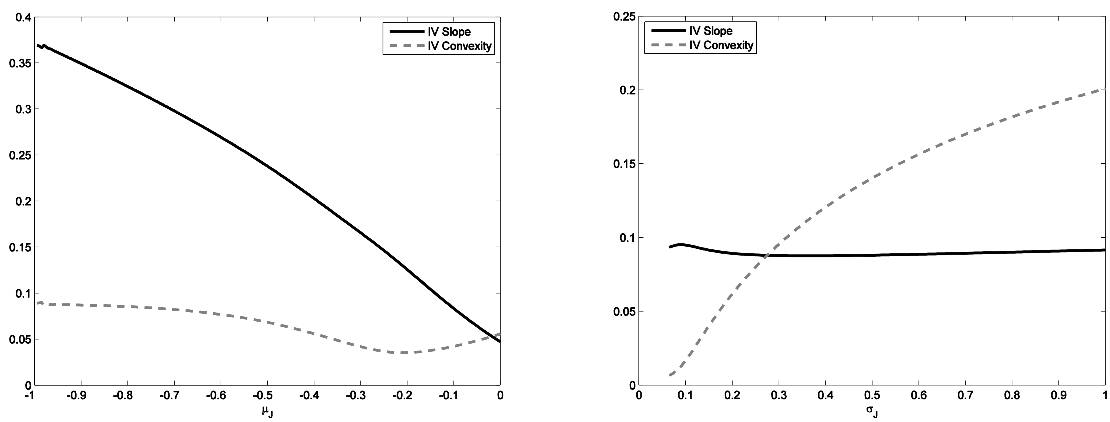

Figure 5. Average *IV convexity* and quintile portfolio returns

This figure shows the time-series behavior of the average *IV convexity* and returns of quintile portfolios from Jan 2000 to Dec 2013. Panel A plots the monthly average *IV convexity* of the quintile portfolios. Panel B shows the monthly average returns of the long-short portfolios Q1-Q5.

Panel A. Average *IV convexity* of quintile portfolios

Panel B. Returns of Q1-Q5

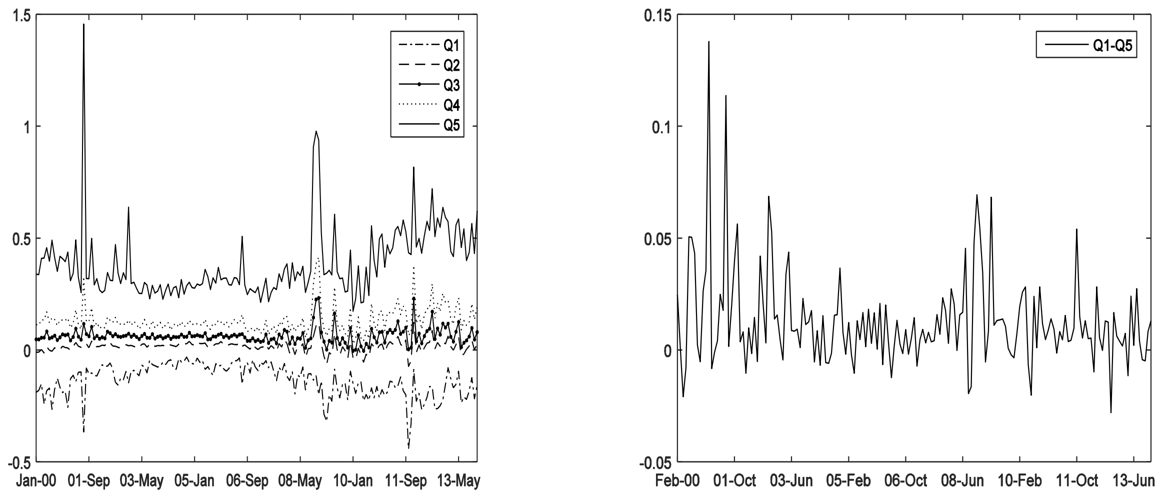

Figure 6. Monthly returns formed on *IV convexity* with different forecasting horizons

This figure shows the monthly average returns and risk-adjusted returns (using Fama-French 3 and 4 factor models) of the long-short *IV convexity* portfolios for various forecasting horizons based on Table 12 results. Q1-Q5 plots the average monthly returns of the long short *IV convexity* portfolio during Jan 2000 to Dec 2013. α_{FF3} and α_{FF4} plots the risk-adjusted (using Fama-French 3 and 4 factor models) monthly returns of the long-short *IV convexity* portfolios for the same period. The 95% and 99% confidence intervals are reported in each figure.