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RESEARCH ARTICLE

Exploring Downside Co-Skewness and Upside Co-Kurtosis: Implications for Asset Pricing Models

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Abstract: This study examines how the investors' preferences for downside co-skewness and upside co-kurtosis may influence the asset pricing. We analyze data from 2000 to 2021, encompassing 2874 companies listed on the Shanghai Stock Exchange. Our methodology includes both time series and cross-sectional analyses, employing the Fama-Macbeth approach. Our findings reveal that the estimated values for downside co-skewness and upside co-kurtosis contribute to a significant premium, one that remains unexplained by traditional market factors such as size, value, profitability, and investment. Furthermore, when these higher-order co-moments are incorporated into the Capital Asset Pricing Model (CAPM), they demonstrate significant explanatory power in understanding the variations in stock returns. This augmented CAPM, with downside co-skewness and upside co-kurtosis, exhibits a superior goodness-of-fit compared to conventional asset pricing models. This suggests a crucial link between these higher-order risk factors and stock valuation, offering new insights into the complexities of investor behavior and market dynamics.

Keywords: Downside co-skewness, Upside co-kurtosis, Augmented CAPM, Asset pricing.
JEL Classification Codes: C1, G12

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1. Introduction

Asset pricing has garnered significant attention within the field of finance, given its crucial role in investment decisions. Numerous models of asset pricing have been developed, with the inaugural mean-variance model crafted by Markowitz (1952). Afterward, Sharpe (1964) and Lintner (1965) developed the CAPM, a famous and widely used model; however, its empirical performance has not been satisfactory (Fama and French, 1992).

Following the failure of CAPM in empirical studies, many asset pricing models have been developed, which are extensions of CAPM. These models can broadly be categorized in two groups (Dong, Kot, Lam and Yu 2022). The first group includes three-factor model and five-factor model (Fama and French, 1993, 2015), which added different factors on the basis of characteristics of firms. The other group has focused on higher order moments and co-moments.

It is well documented and shown in the empirical literature that the distribution of stock returns is not normal (Smith 2007; Doan, Lin and Zurbrueg 2010; Kostakis, Muhammad and Siganos 2012; Boudt, Lu and Peeters 2015), indicating that the mean and variance (first two moments) cannot sufficiently describe the distribution of stock returns. Thus, there is a need for analyzing the higher moments. Measure of skewness (third moment) indicates whether the distribution is asymmetric between left and right tails, while the measure of kurtosis (fourth moment) indicates whether the distribution has fatter or lighter tails than normal. Like covariance measure, co-skewness and co-kurtosis are measured between two variables.

Co-skewness and co-kurtosis have been incorporated in the previous empirical studies of asset pricing (e.g., Harvey and Siddique 2000; Adesi, Gagliardini and Urga 2004; Smith 2007; Saranya and Prasanna 2014; Arif and Sohail 2020; Ahadzie and Jeyasreedharan 2023). However, literature shows that the standard higher order co-moments do not accurately reflect investors' preferences. The investors may be averse to downside (left tail) co-skewness and upside (fat tail) co-kurtosis. Galagadera and Brooks (2007) investigate the practical accuracy of asset pricing models, specifically those incorporating various iterations of third-order co-moments within a downside framework. They conclude that downside co-skewness stands out as a predominant explanatory factor.

Although upside co-kurtosis has been recognized as an important factor in investment decisions, this factor has not been empirically examined in asset pricing models. In our study, we examine asset pricing implications of investors' preference with respect to downside co-skewness and upside co-kurtosis for shares listed on the Shanghai stock exchange.

2. Literature Review & Hypotheses

Investment decisions were viewed to be based on the average returns only. Markowitz (1952) introduced riskiness while Tobin (1958) introduced a risk-free option of investment in investment decisions. The CAPM introduced the relationship between the stock returns and market returns, which is useful for predicting stock prices.

For improving the performance in predicting asset prices, the CAPM has been extended to include more factors in the model. Banz (1981) added the size factor only, while Fama and French (1993) added size and value factors in CAPM, and this model is referred to as three-factor model. By adding two more factors, namely profitability and investment, Fama and French (2015) introduced five factor model.

Many studies have been conducted on the three-factor model and five factor model (e.g., Conley, Hansen and Rossi 2012; Saranya and Prasanna 2014; Lohano and Kashif 2019; Hou and Chen 2021; Yu 2021; Mosoeu and Kodongo 2022; Martinez-Blasco, Serrano, Prior, and Cuadros 2023) and concluded that the performance of these multi-factor models is better than the CAPM. These multi-factor models include different factors measured on the basis of firms' characteristics.

The other type of extension of CAPM has focused on higher co-moments, such as co-skewness and co-kurtosis in asset pricing models. Various empirical studies have incorporated higher co-moments using single-country data or multiple-country data. Using data from Russian Stock Market, Teplova and Shutova (2011) compared different specification of the models and found that the investors assign value to downside risk and higher co-moments. Chhapra and Kashif (2019) investigated the implications of risk-averse investor's preferences for downside risk and higher co-moments using data from Pakistan and found that the investors assign value to these characteristics. Alles and Murray (2013) investigated emerging Asian markets and found that the investors assign value to downside risk and co-skewness. Huynh and Nguyen (2018) explored the impact of higher co-moments on weekly stock returns across 25 emerging stock markets from 2005 to 2017. They found that models incorporating higher co-moments offer a more comprehensive explanation for securities in emerging markets compared to the traditional CAPM. Using data from Australia and United States, Doan, Lin and Zurbruegg (2009) compared model specification with higher co-moments and found that the investors in Australia assign value to co-skewness while the investors in the US assign value to co-kurtosis. Dong, Kot, Lam and Yu (2022) examined the influence of co-skewness on stock returns in both the Chinese and U.S. markets. Their findings indicate that co-skewness negatively affects expected returns in these markets. Investors in both markets seek higher returns for stocks displaying more pronounced negative co-skewness.

The investor's preferences may not be reflected in these higher co-moments, as the investors may be averse to downside co-skewness and upside co-kurtosis. Very limited studies exist to empirically examine the role of downside higher comments. Using data from 27 emerging markets, Galagadera and Brooks (2007) conducted an empirical study and found that the downside co-skewness has significant explanatory power. Hafsa and Hmaied (2012) conducted an empirical study and conclude that, in the presence of non-normal returns, incorporating downside beta and downside higher-order co-moments is crucial and exhibit superior performance compared to the conventional models. Although upside co-kurtosis has been recognized as an important factor in investment decisions, this factor has not been empirically examined in asset pricing models.

3. Methods

This section provides a detailed overview of the data and methods used in this study. We describe the data source, define the estimators of various co-moments, and describe the construction of decile portfolios and the process of factor loading.

3.1. Data Sources

For this study we collect the monthly data for 2874 companies which are listed on the Shanghai Stock Exchange from January 2000 to December 2021. We collected data for all companies including dead and alive companies to avoid survivorship bias. For the dead companies, we set the stock returns equal to – 1 for the month when the company becomes dead, as suggested in the literature (e.g., Soares and Stark 2009). In table 1, we present detailed information of the data. Panel A presents the data used for computing higher co-moments and decile portfolios. Panel B presents the data used for constructing factors including market, size, value, profitability, and investment.

Table 1: ***Data Sources and Description***

Variable Name	***Code***	***Description***	***Source of data***
		A. Data used for computing returns	
Closing Price	P	The monthly closing stock prices of last working day of the month for a total of 2874 companies, spanning both financial and non-financial sectors, have been gathered.	Thomson Reuters Datastream
Risk-free Rate	CHIBOR6M & SHIBOR6M	Prior to 2006, SHIBOR was synonymous with CHIBOR.	Federal Reserve Economic Data
Market Returns	CHSASHR	All-share index for Shanghai Stock Exchange, utilized in the computation of excess returns for portfolio construction	Thomson Reuters Datastream
		B. Accounting data used for constructing factors	
total assets	(WC02999)	Total assets, found on the balance sheet.	Thomson Reuters Datastream
book value	(WC03501)	Common equity denotes the investment made by common shareholders in a company.	Thomson Reuters Datastream
number of shares	NOSH	This corresponds to the overall count of common shares, symbolizing the capital of the company.	Thomson Reuters Datastream
EBT= Net income + tax	(WC01651) +(WC01451)	Earning before tax EBT is the accounting data, so we use proxy as net income plus tax	Thomson Reuters Datastream

3.2. Estimation of Higher Co-Moments

We estimate the co-skewness (CSK) and co-kurtosis (CKT) using the Harvey and Siddique (2000) approach with the following equations, respectively.

$$CSK_i = \frac{E[\varepsilon_{i,t}\varepsilon_{m,t}^2]}{\sqrt{E}[\varepsilon_{i,t}^2]E[\varepsilon_{m,t}^2]} \tag{1}$$

$$CKT_i = \frac{E[\varepsilon_{i,t}\varepsilon_{m,t}^3]}{\sqrt{E}[\varepsilon_{i,t}^2]E[\varepsilon_{m,t}^3]} \tag{2}$$

where $\varepsilon_{m,t}$ is equal to excess market return in month t minus the average value over the corresponding window of observations t - 60 to t, while $\varepsilon_{i,t}$ denotes residuals computed from following regression.

$$R_{i,t} - R_t^f = \alpha_i + \beta_{i,m}(R_{m,t} - R_t^f) + \varepsilon_{i,t} \tag{3}$$

3.3. Estimation of Downside Co-Skewness and Upside Co-Kurtosis

We estimate the downside co-skewness and upside co-kurtosis using the Hogan and Warren (1974) approach with the following equations, respectively.

$$DCSK_i = \frac{E\left[(R_i - R_f)\{\min(R_m - R_f, 0)\}^2\right]}{E\,[\min(R_m - R_f, 0)]^3} \tag{4}$$

$$UCKT_i = \frac{E\left[(R_i - R_f)\{\max(R_m - R_f, 0)\}^3\right]}{E\,[\max(R_m - R_f, 0)]^4} \tag{5}$$

In equation (4), the measure of downside co-skewness includes only non-positive excess market returns while the positive values are replaced with 0. In equation (5), the measure of upside co-kurtosis includes only non-negative excess market returns while the negative values are replaced with 0.

3.4. Portfolio Construction

3.4.1 Decile Portfolio Constructions

After obtaining the four characteristics including CSK, CKT, downside CSK and upside CKT values, we constructed decile portfolios using the post ranking or single sorting method on each of four characteristics. This involves sorting all stock returns in ascending order based on the all four characteristic values for each stock at time t, as well as the market value sorted at time t-1, to compute the sorted portfolio returns at time t. The data is then divided into ten portfolios, or deciles (P1-P10). Portfolio returns are computed using equally weighted (EW) and value-weighted (VW) estimator.

3.4.2 Factors Loading

In this research, our approach involves utilizing monthly excess returns from a portfolio as the dependent variable in all models. We define the market factor as the average excess returns in the market. To derive the size, value, profitability, and investment factors, we analyze returns from 18 distinct portfolios. These portfolios are formed based on specific company characteristics: size (measured by market capitalization), value (evaluated through book-to-market value), profitability (gauged by operating profit), and investment (assessed by the rate of change in total assets). We categorize each factor into several groups: size into small and big; value into high, neutral, and low; profitability into robust, neutral, and weak; and investment into conservative, neutral, and aggressive. For portfolio construction, we merge size categories with each of the value, profitability, and investment categories, resulting in 18 unique combinations. These include six combinations for size with value (SH SN SL and BH BN BL), size with profitability (SR SN SW and BR BN BW), and size with investment (SC SN SA and BC BN BA). Consequently, we form 18 portfolios corresponding to these combinations and use them to calculate the size, value, profitability, and investment factors.

We compute size factor, referred to as small minus big, as follows:

$$SMB_{i,t} = \frac{SMB_{(HML)} + SMB_{(RMW)} + SMB_{(CMA)}}{3} \tag{6}$$

In the above equation, the numerator is computed using the following equations:

$$SMB_{(HML)} = \frac{(SL+SN+SH)-(BL+BN+SH)}{3} = \frac{(SL-BL)+(SN-BN)+(SH-BH)}{3} \tag{7}$$

$$SMB_{(RMW)} = \frac{(SR+SN+SW)-(BR+BN+SW)}{3} = \frac{(SR-BR)+(SN-BN)+(SW-BW)}{3} \tag{8}$$

$$SMB_{(CMA)} = \frac{(SC+SN+SA)-(BC+BN+SA)}{3} = \frac{(SC-BC)+(SN-BN)+(SA-BA)}{3} \tag{9}$$

Value factor, referred to as high minus low (HML), is computed as follows:

$$HML_{i,t} = \frac{(SH+BH)-(SL+BL)}{2} \tag{10}$$

Profitability factor, referred to as robust minus weak (RMW), is computed as follows:

$$RMW_{i,t} = \frac{(SR+BR)-(SW+BW)}{2} \quad (11)$$

Investment factor, referred to as conservative minus aggressive (CMA), is computed as follows:

$$CMA_{i,t} = \frac{(SC+BC)-(SA+BA)}{2} \quad (12)$$

4. Empirical Results

4.1 Performance of Portfolios

In table 2, we present the performance of portfolios sorted by co-skewness using data from January 2000 to December 2021 on Shanghai Stock Exchange. The average monthly returns with equally weighted (EW) and value-weighted (VW) of portfolio stocks are sorted into deciles based on co-skewness values. Portfolio P1 has the most negatively co-skewed values, whereas portfolio P10 signifies those with the most positively co-skewed values. To determine whether portfolio P1 generates higher average excess returns compared to portfolio P10, we calculate the difference in average returns between them. The difference is significant at 5 percent for EW but not significant for VW. Additionally, table 2 also reports the average market value (MV) in million yuans of shares in each portfolio P1 to P10. The results show that MV is highest in portfolio P10. We find that the difference in MV between portfolios P1 and P10 is negative and statistically significant at the 1 percent level. Table 2 also presents the CAPM beta estimates for the VW portfolio returns. The findings indicate that the portfolio containing shares with the most negatively co-skewed values displays a considerably higher beta compared to the portfolio comprising shares with the most positively co-skewed values. The difference in beta estimates between them is significant only at 10 percent.

Table 3 presents the performance of portfolios sorted by co-kurtosis. In this case also, we construct ten decile portfolios. Portfolio P1 has the most negative co-kurtosis values, while portfolio P10 includes those with the most positive co-kurtosis values. In assessing whether portfolio P1 delivers higher average excess returns compared to portfolio P10, we calculate the disparity in average returns between these two. The estimated difference is not significant for both EW and VW. Moreover, table 3 reports the average market value (MV) in million yuans of shares in each portfolio P1 to P10. The results show that MV is highest in portfolio P1. We find that the difference in MV between portfolio P10 and portfolio P1 is negative and statistically significant at 5 percent level. Table 3 also provides the CAPM beta estimates for VW portfolio returns. The results reveal that the portfolio containing shares with the most negative co-kurtosis values exhibits a lower beta compared to the portfolio consisting of shares with the most positive co-kurtosis values. Nevertheless, the disparity in beta estimates between them lacks statistical significance.

Table 4 presents the performance of portfolios sorted by downside co-skewness. In this case also, we construct ten decile portfolios. Portfolio P1 corresponds to portfolios with the most negative downside co-skewness values, whereas portfolio P10 signifies those with the most positive downside co-skewness values. We calculate the difference in average returns between portfolios P1 and P10 to determine whether portfolio P1 generates higher average excess returns compared to portfolio P10. The difference is statistically significant at the 1 percent level for both EW and VW portfolios. Furthermore, table 4 reports the average market value (MV) in million yuans of shares in each portfolio P1 to P10. The results show that MV is highest in portfolio P1. The difference in MV between portfolio P1 and portfolio P10 is positive and significant at 1 percent.

Table 4 also reports the CAPM beta estimates for VW portfolio returns. The findings indicate that portfolio P1 displays a lower beta compared to portfolio P10. The difference in beta estimates between P1 and P10 is negative and significant at the 1 percent level. The CAPM beta estimates suggest that portfolio P10 would have higher average returns compared to Portfolio P1. However, Table 4 contradicts this by revealing a significant downside co-skewness premium in the Shanghai Stock market. Shares with the most positive downside co-skewness command a premium, indicating an incentive for investors to retain them. Conversely, this investor is willing to receive a significantly lower return in order to retain shares characterized by the most positive downside co-skewness values. The difference of returns portfolios P1 and P10 is 10.34 percent per annum, which is significant at 1 percent. As in Harvey and Siddique (2000), our research also finds that the investors would demand a premium to bear the risk associated with negative downside co-skewness in returns.

Conversely, these investors are willing to accept a reduced return for shares with positive downside co-skewness in returns.

Table 5 presents the performance of portfolios sorted by upside co-kurtosis. In this case also, we also construct ten decile portfolios. Portfolio P1 corresponds to portfolios with the most negative upside co-kurtosis values, while portfolio P10 includes those with the most positive upside co-kurtosis values. In examining whether portfolio P10 delivers higher average excess returns compared to portfolio P1, we calculate the difference in average returns between them. The estimated difference is statistically significant for both EW and VW portfolios. Moreover, table 5 reports the average market value (MV) in million yuans of shares in each portfolio P1 to P10. The results show that MV is highest in portfolio P1. We find that the difference in MV between portfolios P10 and P1 is significant at 1 percent. Table 5 also reports the CAPM beta estimates for the VW portfolio returns and the results shows that the portfolio containing the shares with the most negative upside co-kurtosis values portfolio has lower beta relative to the portfolio of shares with the most positive upside co-kurtosis values portfolio. The difference in beta estimates between them is significant at 1 percent.

Table 2: ***Performance of portfolios sorted by Co-Skewness***

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P1-P10	t-stat
Excess EW Returns %	12.44	14.07	11.85	12.91	7.97	10.07	10.06	11.12	10.46	5.73	6.71	2.04
Excess VW Returns %	5.28	12.44	7.95	8.84	5.59	3.77	3.24	7.43	3.38	3.21	2.07	1.11
MV (million yuans)	1.515	0.912	0.856	0.870	0.824	0.866	0.840	1.089	1.571	3.192	-1.68	-5.14
CAPM Beta	1.08	1.08	0.97	1.05	0.99	1.01	1.02	1.02	0.99	0.99	0.09	1.87

Notes: EW, VW and MV denote for equally weighted, value-weighted, and market value respectively. Returns are per annum.
Source: Authors' computation using data from 2000 to 2021 on Shanghai Stock Exchange.

Table 3: ***Performance of portfolios sorted by Co-Kurtosis***

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
Excess EW Return %	8.57	12.04	10.22	11.80	10.53	12.93	12.10	11.33	10.40	6.73	-1.84	-0.57
Excess VW Returns %	5.55	12.88	2.20	5.00	3.66	11.45	5.91	4.67	3.38	4.25	-1.30	-0.65
MV (¥millions)	2.54	1.54	1.11	0.93	0.86	0.82	0.79	0.91	1.19	1.86	-0.68	-2.25
CAPM Beta	0.99	1.07	1.00	1.04	1.04	1.05	0.98	1.03	1.03	1.04	-0.06	1.21

Notes: EW, VW and MV denote for equally weighted, value-weighted, and market value respectively. Returns are per annum.
Source: Authors' computation using data from 2000 to 2021 on Shanghai Stock Exchange.

Table 4: ***Performance of portfolios sorted by Downside Co-Skewness***

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P1-P10	t-stat
Excess EW Return %	22.28	18.42	13.75	13.14	11.02	8.72	10.28	6.66	7.45	-2.09	24.37	3.48
Excess VW Returns %	14.28	8.28	6.90	7.55	5.86	6.19	5.74	-1.11	3.38	3.94	10.34	2.76
MV (¥millions)	1.54	1.33	1.12	0.90	0.88	0.72	0.68	0.65	0.62	0.74	0.80	8.16
CAPM Beta	0.63	0.80	0.87	0.97	1.04	1.09	1.17	1.15	1.21	1.28	-0.65	-9.66

Notes: EW, VW and MV denote for equally weighted, value-weighted, and market value respectively. Returns are per annum.
Source: Authors' computation using data from 2000 to 2021 on Shanghai Stock Exchange.

Table 5: ***Performance of portfolios sorted by Upside Co-Kurtosis***

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	t-stat
Excess EW Return %	0.93	6.56	8.61	9.53	12.62	13.39	11.74	13.73	13.15	17.89	16.96	2.21
Excess VW Returns %	-2.74	1.85	2.34	4.10	7.28	6.78	4.73	7.38	3.38	8.94	11.68	1.65
MV (¥millions)	0.901	0.706	0.732	0.658	0.639	0.831	0.811	1.175	1.209	1.491	-0.589	6.34
CAPM Beta	0.62	0.82	0.85	0.89	0.95	1.01	0.97	1.02	1.11	1.32	-0.70	9.48

Notes: EW, VW and MV denote for equally weighted, value-weighted, and market value respectively. Returns are per annum.
Source: Authors' computation using data from 2000 to 2021 on Shanghai Stock Exchange.

4.2 Time Series Analysis

In this section, we conduct the time-series analysis for the ten portfolios that we constructed based on co-skewness, co-kurtosis, downside co-skewness, and upside co-kurtosis measures correspondingly. For time series analysis, we estimate the three common asset pricing models including CAPM, three-factor model, and five-factor model using following equations, respectively.

$$R_{i,t} - R_t^f = \alpha_i + \beta_{i,m}(R_{m,t} - R_t^f) + u_{i,t} \quad (13)$$

$$R_{i,t} - R_t^f = \alpha_i + \beta_{i,m}(R_{m,t} - R_t^f) + \beta_{i,smb}SMB_t + \beta_{i,hml}HML_t + u_{i,t} \quad (14)$$

$$R_{i,t} - R_t^f = \alpha_i + \beta_{i,m}\left(R_{m,t} - R_t^f\right) + \beta_{i,smb}SMB_t + \beta_{i,hml}HML_t + \beta_{i,rmw}RMW_t + \beta_{i,cma}CMA_t + u_{i,t} \quad (15)$$

In the above equations, $R_{i,t}$ is the return of portfolio i in month t, R_t^f is the risk-free returns for month t, $R_{m,t}$ is the market portfolio return in month t, and $SMB_t, HML_t, RMW_t \; and \; CMA_t$ are the size, value, profitability, and investment factors, respectively. We estimate the above models using generalized method of moments with Newey-West approach of heteroscedasticity and serial correlation corrected standard errors. For time analysis, we test the significance of the difference in alpha coefficient between two extreme decile portfolios and also test the joint significance of all alpha coefficients in the ten portfolios.

Table 6 presents the estimates of alpha coefficients for ten portfolios sorted based on co-skewness. The table is divided into two panels: Panel A details the results for equally weighted (EW) portfolios while Panel B focuses on value-weighted (VW) portfolios. In the case of EW, the disparity in the alpha coefficient between portfolios P1 and P10 is statistically significant at the 5 percent level when analyzed using the CAPM, and at the 10 percent level under the three-factor model. However, this difference does not hold statistical significance in the context of the five-factor model. On the other hand, Panel B indicates that for VW, the alpha coefficient difference is not statistically significant across all asset pricing models examined. Additionally, the last column of Table 6 highlights that the alpha coefficients for the ten portfolios, in both EW and VW, are not jointly significant across all models, as shown in Panels A and B, respectively. This suggests a nuanced understanding of how co-skewness impacts portfolio performance under different asset pricing frameworks.

Table 7 reports the estimates of alpha coefficients of the ten portfolios sorted based on co-kurtosis. Panel A and panel B report the results for the EW and VW portfolios, respectively. The results for EW portfolios show that the difference in alpha coefficient between portfolios P10 and P1 is not statistically significant for all three asset pricing models. Furthermore, as shown in Panel B, for VW portfolio, the difference is statistically significant only for CAPM. The results in last column of table 7 show that alpha coefficients of the ten portfolios are jointly significant only in the five-factor model for EW portfolios, reported in panel A. For the VW portfolios, reported in panel B, all alpha coefficients are jointly significant in all three asset pricing models.

Table 8 presents the estimates of alpha coefficients for ten portfolios sorted based on downside co-skewness, for EW and VW in panel A and panel B, respectively. Notably, for both EW and VW portfolios, there is a statistically significant difference in the alpha coefficients between portfolios P1 (most negative downside co-skewness) and P10 (most positive downside co-skewness) across all three asset pricing models examined. For EW, this difference amounts to an annualized rate of 24.33 percent under the CAPM, 25.41 percent under the three-factor model, and 22.47 percent under the five-factor model. Similarly, for VW, the annualized difference is 18.68 percent under the CAPM, 16.04 percent under the three-factor model, and 13.60 percent under the five-factor model. These substantial disparities underscore the significant economic and statistical premium of portfolios with the most negative downside co-skewness over those with the most positive downside co-skewness on the Shanghai Stock Exchange. This premium persists beyond the market, size, value, profitability, and investment factors.

Further, the last column of Table 8 reveals that the alpha coefficients for the ten portfolios are jointly significant across all three asset pricing models, for both EW and VW portfolios, as indicated in panels A and B. This suggests that portfolios constructed using downside co-skewness estimates yield returns that cannot be fully explained by the standard asset pricing models. This result strongly supports the view that downside co-skewness is a priced factor in the Shanghai Stock Exchange, contributing to anomalous returns that challenge the explanatory scope of conventional asset pricing theories.

Table 9 reports the estimates of alpha coefficients of the ten portfolios sorted based on upside co-kurtosis. Panel A and panel B report the results for the EW and VW portfolios, respectively. The results for EW portfolios show that the difference in alpha coefficient between portfolios P10 and P1 is statistically significant for the CAPM and three-factor model. For the VW portfolios, the difference is statistically significant for the CAPM only. These findings show some evidence for the argument that the portfolio with most negative upside co-kurtosis is significantly priced (lower premium) as compared to the portfolio with most positive upside co-kurtosis on Shanghai Stock Exchange.

The findings presented in the last column of Table 9 reveal a noteworthy observation: the alpha coefficients of the ten portfolios, when considered collectively, are jointly significant across all three asset pricing models, but this significance is observed only in the case of equally weighted (EW) portfolios. This pattern indicates that portfolios formed on the basis of upside co-kurtosis estimates are associated with anomalous returns, which extend beyond what is typically explained by conventional asset pricing models. Such a result underscores the argument that upside co-kurtosis represents an additional dimension of risk, one that investors on the Shanghai Stock Exchange appear to price into their valuation of assets.

Table 6: ***Alpha Estimates from Portfolios sorted by Co-Skewness***

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P1-P10	Wald Chi2
Panel A: EW												
CAPM α (%)	12.308	13.943	11.709	12.777	7.840	9.952	9.938	11.020	10.342	5.637	6.672	13.72
	(1.89) *	(2.07) **	(1.77) *	(1.96)**	(1.16)	(1.52)	(1.53)	(1.68) *	(1.66) *	(0.91)	(2.05)**	[0.18]
3-Factor α (%)	14.645	15.299	13.555	15.063	10.979	12.681	12.603	14.866	13.593	7.176	7.469	12.68
	(2.16)**	(2.22)**	(2.00)**	(2.27)**	(1.62)	(1.90)*	(1.89) *	(2.07)**	(2.07)**	(1.11)	(1.85)*	[0.24]
5-Factor α (%)	12.034	10.769	10.680	12.354	8.315	9.914	10.684	12.706	12.890	5.623	6.411	10.84
	(1.60)	(1.38)	(1.42)	(1.64)*	(1.08)	(1.32)	(1.40)	(1.65)*	(1.72)*	(0.75)	(1.55)	[0.37]
Panel B: VW												
CAPM α (%)	5.154	12.317	7.831	8.731	5.467	3.646	3.146	7.348	3.127	0.627	4.527	13.410
	(0.79)	(1.86)*	(1.28)	(1.38)	(0.91)	(0.59)	(0.52)	(1.21)	(0.53)	(0.11)	(1.11)	[0.20]
3-Factor α (%)	5.154	12.317	7.831	8.731	5.467	3.646	3.146	7.348	3.127	0.627	4.527	12.26
	(1.27)	(2.03)**	(1.53)	(1.63)	(1.21)	(0.91)	(0.72)	(1.47)	(0.77)	(0.35)	(1.50)	[0.27]
5-Factor α (%)	6.383	11.025	8.344	7.756	5.532	3.993	4.095	7.839	4.163	2.225	4.158	11.64
	(0.86)	(1.45)	(1.19)	(1.02)	(0.80)	(0.56)	(0.58)	(1.08)	(0.64)	(0.34)	(1.01)	[0.31]

Notes: Alpha values are per annum. T-statistics are reported in parentheses and p-values are reported in brackets in the last column. *, **, and *** report that corresponding coefficients are statistically significant at 10%, 5%, and 1% levels, respectively. EW and VW denote for equally weighted and value-weighted, respectively

Source: Authors' computation using data from 2000 to 2021 on Shanghai Stock Exchange.

Table 7: ***Alpha Estimates from Portfolios sorted by Co-Kurtosis***

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	Wald Chi2
Panel A: EW												
CAPM α (%)	8.562	12.032	10.207	11.796	10.527	12.925	12.095	11.320	10.394	6.720	1.842	12.47
	(1.34)	(1.80)*	(1.49)	(1.76)*	(1.62)	(1.99)**	(1.87)*	(1.77)*	(1.67)*	(1.06)	(0.57)	[0.25]
3-Factor α (%)	9.935	13.536	12.517	14.092	12.526	15.468	15.785	14.551	13.565	8.567	1.368	13.91
	(1.51)	(1.98)**	(1.80)*	(2.07)**	(1.90)*	(2.32)***	(2.31)**	(2.17)**	(2.12)**	(1.29)	(0.33)	[0.17]
5-Factor α (%)	6.511	10.054	10.240	10.960	9.264	13.067	13.597	12.977	12.171	6.619	-0.108	16.75
	(0.86)	(1.31)	(1.28)	(1.41)	(1.22)	(1.77)*	(1.79)*	(1.71)*	(1.69)*	(0.86)	(-0.02)	[0.08]*
Panel B: VW												
CAPM α (%)	5.542	12.869	2.197	4.988	3.653	11.440	5.899	4.669	4.245	2.926	2.616	24.75
	(1.75)*	(1.48)	(1.57)	(1.49)	(0.92)	(1.48)	(1.07)	(0.85)	(0.59)	(-0.81)	(3.14)***	[0.01]
3-Factor α (%)	6.754	13.637	4.442	6.020	5.397	12.907	7.397	6.718	6.187	5.486	1.268	21.74
	(1.10)	(2.01)**	(0.71)	(0.95)	(0.86)	(2.07)**	(1.24)	(1.09)	(1.03)	(0.89)	(0.29)	[0.02]
5-Factor α (%)	4.449	10.943	3.836	4.214	4.664	12.209	6.291	5.745	4.954	4.252	0.197	18.190
	(0.62)	(1.47)	(0.53)	(0.56)	(0.62)	(1.72)*	(0.90)	(0.79)	(0.71)	(0.63)	(0.05)	[0.05]

Notes: Alpha values are per annum. T-statistics are reported in parentheses and p-values are reported in brackets in the last column. *, **, and *** report that corresponding coefficients are statistically significant at 10%, 5%, and 1% levels, respectively. EW and VW denote for equally weighted and value-weighted, respectively.
Source: Authors' computation using data from 2000 to 2021 on Shanghai Stock Exchange.

Table 8: ***Alpha Estimates from Portfolios sorted by Downside Co-Skewness***

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P1-P10	WaldChi2
Panel A: EW												
CAPM α (%)	22.132	18.302	13.616	13.015	10.902	8.604	10.143	6.555	7.337	-2.198	24.331	38.84
	(3.75)***	(3.19)***	(2.34)***	(2.12)**	(1.70)*	(1.30)	(1.42)	(0.91)	(0.97)	(1.46)	(3.49)***	[0.00]***
3-Factor α (%)	26.963	21.087	15.279	15.166	12.667	10.384	12.106	8.454	10.040	1.557	25.406	37.41
	(3.44)***	(3.40)***	(2.51)***	(2.39)***	(1.96)*	(1.55)	(1.68)*	(1.15)	(1.31)	(0.19)	(3.07)***	[0.00]***
5-Factor α (%)	23.970	18.870	13.035	13.224	9.650	7.521	7.874	4.522	7.199	1.501	22.470	23.73
	(3.16)***	(2.77)***	(1.94)*	(1.87)*	(1.31)	(0.97)	(0.95)	(0.54)	(0.81)	(0.16)	(2.65)***	[0.01]***
Panel B: VW												
CAPM α (%)	14.173	8.182	6.808	7.452	5.764	6.076	5.614	-1.192	3.860	-4.510	18.683	26.600
	(2.70)***	(1.65)*	(1.26)	(1.28)	(0.92)	(0.92)	(0.80)	(-0.17)	(0.51)	(-0.58)	(2.77)***	[0.00]***
3-Factor α (%)	14.895	8.811	6.828	8.021	7.378	7.413	7.460	0.422	6.897	-1.145	16.040	24.260
	(2.67)***	(1.72)*	(1.25)	(1.36)	(1.16)	(1.12)	(1.07)	(0.06)	(0.91)	(-0.15)	(2.38)***	[0.00]***
5-Factor α (%)	12.052	8.097	5.587	6.785	5.759	5.913	6.288	-2.669	4.866	-1.550	13.601	21.790
	(1.99)*	(1.35)	(0.88)	(0.99)	(0.77)	(0.76)	(0.77)	(-0.34)	(0.55)	(-0.17)	(1.79)*	[0.02]***

Notes: Alpha values are per annum. T-statistics are reported in parentheses and p-values are reported in brackets in the last column. *, **, and *** report that corresponding coefficients are statistically significant at 10%, 5%, and 1% levels, respectively. EW and VW denote for equally weighted and value-weighted, respectively.
Source: Authors' computation using data from 2000 to 2021 on Shanghai Stock Exchange.

Table 9: ***Alpha Estimates from Portfolios sorted by Upside Co-Kurtosis***

Notes: Alpha values are per annum. T-statistics are reported in parentheses and p-values are reported in brackets in the last column. *, **, and *** report that corresponding coefficients are statistically

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	Wald Chi2
Panel A: EW												
CAPM α (%)	0.918	6.553	8.606	9.520	12.612	13.382	11.736	13.725	13.145	17.875	-16.957	17.92
	(0.15)	(1.07)	(1.38)	(1.50)	(1.95)*	(2.02)**	(1.74)*	(2.01)**	(1.88)*	(2.13)**	(-2.22)**	[0.06]*
3-Factor α (%)	6.778	8.922	11.095	11.549	15.268	16.010	13.867	15.850	14.783	18.526	-11.749	17.590
	(1.04)	(1.40)	(1.71)*	(1.77)*	(2.26)**	(2.33)***	(2.04)**	(2.27)**	(2.12)**	(2.31)***	(-1.77)*	[0.06]*
5-Factor α (%)	5.743	5.397	7.642	8.217	12.761	13.023	10.837	13.226	11.747	16.729	-10.985	18.06
	(0.88)	(0.79)	(1.07)	(1.13)	(1.68)*	(1.66)*	(1.36)	(1.64)	(1.43)	(1.72)*	(-1.48)	[0.05]***
Panel B: VW												
CAPM α (%)	-2.745	1.849	2.334	4.093	7.273	6.779	4.719	7.368	8.933	9.596	-12.342	8.950
	(-0.49)	(0.32)	(0.40)	(0.68)	(1.19)	(1.08)	(0.80)	(1.20)	(1.40)	(1.20)	(-1.65)*	[0.53]
3-Factor α (%)	1.111	4.588	4.798	6.055	8.597	8.005	6.013	7.295	9.729	9.977	-8.865	5.57
	(0.19)	(0.77)	(0.79)	(0.97)	(1.35)	(1.31)	(1.01)	(1.22)	(1.56)	(1.33)	(-1.29)	[0.84]
5-Factor α (%)	-1.498	2.674	2.858	3.955	6.504	7.444	4.448	8.180	9.921	10.596	-12.093	6.05
	(-0.24)	(0.42)	(0.42)	(0.57)	(0.91)	(1.07)	(0.64)	(1.15)	(1.34)	(1.17)	(-1.57)	[0.81]

significant at 10%, 5%, and 1% levels, respectively. E.W and VW denote for equally weighted and value-weighted, respectively.
Source: Authors' computation using data from 2000 to 2021 on Shanghai Stock Exchange.

4.3 Cross-Sectional Analysis

4.3.1 CAPM, Three-Factor Model and Five-Factor Model

In the contrast to the previous section that conducted time series analysis of portfolios sorted based on co-skewness, co-kurtosis, downside co-skewness and upside co-kurtosis values, this section examines whether the cross-sectional variation in these portfolio returns can be explained. For cross-sectional analysis, we follow the approach developed by Fama and MacBeth (1973) regressions using these portfolios. In the first stage, we estimate beta coefficients by time-series regressions for each of ten portfolios, as given in the equations (13) to (15).

In the second stage, we estimate cross-sectional regressions of portfolio returns on the beta coefficients, which were estimated in the first stage. The cross-sectional regression models for the three asset pricing models including CAPM, three-factor model, and five-factor model are specified in the following equations, respectively.

$$R_{i,t} - R_t^f = \lambda_0 + \lambda_{m,t}\,\hat{\beta}_{i,m} + v_{i,t} \tag{16}$$

$$R_{i,t} - R_t^f = \lambda_0 + \lambda_{m,t}\,\hat{\beta}_{i,m} + \lambda_{smb,t}\,\hat{\beta}_{i,smb} + \lambda_{hml,t}\,\hat{\beta}_{i,hml} + v_{i,t} \tag{17}$$

$$R_{i,t} - R_t^f = \lambda_0 \lambda_{m,t}\,\hat{\beta}_{i,m} + \lambda_{smb,t}\,\hat{\beta}_{i,smb} + \lambda_{hml,t}\,\hat{\beta}_{i,hml} + \lambda_{rmw,t}\,\hat{\beta}_{i,rmw} + \lambda_{cma,t}\,\hat{\beta}_{i,cma} + v_{i,t} \tag{18}$$

Using these equations, λ coefficients are estimated using data on portfolio returns and estimated beta coefficients from the first stage.

Table 10 and 11 present the results of the cross-sectional analysis for both equally weighted (EW) and value-weighted (VW) portfolios constructed by co-skewness and co-kurtosis, respectively. The results in both tables show that λ_0 is not statistically significant in all three asset pricing models for both EW and VW portfolios, indicating λ_0 is equal to zero, as desired based on the finance theory (Kostakis, Muhammad & Siganos, 2012). However, the factors of the models are not statistically significant except for CAPM, where the adjusted R-squared is low. The findings suggest that the CAPM, three-factor, and five-factor models are inadequate in accounting for the cross-sectional variations in asset returns. This implies that well-known asset pricing models suffer from model misspecification issues and lack certain risk factors that could more effectively explain the observed diversity in cross-sectional asset returns.

Table 12 and 13 present the results of the cross-sectional analysis for both EW and VW portfolios constructed by downside co-skewness and upside co-kurtosis, respectively. The results in both tables show that λ_0 is not statistically significant in almost all asset pricing models for both EW and VW portfolios, indicating λ_0 is equal to zero. However, the factors of the models are statistically significant in some models. The factors are statistically significant in the three-factor model, as shown in table 12 for downside co-skewness portfolios, and in the CAPM, as shown in table 13 for upside co-kurtosis portfolios. Furthermore, the adjusted R-squared is still low but has improved as compared results presented in tables 10 and 11 for co-skewness and co-kurtosis.

Table 10: ***Cross-Sectional Tests for Portfolios sorted by Co-Skewness***

	λ_0	λ_m	λ_{smb}	λ_{hml}	λ_{cma}	λ_{rmw}	R^2	$Adj\ R^2$
Panel A: EW								
CAMP	-0.003	0.054						
	(-0.41)	(1.30)					0.23	0.13
FF3F	0.000	0.032	0.007	0.014				
	(-0.01)	(0.49)	(0.45)	(0.51)			0.43	0.15
FF5F	0.006	-0.051	0.036	0.039	-0.002	-0.002		
	(0.55)	(-0.68)	(1.46)	(1.22)	(-0.21)	(-0.30)	0.62	0.14
Panel B: VW								
CAPM	-0.004	0.043						
	(-0.81)	(1.71) *					0.21	0.13
FF3F	-0.004	0.056	-0.013	0.007				
	(-0.65)	(2.22) **	(-1.13)	(0.60)			0.42	0.18
FF5F	0.001	0.010	-0.016	0.010	0.032	-0.033		
	(0.12)	(0.27)	(-1.38)	(0.67)	(2.74)***	(-2.54)***	0.62	0.15

Notes: Lambda values are per annum. T-statistics are in parentheses. *, **, and *** report that corresponding coefficients are statistically significant at 10, 5, and 1 percent, respectively. E.W and VW denote for equally weighted and value-weighted, respectively.
Source: Authors' computation using data from 2000 to 2021 on Shanghai Stock Exchange.

Table 11: ***Cross-Sectional Tests for Portfolios sorted by Co-Kurtosis***

	λ_0	λ_m	λ_{smb}	λ_{hml}	λ_{cma}	λ_{rmw}	R^2	$Adj\ R^2$
Panel A: EW								
CAMP	0.001	0.219						
	(0.22)	(2.91)***					0.17	0.18
FF3F	-0.004	0.036	0.016	0.000				
	(-0.69)	(1.83) *	(0.84)	(0.01			0.40	0.10
FF5F	-0.008	0.032	0.004	-0.029	0.009	-0.017		
	(-1.07)	(1.63) *	(0.22)	(-0.97)	(0.42)	(-0.80)	0.62	0.11
Panel B: VW								
CAPM	-0.006	0.053						
	(-1.03)	(2.55) ***					0.16	0.06
FF3F	-0.005	0.045	-0.009	-0.017				
	(-0.55)	(1.37)	(-0.53)	(-0.97)			0.36	0.04
FF5F	-0.016	0.073	0.008	-0.054	0.004	0.002		
	(-1.45)	(2.18)**	(0.38)	(-1.96)**	(0.31)	(0.15)	0.58	0.05

Notes: Lambda values are per annum. T-statistics are in parentheses. *, **, and *** report that corresponding coefficients are statistically significant at 10, 5, and 1 percent, respectively. E.W and VW denote for equally weighted and value-weighted, respectively.
Source: Authors' computation using data from 2000 to 2021 on Shanghai Stock Exchange.

Table 12: ***Cross-Sectional Tests for Portfolios sorted by Downside Co-Skewness***

	λ_0	λ_m	λ_{smb}	λ_{hml}	λ_{cma}	λ_{rmw}	R^2	$Adj\ R^2$
Panel A: EW								
CAMP	-0.036	0.242	-	-	-	-		
	(-2.30)***	(3.53)***	-	-	-	-	0.27	0.17
FF3F	0.003	0.049	-0.049	-0.076	-	-		
	(0.30)	(1.75)*	(-1.77)*	(-2.71)***	-	-	0.57	0.35
FF5F	0.007	-0.014	-0.039	-0.090	0.072	-0.039		
	(0.90)	(-0.27)	(-2.69)***	(-2.70)***	(1.99)**	(-2.47)***	0.71	0.35
Panel B: VW								
CAPM	-0.014	0.111	-	-	-	-		
	(-1.70)*	(3.36)***	-	-	-	-	0.14	0.04
FF3F	-0.002	0.048331	-0.010	0.023	-	-		
	(-0.40)	(1.94)*	(-0.62)	(1.43)	-	-	0.63	0.17
FF5F	-0.002	0.048	-0.010	0.023	0.017	-0.009		
	(-0.40)	(1.94)*	(-0.89)	(1.43)	(0.96)	(-0.74)	0.64	0.18

Notes: Lambda values are per annum. T-statistics are in parentheses. *, **, and *** report that corresponding coefficients are statistically significant at 10, 5, and 1 percent, respectively. E.W and VW denote for equally weighted and value-weighted, respectively.
Source: Authors' computation using data from 2000 to 2021 on Shanghai Stock Exchange.

Table 13: ***Cross-Sectional Tests for Portfolios sorted by Upside Co-Kurtosis***

	λ_0	λ_m	λ_{smb}	λ_{hml}	λ_{cma}	λ_{rmw}	R^2	$Adj\ R^2$
Panel A: EW								
CAMP	-0.011	0.103	-	-	-	-		
	(-1.10)	(1.80)*	-	-	-	-	0.290	0.20
FF3F	0.005	0.036	-0.019	-0.001	-	-		
	(0.50)	(0.73)	(-0.89)	(-0.05)	-	-	0.54	0.32
FF5F	0.050	-0.170	-0.035	-0.037	0.04	0.01		
	(3.10)***	(-2.93)***	(-2.19)**	(-1.67)*	(2.40)***	1.10	0.70	0.34
Panel B: VW								
CAPM	0.003	-0.012	-	-	-	-		
	(0.40)	(-0.31)	-	-	-	-	0.11	0.00

FF3F	0.011	-0.038	-0.017	0.016	-	-		
	(1.40)	(-1.00)	(-0.82)	(0.77)	-	-	0.45	0.18
FF5F	0.009	-0.034	-0.008	0.027	0.019	-0.012		
	(1.20)	(-0.82)	(-0.65)	(0.95)	(1.82)*	(-0.85)	0.66	0.25

Notes: Lambda values are per annum. T-statistics are in parentheses. *, **, and *** report that corresponding coefficients are statistically significant at 10, 5, and 1 percent, respectively. E.W and VW denote for equally weighted and value-weighted, respectively.
Source: Authors' computation using data from 2000 to 2021 on Shanghai Stock Exchange.

4.3.2 Augmented CAPM

The analysis of cross-sectional models discussed above shows that the three asset pricing models are not able to sufficiently explain the variation in the portfolio returns. Thus, next we develop augmented CAPM model by adding factors based on the co-skewness, co-kurtosis, downside co-skewness, and upside co-kurtosis, and test their ability to explain the variation in the portfolio returns. We construct each of these four factors following the methodology outlined by Harvey and Siddique (2000) and Moreno and Rodriguez (2009). For constructing co-skewness factor, we sort all stocks for each month based on their co-skewness. We then extract the 15 percent of the shares which have the most positive co-skewness values, and the 15 percent of the shares which have the most negative co-skewness values. The co-skewness factor (*CSK*) is equal to the average return from the most negative co-skewness shares (CSK^{-}) minus the average returns from the most positive co-skewness shares (CSK^{+}). However, the average returns are computed by two methods, so we compute the co-skewness factor using both equally weighted and value-weighted returns. Following the above method, we construct co-kurtosis factor (*CKT*), downside co-skewness factor (*DCSK*), and upside co-kurtosis factor (*UCKT*).

After creating these factors, we incorporate them into the CAPM and estimated the augmented CAPM following the approach developed by Fama and MacBeth (1973) regressions. In the first stage, we estimate beta coefficients by time-series regressions as specified in equations (19) and (20).

$$R_{i,t} - R_t^f = \alpha_i + \beta_{i,m}\left(R_{m,t} - R_t^f\right) + \beta_{i,csk}\, CSK_t + \beta_{i,ckt}\, CKT_t + u_{i,t} \quad (19)$$
$$R_{i,t} - R_t^f = \alpha_i + \beta_{i,m}\left(R_{m,t} - R_t^f\right) + \beta_{i,dcsk}\, DCSK_t + \beta_{i,uckt}\, UCKT_t + u_{i,t} \quad (20)$$

In the second stage, we estimate cross-sectional regressions of portfolio returns on the beta coefficients, which were estimated in the first stage, specified in equations (21) and (22).

$$R_{i,t} - R_t^f = \lambda_0 + \lambda_{m,t}\, \hat{\beta}_{i,m} + \lambda_{csk,t}\, \hat{\beta}_{i,csk} + \lambda_{ckt,t}\, \hat{\beta}_{i,ckt} + v_{P,t} \quad (21)$$
$$R_{p,t} - R_t^f = \lambda_0 + \lambda_m\, \hat{\beta}_m + \lambda_{dcsk}\, \hat{\beta}_{dcsk} + \lambda_{uckt}\, \hat{\beta}_{uckt} + v_{P,t} \quad (22)$$

Tables 14 to 17 present the results of the cross-sectional analysis for augmented CAPM. Tables 14 reports the results for augmented CAPM with market, co-skewness, and co-kurtosis factors, where the portfolios are sorted by co-skewness. Table 15 reports the results of the same model but the portfolios are sorted by co-kurtosis. Table 16 reports the results for augmented CAPM with market, downside co-skewness, and upside co-kurtosis factors, where the portfolios are sorted by downside co-skewness. Table 17 reports the results of the same model, but the portfolios are sorted by upside co-kurtosis. These models have been estimated for equally weighted (EW) as well as value-weighted (VW) portfolios.

The results in table 14 show that the coefficient λ_0 is not statistically significant, suggesting that its value is effectively zero. This outcome holds true for both EW and VWs. In contrast, the market factor and co-kurtosis factor display statistical significance in this context. However, it's noteworthy that the co-skewness factor does not achieve statistical significance for either portfolio type. Moving to table 15, the findings take a different turn. Here, λ_0 is statistically significant for EW portfolios, indicating its non-zero impact in this setting. Yet, for VW portfolios, λ_0 maintains its lack of statistical significance. Additionally, most of the other factors analyzed in this table do not demonstrate statistical significance. These results collectively suggest a nuanced interplay between various factors in asset pricing models.

The results in panel A of table 16 show that λ_0 is not statistically significant, indicating λ_0 is equal to zero. The new factors, downside co-skewness and upside co-kurtosis factors, have statistically significant explanatory power with downside co-skewness portfolio returns. The table also presents the results of restricted model where we impose $\lambda_0 = 0$. In this case, we also find that both new factors are statically significant. The results in panel B show that λ_0 is not statistically significant. The market factor and downside co-skewness are statistically significant for both unrestricted and restricted models.

The results in panel A of table 17 show that λ_0 is not statistically significant, indicating λ_0 is equal to zero. The market factor and upside co-kurtosis factors are statistically significant. When we out restriction $\lambda_0 = 0$, we find that upside co-kurtosis is statically significant. The results in panel B show that λ_0 is not statistically significant. The upside co-kurtosis factor is statistically significant for both unrestricted and restricted models.

The adjusted R-squared is a useful measure of a goodness of fit for comparing different models which have different number of explanatory variables. The results show that the adjusted R-squared in the augmented CAPM with downside co-skewness and upside co-kurtosis factors is higher relative to almost all other models.

Table 14: ***Cross-Sectional Tests with CSK and CKT factors for Portfolios Sorted by Co-Skewness***

			Panel A: EW			
	λ_0	λ_m	λ_{csk}	λ_{ckt}	R^2	$Adj\ R^2$
Augmented CAPM Unrestricted	-0.004	0.080	-0.002	-0.030		
	(-0.55)	(2.58)***	(-0.29)	(-2.85)***	0.53	0.30
Augmented CAPM Restricted	-	0.064	-0.005	-0.027		
	-	(2.78)***	(-0.87)	(-2.70)***		
			Panel B: VW			
Augmented CAPM Unrestricted	-0.001	0.083	0.011	-0.069		
	(-0.23)	(3.40)***	(0.99)	(-2.57)***	0.52	0.28
Augmented CAPM Restricted	-	0.077	0.010	-0.069		
	-	(3.15)***	(0.88)	(-2.64)***		

Notes: Lambda values are per annum. T-statistics are in parentheses. *, **, and *** report that corresponding coefficients are statistically significant at 10, 5, and 1 percent, respectively. E.W and VW denote for equally weighted and value-weighted, respectively.
Source: Authors' computation using data from 2000 to 2021 on Shanghai Stock Exchange.

Table 15: ***Cross-Sectional Tests with CSK and CKT factors for Portfolios Sorted by Co-Kurtosis***

			Panel A: EW			
	λ_0	λ_m	λ_{csk}	λ_{ckt}	R^2	$Adj\ R^2$
Augmented CAPM (Unrestricted)	0.034	-0.084	-0.010	0.015		
	(2.86)***	(-2.24)***	(-1.20)	(1.51)	0.51	0.26
Augmented CAPM (Restricted)	-	0.051	-0.003	0.007		
	-	(1.79)*	(-0.61)	(0.75)		
			Panel B: VW			
Augmented CAPM (Unrestricted)	0.011	-0.052	-0.016	0.016		
	(1.40)	(-1.32)	(-1.66)*	(1.42)	0.46	0.19
Augmented CAPM (Restricted)	-	0.002	-0.002	0.017		
	-	(0.08)	(-0.24)	(1.47)		

Notes: Lambda values are per annum. T-statistics are in parentheses. *, **, and *** report that corresponding coefficients are statistically significant at 10, 5, and 1 percent, respectively. E.W and VW denote for equally weighted and value-weighted, respectively.
Source: Authors' computation using data from 2000 to 2021 on Shanghai Stock Exchange.

Table 16: ***Cross-Sectional Tests with CSK and CKT factors for Portfolios Sorted by Downside Co-Skewness***

	λ_0	λ_m	λ_{dcsk}	λ_{uckt}	R^2	$Adj\ R^2$
Panel A: EW						
Augmented CAPM (Unrestricted)	0.003	0.027	0.017	0.027		
	(0.36)	(0.97)	(3.52)***	(1.88)*	0.57	0.36
Augmented CAPM (Restricted)	-	0.036	0.018	0.027		
	-	(1.23)	(3.53)***	(2.15)**		
Panel B: VW						
Augmented CAPM (Unrestricted)	0.001	0.059	0.012	-0.006		
	(0.13)	(2.22)**	(2.38)***	(-0.22)	0.53	0.30
Augmented CAPM (Restricted)	-	0.054	0.012	0.000		
	-	(1.98)**	(2.40)***	(-0.01)		

Notes: Lambda values are per annum. T-statistics are in parentheses. *, **, and *** report that corresponding coefficients are statistically significant at 10, 5, and 1 percent, respectively. E.W and VW denote for equally weighted and value-weighted, respectively.
Source: Authors' computation using data from 2000 to 2021 on Shanghai Stock Exchange.

Table 17: ***Cross-Sectional Tests with CSK and CKT factors for Portfolios Sorted by Co-Kurtosis***

	λ_0	λ_m	λ_{dcsk}	λ_{uckt}	R^2	$Adj\ R^2$
Panel A: EW						
Augmented CAPM (Unrestricted)	0.017	-0.074	0.002	0.012		
	(1.34)	(-2.04)**	(0.10)	(2.25)**	0.57	0.35
Augmented CAPM (Restricted)	-	-0.029	-0.017	0.012		
	-	(-0.82)	(-1.09)	(2.22)**		
Panel B: VW						
Augmented CAPM (Unrestricted)	-0.000	-0.033	-0.009	0.009		
	(-0.02)	(-0.90)	(-0.60)	(1.69)*	0.49	0.24
Augmented CAPM (Restricted)	-	-0.032	-0.008	0.009		
	-	(-1.02)	(-0.81)	(1.69)*		

Notes: Lambda values are per annum. T-statistics are in parentheses. *, **, and *** report that corresponding coefficients are statistically significant at 10, 5, and 1 percent, respectively. E.W and VW denote for equally weighted and value-weighted, respectively.
Source: Authors' computation using data from 2000 to 2021 on Shanghai Stock Exchange.

5. Conclusion

Empirical studies have consistently demonstrated that stock return distributions deviate from normality, underscoring the importance of examining higher moments like skewness and kurtosis. The concepts of co-skewness and co-kurtosis have been integrated into asset pricing models, yet existing literature suggests that these standard higher-order co-moments may not fully capture investors' preferences. In our study, we delve into the asset pricing implications of investors' preferences concerning co-skewness and co-kurtosis, with a specific focus on downside co-skewness and upside co-kurtosis. Using data from companies listed on the Shanghai Stock Exchange, our analysis seeks to offer a more nuanced understanding of how these downside and upside higher-order co-moments influence investor decision-making in this market context. This approach aims to bridge the gap between theoretical asset pricing models and the actual behavioral patterns observed among investors, particularly in the context of Chinese equity markets.

This research represents a significant addition to the existing body of literature by highlighting the pivotal role of downside co-skewness and upside co-kurtosis in asset pricing. Our findings reveal that the premiums associated with estimated downside co-skewness and upside co-kurtosis are substantial and cannot be fully explained by traditional factors such as market, size, value, profitability, and investment. Moreover, when these elements are incorporated into the CAPM, there is a notable enhancement in its explanatory power regarding the cross-section of stock returns. This augmented CAPM, featuring downside co-skewness and upside co-kurtosis, not only provides a more comprehensive understanding of stock returns but also demonstrates a superior fit compared to other asset pricing models. This suggests that accounting for these higher-order moments is crucial for a more accurate and thorough understanding of asset pricing dynamics, especially in complex and evolving market conditions.

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