The International Journal of Business and Finance Research ♦ Volume 6 ♦ Number 1 ♦ 2012

ARE DOWNSIDE HIGHER ORDER CO-MOMENTS PRICED? : EVIDENCE FROM THE FRENCH MARKET

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ABSTRACT

This study examines the role of downside higher order co-moments in asset pricing models when stock returns are not normal. We test the effect of higher order downside co-moments using a data set of daily returns of Société des Bourses Françaises 250 Index stocks during the period 1987-2009. The results suggest that the downside Beta and higher order co-moments in the downside framework should be considered together when returns are non normal and that they out-perform the traditional beta.

JEL: G12, G15, C21

KEYWORDS: downside Beta, downside higher order co-moments, CAPM, French stock market.

INTRODUCTION

The capital asset pricing model (CAPM) developed by Sharpe (1964) and Lintner (1965) is still the most widely used approach for relative asset pricing, sharing a common idea of the mean-variance efficient portfolio as initiated by Markowitz (1952). The theory predicts that variance is the only measure of risk and the investor chooses his optimal portfolio according to the mean-variance approach implying that the returns are normal or investors have a quadratic utility function.

However several researches report the inadequacy of the variance for two main reasons: first the CAPM may be limited when the assumption of normality of returns distribution is not met. In fact there have been many empirical studies (Mandelbrot, 1963; Fama, 1965; and Levy, 1969) that present evidence of non- normality of return distributions and particularly showed that return distributions are asymmetric and fat tailed. Also it was established that investors have non-quadratic utility functions. This implies that the variance is not sufficient to capture the empirical shape characteristics (asymmetry and fat tail) of the distribution and all moments of the returns distribution should be considered. so there is no reason to stop at the two first moments the mean and the variance (Rubinstein, 1973 and Scott &Horvath, 1980).

Another limitation of the CAPM is the variance is not consistent with investors' perception of risk as long as it considers upside and downside variations both as undesirable events. Rational investors are only sensitive to losses or downside variations. This is a powerful argument for rejecting variance and replacing it by measures of downside risk.

A growing literature argue that, when returns are not normal, higher-order co-moments matter to risk-averse investors and that they are relevant in explaining stock returns. Kraus and Litzenberger (1976), Harvey and Siddique (2000) among others introduce co-skewness into asset pricing models to take into account the asymmetry. Others have looked at co-kurtosis (Fang and Lai, 1997; Dittmar, 2002; Chung, Johnson and Schill, 2006…) to account for the leptokurticity of the returns distribution. However, we suggest that the standard higher order moments present the same limitation as the variance and, therefore, they do not accurately reflect investors' preferences for minimizing only possible losses. For example, the kurtosis identifies extreme gains as well as extreme losses as undesirable events whereas individuals are concerned only about the left tail of returns and hence only about the extreme losses. For this reason, we introduce downside higher order co-moments in pricing models instead of standard higher order co-moments. Downside higher order co-moments enable us to account, both, for the investors' perception of risk and for the non normality of returns distribution.

In this paper, we investigate the risk return relation in a downside framework using higher order co-moments. The aim is to show whether they significantly explain the cross section of daily stock returns on the French stock market and to investigate the extent that they out-perform traditional measures of market risk. For the cross sectional analyses conducted over the period 01/1987-12/2009, we use two methodologies; the first is the methodology used previously by Estrada (2002) which regresses mean returns on estimated measures of risk and the second is the Fama-MacBeth methodology. We find that the downside higher order co-moments, considered together, have additional explanatory power in explaining the cross section of returns. We also find that this result depends on market conditions.

The contribution of this paper is twofold; first it introduces new measures of risk that take into account both the investors' risk perception and the non normality of returns. Using the new measures of risk, the paper provides an explanation of the poor performance of the CAPM and downside CAPM especially when returns are non normal. Second, it is an innovating empirical investigation which contributes to the debate on whether systematic higher order co-moments are able to explain cross sectional stock returns in a downside framework in the French stock market. Therefore studying downside co-skewness and co-kurtosis may provide insight regarding additional factors that could improve the explanatory power of the CAPM and downside CAPM.

The reminder of this paper is organized as follows. Section 2 presents a literature review on downside risk measures. The data and the methodology will be briefly presented in section 3 and the empirical results are discussed in section 4. In Section 5 and 6 some sensitivity analysis to the regression methodology used and to downturns periods of the market are conducted. Finally, section 7 concludes the paper.

LITERATURE REVIEW

The theoretical and empirical attack on the traditional mean-variance model motivated researchers to investigate alternatives to the variance measure of risk. Roy (1952) first suggested the idea of "Safety First". According to this concept individuals consider only outcomes below a certain value defined as a "disaster" and seek to minimize the probability of falling below this level without paying attention to the utility function.

Recognizing the importance of Roy's approach (1952) to describe in an adequate way to perceive risk, Markowitz (1959) realized that investors are interested in minimizing downside risk for two reasons: (1) only downside risk or safety first is relevant to an investor and (2) security returns distribution may not be normally distributed. Therefore a downside risk measure would help investors make proper decisions when faced with a non normal security returns distribution. He proposed an alternative measure of risk called semivariance that weights downside losses differently from upside gains. Statistically, the semivariance is defined as the squared deviation of returns below a target return.

Research on downside risk measures has continued with the development of lower partial moment (LPM) risk measures by Bawa (1975) and Fishburn (1977). The LPM liberates the investor from a constraint of having only one utility function, which is fine if investor utility is best represented by a quadratic equation (variance or semivariance). Lower partial moments represent a significant number of the known Von Neumann-Morgenstern utility functions. Furthermore, the LPM represents the whole range of human behavior from risk seeking to risk aversion. Therefore LPM describes below target risk in terms of risk tolerance. Given an investor's risk tolerance value, the general measure, the lower partial moment, is defined as: $LPM(a,t) = \frac{1}{K}\sum_{T=1}^{K} Min[0,(R_T - t)]^a$, where K is the number of observations, R_T is the security return during time period T, t is the threshold or target return and *a* is the degree of the lower partial moment.

Hogan and Warren (1974) and Bawa and Lindenberg (1977) developed the mean-semivariance CAPM (MS CAPM). Their model preserves all key characteristics of the Mean-variance CAPM, including the two-fund separation principle, efficiency of the market portfolio and the linear risk return relationship. The only difference is the use of the relevant risk measures (semivariance and downside Beta instead of variance and regular beta). The importance of this difference depends on the shape of the returns distribution. For a normal returns distribution, regular beta and downside beta are identical. However, for skewed distributions such as the lognormal, the two models diverge.

Jahankhani (1976) was the first to perform empirical tests comparing the expected return-variance CAPM and the expected return-standard semivariance CAPM developed by Hogan and Warren (1974) using the Fama and Macbeth (1973) methodology. His sample contained all securities in the CRSP database for the period July 1947 to June 1969. The author fails to find any improvement over the traditional CAPM by using downside Beta. The study reveals the following results: (a) The linearity hypothesis between expected returns and downside beta cannot be rejected; (b) The residual hypothesis cannot be rejected; (c) There is a positive relationship between expected returns and downside beta. Price, Price and Nantell (1982) show that the regular beta systematically underestimates the downside beta for low-beta stocks and overestimates the downside beta for high-beta stocks. This finding may help explain why empirical tests of the CAPM find that low-beta stocks are systematically underpriced and high-beta stocks are overpriced (See for example Reinganum, 1981 and Fama and French, 1992). Harlow and Rao (1989) derive a LPM model for any arbitrary benchmark return, thus making the Hogan-Warren and the Bawa-Lindenberg models special cases of their general model. Their empirical tests reject the CAPM as a pricing model but cannot reject their version of the MLPM model.

Post and Van Vliet (2006) used monthly US security data for a long sample period (1926-2002). They used unconditional mean-variance (MV) and mean-semi-variance (MS) tests as well as conditional tests that account for the economic state-of-the-world. They concluded that the MS CAPM seems to capture better the cross section stock returns than the MV CAPM in explaining cross-sectional mean returns. Furthermore they inferred that the explanatory power of the conditional downside beta persists after controlling for size and momentum effects.

Taking into account the limitation of downside risk measures proposed by earlier studies, Estrada (2002) defined a systematic downside risk measure based on a different definition of cosemivariance. The main difference between the two definitions is that the Estrada cosemivariance between assets i and j and the one between assets j and i, are equal whereas it is not true for the cosemivariance used to estimate the downside beta of previous studies. Estrada (2001, 2002, 2004) reveal that downside risk measures excel over the standard risk measures in explaining variability in the cross-section of returns in emerging markets, industries in emerging markets and internet stocks. More recently, Estrada (2005) extended his database and added the entire MSCI of developed markets. The empirical evidence clearly supports the downside Beta and the pricing model based on it over the standard beta and CAPM for joint and separate samples of developed markets and Emerging markets.

Pederson and Hwang (2003) in an investigation of UK equity data show that even though the downside beta explains a proportion of equities over the CAPM beta the proportion of equities benefiting from using the downside beta is not large enough to improve asset pricing models significantly. Ang, Chen, and Xing (2005) find a similar result in the US market. They measured downside risk by correlations, conditional on downside moves of the market. The authors observed that the portfolio with the greatest downside stock correlations outperforms the portfolio with the lowest downside stock correlations and they suggested that this effect cannot be explained by the Fama and French (1993) factors.

Galagedera and Brooks (2007) investigate the issue of co-skewness as a measure of risk in a downside framework. They argue that downside co-variance and downside co-skewness between security returns and market portfolio returns may be alternative measures of downside risk. In other words, in a downside framework, it may be sufficient to include a measure that accounts for the co-semi-skewness in the pricing model rather than a measure of the co-semi-variance. They find that in the cross sectional analysis, downside co-skewness is a better explanatory variable of emerging market monthly returns than downside beta. The motivation behind this study is that securities returns distributions are not normal but they, are typically asymmetric and have fat tails. They also argued that the downside beta and the traditional co-skewness even though they both capture the asymmetry of the distribution they are distinct measures of risk. They explained that downside beta is explicitly conditional on market downside movements whereas the traditional co-skewness measure does not explicitly accentuate asymmetries across up and down markets and may be thought of as a symmetric measure of risk.

Although the downside beta and the downside co-skewness tell us something about the asymmetry of the returns distribution, they fall far short of specifying precisely the peekness encountered in empirical distributions. For this reason we consider the downside co-kurtosis besides the downside co-skewness proposed by Galagedera and Brooks (2007) in the pricing models. This enables us to detect with more precision the departure from normality. In the remainder of the paper, we will empirically analyze the role of downside higher order co-moments in explaining the cross sectional daily returns on the French market.

DATA AND MODELING FRAMEWORK

Sample and Data

This study explores daily security returns for the sample period 1987 to 2009. The sample period is selected to include the bear markets of 1987, 2000-2001 and 2009. We use all stocks of the SBF250 index. Only stocks that entered the index before the 1st of January 2000 and remained in the index until 31/12/2009 and with available market data are maintained in our sample. The composition of the SBF250 is available from 2000. Therefore, our sample is composed of 38 stocks. We investigate the French market for several reasons: (i) the traditional CAPM has failed to explain the variation in equity prices (Molay, 2002), (ii) returns distributions are found to be skewed and (most notably) fat tailed (Aparacio and Estrada, 2001), (iii) the introduction of higher order moments in asset pricing models have improved the explanatory power of the models on the French market (Lajili, 2005) and finally (iv) to our knowledge no other study has previously investigate the issue of higher order co-moments in a downside framework on this market. Daily data on closing prices and dividends are collected from the Datastream database. The yield on the 3-months Treasury bill is chosen to proxy for the risk free rate and the average return of the selected stocks is chosen to proxy for the market return. In order to check the performance of our results, we further use the CAC40 index to proxy the market returns. The results are similar but not reported here.

To investigate the normality assumption, we provide statistics for two standard tests of normality: the third and fourth sample moments against those of a normal distribution and the Jarque-Bera test. Table 1 presents summary statistics of daily returns of the 38 selected stocks and the results of the normality test.

The summary statistics show that daily returns have modest negative asymmetry in the sense of skewness. The values of excess kurtosis indicate clearly that all stocks have leptokurtic behavior which is described by fat tails in the literature. The results of Jarque Bera joint test of normality are consistent with the results of skewness and kurtosis, it strongly rejects normality for all selected stocks at the 1% level. Thus the main features of data are that returns are slightly asymmetric and have fat tails. This first empirical result supports the objective of our study and provides a strong argument to use higher order moments in asset pricing models.

Table 1: Summary Statistics of Securities Daily Returns

stock	rm*10³	Standard Deviation*10³	Skewness	Kurtosis	j-b statistic
accor	0.345	19.589	-0.05	3.997	4.492
air france klm	0.138	45.773	-4.222	469.09	61,853,100
air liquide	0.411	16.201	0.043	3.425	3,299
axa	0.392	23.574	0.249	7.804	17,183
bic	0.39	19.523	0.164	5.197	7,619
bongrain	0.154	19.324	-0.165	4.913	6,812
bouygues	0.46	22.66	0.36	6.338	11,434
carrefour	0.55	18.11	-0.113	4.451	5,581
casino guichard	0.384	19.51	0.158	4.234	5,066
cie gl de gphyq	-0.041	28.903	-0.189	5.628	8,940
ciments francai	0.392	23.929	-1.045	22.798	147,273
club mediterran	-0.159	22.661	-0.057	7.811	17,147
danone	0.402	15.445	0.015	3.961	4,409
eiffage	0.702	23.267	-0.777	25.455	182,761
essilor intl	0.454	18.77	0.121	5.753	9,318
esso	0.361	18.858	-0.124	11.358	36,268
faurecia	0.149	23.028	0.684	10.206	29,796
havas	0.097	25.013	0.039	4.422	5,496
imerys	0.531	21.846	0.115	5.432	8,305
l oreal	0.545	18.663	0.017	4.223	5,011
lafarge	0.412	20.602	-0.044	5.062	7,203
locindus	0.165	14.509	0.454	12.168	41,838
lvmh	0.536	20.058	0.12	8.457	20,112
michelin	0.327	22.174	-0.031	3.989	4,473
pernod ricard	0.512	18.885	-0.024	4.611	5,974
peugeot	0.412	21.032	0.001	5.238	7,710
ppr	0.542	22.154	0.225	5.492	8,532
seb	0.406	21.489	-0.102	7.149	14,373
safran	0.441	22.595	-0.81	21.566	131,430
sanofi aventis	0.446	19.021	0.049	3.618	3,681
schneider elect	0.651	22.29	-0.101	6.511	11,926
sodexo	0.417	19.04	-0.869	21.412	129,686
thales	0.34	22.13	-0.002	4.113	4,755
total	0.635	18.115	-0.012	3.816	4,092
unibail rodamco	0.532	15.708	0.004	4.568	5,863
valeo	0.236	22.773	-0.057	4.584	5,908
vallourec	0.694	27.427	-0.262	7.708	16,773
vivendi	0.275	21.484	-0.936	22.63	144,886
max	**0.702**	**45.773**	**0.684**	**469.09**	**61,853,100**
min	**-0.159**	**14.509**	**-4.222**	**3.425**	**3,299**
mean	**0.385**	**21.477**	**-0.189**	**20.242**	**1,656,277**
median	**0.408**	**21.258**	**-0.018**	**5.462**	**8,418**

The table report summary statistics of daily returns of the 38 selected stocks.over the full sample period going from January 1987 to December 2009

METHODOLOGY

Considering that downside measures more appropriately reflect the way investors perceive risk, we suggest that downside co-skewness and downside co-kurtosis should be included in pricing models to account for asymmetry and fat tails observed in stock returns data. To estimate the downside risk co-moments, we consider three well known measures proposed by Hogan and Warren (1974), Harlow and Rao (1989) and Estrada (2002). To provide measure of downside beta and substitute the standard beta, these studies assume perfect markets; a risk-free asset, homogeneous expectations and investors are downside risk averse.

Hogan and Warren (1974) defined the downside beta as:

$$\beta_{im}^{(HW)} = \frac{E\left[\left(R_i - R_f\right).min\left(R_m - R_f, 0\right)\right]}{E\left[min\left(R_m - R_f, 0\right)\right]^2} \tag{1}$$

R_i , R_m are the stock and the market return respectively and R_f the risk free rate.

Hogan and Warren (1974) used the risk-free rate as the benchmark return and consider it as the reasonable threshold that investors should at least guarantee, whereas Harlow and Rao (1989) argue that the relevant benchmark return implied by the data is related to equity mean returns rather than to the risk-free rate. However Estrada proposes a systematic downside risk measure defined by the ratio between an asset's semi-deviation of returns and the market's semi-deviation of returns.

To construct downside co-skewness and co-kurtosis, we follow Galagedera and Brooks (2007). We adopt the methodology of Rubinstein (1973) for building the standard higher order co-moments and adapt it to each of the considered downside risk measures. We propose the following measures. We define the downside co-skewness or the downside gamma corresponding to Hogan and Warren risk measure as:

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

Similarly the downside co-kurtosis or the downside delta corresponding to Hogan and Warren measure is defined as:

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

For clarity, we present here only the downside risk measures of Hogan and Warren. The other measures are presented in the appendix 2.

For testing the pricing of downside co-skewness and downside co-kurtosis in the cross-section, we adopt the procedure employed previously by Estrada (2002). For each stock, we compute the average return and estimate the risk measures considered in this study: beta, downside beta, downside gamma and downside delta using the full set of the sample data. Returns are regressed on each of the estimated risk measures. First, we estimate models with a single measure of risk in order to analyze the separately explanatory power of each of the considered measures of risk. Next we estimate models including jointly two or three measures of risk. This enables us to examine the incremental explanatory power of downside higher order co-moments in explaining the cross sectional of average returns. The present work employs the following regressions:

Model 1: $R_i = \lambda_0 + \lambda_1 \hat{\beta}_{im} + \varepsilon_i$

Model 2: $R_i = \lambda_0 + \lambda_2 \hat{\beta}_{im}^D + \varepsilon_i$

Model 3: $R_i = \lambda_0 + \lambda_3 \hat{\gamma}_{im}^D + \varepsilon_i$

Model 4: $R_i = \lambda_0 + \lambda_4 \hat{\delta}_{im}^D + \varepsilon_i$

Model 5: $R_{i,} = \lambda_0 + \lambda_2 \hat{\beta}_{\mathrm{im}}^{\mathrm{D}} + \lambda_3 \hat{\gamma}_{im}^D + \varepsilon_i$

Model 6: $R_i = \lambda_0 + \lambda_2 \hat{\beta}_{\mathrm{im}}^{\mathrm{D}} + \lambda_4 \hat{\delta}_{im}^D + \varepsilon_i$

Model 7: $R_i = \lambda_0 + \lambda_3 \hat{\gamma}_{im}^D + \lambda_4 \hat{\delta}_{im}^D + \varepsilon_i$

Model 8: $R_i = \lambda_0 + \lambda_2 \hat{\beta}^{\mathrm{D}}_{\mathrm{im}} + \lambda_3 \hat{\gamma}^{D}_{im} + \lambda_4 \hat{\delta}^{D}_{im} + \varepsilon_i$

Where R_i is the average stock return, β_{im} is the estimated standard beta, $\hat{\beta}^{D}_{im}$, $\hat{\gamma}^{D}_{im}$ and $\hat{\delta}^{D}_{im}$ are the estimated downside Beta, downside gamma and downside delta respectively. Here the index ***D*** indicates ***D***ownside and in what follows it will be replaced by HW, HR or E to refer to Hogan and Warren, Harlow and Rao or Estrada measures respectively.

λ_0, λ_1, λ_2, λ_3 And λ_4 are the parameters of the models estimated using the White's weighted least square method.

RESULTS AND DISCUSSION

Pair wise correlations between estimated measures of risk and the mean stocks return are not presented here but are available from authors upon request. They indicate clearly that the mean return has higher correlation with downside risk measures than with the standard beta. The results indicate also that for each of the three measures of risk, the downside co-moments (downside beta, gamma and delta) are highly correlated. We also find that the correlations between downside beta and downside gamma are higher than correlations between downside beta and downside delta or between downside gamma and downside delta for each of the considered measures of downside risk. This result is not surprising since downside beta and downside gamma, both have the potential to capture the same thing, the asymmetry of the returns distribution. For this reason Galagedera and Brooks (2007) state that "in pricing models in a downside framework it may be sufficient to include a risk measure that accounts for co-semi-variance or co-semi-skewness and not both".

In Table 2, we report estimates of the parameters of models 1 to 8. Panel A, B and C of Table 4 provides respectively the HW, HR and E parameters estimates. The three panels provide merely similar results. Table 2 shows that the standard beta fails to explain mean security returns in a cross section of data. Results reveal also that the downside beta and downside gamma (except the Estrada downside gamma) are potential explanatory variables of the variability of mean returns in the French stock market when they are considered separately in the pricing model.

In order to estimate the incremental explanatory power of downside gamma in explaining mean returns, we test the model introducing jointly the downside beta and downside gamma (Model 5). The results reveal that two variables remain significant at least at the 10% level and the explanatory power in terms of adjusted R^2 reaches more than 20% while it does not exceed 9% in case of single regression models (Models 2-3). This result means that the downside gamma have a significant additional explanatory power in explaining the variability of cross sectional security mean returns. We note as well that downside gamma has slightly more explanatory power than downside beta. Consistent with the results obtained by Galagedera and Brooks (2007) for emerging markets, our results reveal that the risk premium associated to downside beta is positive and the risk premium associated to downside gamma is negative when the two variables are considered together in the same pricing model.

Now considering only downside co-kurtosis (Model 4), the findings indicate that downside co-kurtosis has no significant explanatory power regardless of the model used. However, the later becomes significant when it is considered jointly with the downside beta or the downside gamma (Models 6- 7) and the two variables explain at least 30% of the variability of mean returns.

Finally, when all downside co-moments are jointly considered (Model 8), all the variables come out statistically insignificant for the HW and HR measures, however they are highly significant in the case of

Estrada measures and the total explanatory power of the model exceeds 50%. These ambiguous findings are likely due to high correlation between these three explanatory variables.

Table 2: Cross-sectional Analysis

Panel A: Cross Sectional Regressions Results for the HW-Measures							
Models	***λ0***	***λ 1***	***λ 2***	***λ 3***	***λ 4***	***Adj R2***	***F-stat***
Model 1	0.451***	-0.162				2.10%	1.78
	(3.64)	(-1.335)					
Model 2	0.593***		-0.296**			9.00%	4.65**
	(4.146)		(-2.157)				
Model 3	0.495***			-0.226**		9.30%	4.81**
	(4.223)			(-2.192)			
Model 4	0.419***				-0.14	2.80%	2.07
	(4.478)				(-1.442)		
Model 5	0.599***		0.79*	-1.079*		22.20%	6.27***
	(5.749)		(1.683)	(-1.956)			
Model 6	0.569***		0.358		-0.61**	31.30%	9.42***
	(6.201)		(1.2)		(-2.38)		
Model 7	0.575***			0.741	-0.998*	35.20%	11.03***
	(6.156)			(1.232)	(-1.817)		
Model 8	0.631***		0.023	0.333	-0.681	16.20%	3.39**
	(5.305)		(0.021)	(0.158)	(-0.612)		
Panel B: Cross Sectional Regression Results for the HR-measures							
Models	***λ0***	***λ 1***	***λ 2***	***λ 3***	***λ 4***	***Adj R2***	***F-stat***
Model 1	0.451	-0.162				2.10%	1.78
	(3.64***)	(-1.335)					
Model 2	0.548***		-0.253			5.80%	3.27*
	(3.765)		(-1.808*)				
Model 3	0.547***			-0.262**		8.60%	4.47**
	(4.155)			(-2.114)			
Model 4	0.359***				-0.095	3.50%	1.29
	(4.394)				(-1.138)		
Model 5	0.569***		1.237**	-1.507**		21.70%	6.13**
	(5.105)		(2.065)	(-2.546)			
Model 6	0.487***		0.624**		-0.796***	31.80%	9.64***
	(5.975)		(2.2)		(-3.2)		
Model 7	0.529***			1.007*	-1.217**	40.50%	13.6***
	(6.1)			(1.707)	(-2.275)		
Model 8	0.673***		1.043	-1.717	0.297	17.20%	3.56**
	(5.261)		(0.915)	(-0.811)	(0.27)		
Panel C : Cross Sectional Regressions Results for the E-measures							
Models	***λ0***	***λ 1***	***λ 2***	***λ 3***	***λ 4***	***Adj R2***	***F-stat***
Model 1	0.451***	-0.162				2.90%	2.09
	(3.64)	(-1.335)					
Model 2	0.680***		-0.333**			5.80%	3.27*
	(3.856)		(-2.146)				
Model 3	0.47***			-0.173		8.90%	4.6**
	(3.874)			(-1.448)			
Model 4	0.436***				-0.154	42.15%	2.35
	(4.396)				(-1.534)		
Model 5	0.538***		1.137*	-1.432**		21.70%	14.48***
	(3.252)		(1.721)	(-2.437)			
Model 6	0.565***		0.375		-0.653**	38.60%	12.63***
	(3.788)		(0.976)		(-2.113)		
Model 7	0.553***			0.809	-1.061*	31.80%	9.65***
	(4.511)			(1.19)	(-1.727)		
Model 8	0.495***		3.034***	-5.633***	2.25**	50.30%	13.5***
	(3.016)		(2.819)	(-2.833)	(2.171)		

*The table reports the estimates coefficients associated to each of the considered measures of risk expressed in percentages, their t-Statistics in parenthesis, the adjusted R^2 and the Fisher-statistics issued from the cross-sectional regressions of mean return on the estimated measures of risk over the models 1 to 8. The parameters are White heteroscedasticity–consistent. Pane1 A, B and C report results relative to HW, HR and E measures respectively. ***, ** and * denote significance at 1%, 5% and 10% level respectively.*

To mitigate this problem we perform the analysis by using orthogonalized components. This technique allows measuring the marginal effect of downside higher order co-moments. The explanatory variables considered here are downside beta, orthogonalized downside gamma ($o\gamma_{im}^D$) and orthogonalized downside delta($o\delta_{im}^D$). The downside gamma is defined as the component independent from the corresponding downside beta and downside delta. Explicitly, the orthogonalized gamma is equal to the intercept plus the individual residual from the cross-sectional regression $\gamma_{im}^D = a_0 + a_1\beta_{im}^D + a_2\delta_{im}^D + \epsilon_i$. Similarly the orthogonalized downside delta is defined as the component independent from the corresponding downside beta and downside gamma and it is equal to the intercept and residual from the cross-sectional regression $\delta_{im}^D = a_0 + a_1\beta_{im}^D + a_2\gamma_{im}^D + \epsilon_i$

Table 3 reports the results from regressions of Models 3 to 8 with the orthogonalized components. Several important findings can be drawn from the analysis; first we observe that downside beta remains statistically significant even when we consider with it the orthogonalized components of downside gamma or downside delta in pricing models considering HW and HR measures. This result is less obvious if we consider the Estrada measures. The downside beta is significant when considered alone becomes insignificant when we include the downside gamma or the downside delta.

The orthogonalized components of downside higher order co-moments are not priced when considered alone or jointly with the downside beta but they do when they are considered together in the same pricing model (Models 7 and 8). This implies they are complementary measures of risk and the isolated component of each do not contain information which is not included in the downside beta.

Overall we find evidence that Model 8 has the highest adjusted R^2 (50% for Estrada measures and 15.5% for HW and HR measures) indicating that the introduction of downside gamma and downside delta improve the explanatory power of the downside CAPM suggested by earliest studies. This finding suggests that the three downside co-moments should be considered in explaining cross sectional variation of selected security returns. Further when downside risk measures are priced, the premiums associated with them have the opposite sign (negative) of that expected. This result is counter intuitive but it is somewhat in line with the results of previous studies. Most interestingly, Artavanis and al. (2010) find that the slope coefficient of the downside Beta is negative in the French market (and also in the UK Market). This result could be explained by the fact that the market is not sufficiently mature to reveal the anticipated direction of the risk-return relationship.

Sensitivity Analysis to the Estimation Methodology

This section examines sensitivity of the results reported in the previous section to alternative regression estimation methodologies. Here we run the regression using the Fama and MacBeth (1973) two pass regression methodology often adopted by cross-sectional studies. For each stock the CAPM beta, the downside beta, gamma and delta are estimated using time series data over the previous 3-years period. Then, for each day inside the period 02/01/1987-31/12/2009, security returns in the subsequent testing period are cross sectionally regressed on the risk measure estimated over the previous estimation period. We repeat this process for all days in the sample period producing T sets of coefficient estimates. We then average the T estimates to produce a sample of Fama-MacBeth coefficient estimates.

Table 3: Results From Cross-Sectional Analysis Using Orthogonalized Components of the Downside Gamma and Downside Delta

Panel A : Cross Sectional Regressions Results for the HW- measures

Models	*λ0*	*λ 1*	*λ 2*	*λ 3*	*λ 4*	*Adj R2*	*F-stat*
Model 3	0.305***			0.684		0.10%	0.06
	(8.878)			(0.242)			
Model 4	0.312***				-0.922	1.00%	0.38
	(8.892)				(-0.621)		
Model 5	0.6***		-0.298**	0.676		7.40%	2.48
	(4.053)		(-2.216)	(0.249)			
Model 6	0.621***		-0.311**		-0.98	11.20%	3.34**
	(4.658)		(-2.548)		(-0.679)		
Model 7	0.424***			-14.228**	-8.347**	8.40%	2.69***
	(7.803)			(-2.264)	(-2.302)		
Model 8	0.586***		-0.165	-13.828*	-8.193**	15.25%	3.21**
	(5.234)		(-1.483)	(-1.865)	(-2.114)		

Panel B: Cross Sectional Regressions Results for the HR-measures

Models	*λ0*	*λ 1*	*λ 2*	*λ 3*	*λ 4*	*Adj R2*	*F-stat*
Model 3	0.305***			-0.168		0.10%	0.003
	(7.853)			(-0.061)			
Model 4	0.306***				-0.315	0.10%	0.05
	(8.073)				(-0.214)		
Model 5	0.563***		-0.259*	0.226		4.50%	1.87
	(3.571)		(-1.91)	(0.081)			
Model 6	0.588***		-0.283**		-0.593	7.00%	1.87
	(4.056)		(-2.174)		(-0.408)		
Model 7	0.306***			-16.198**	-8.897*	5.00%	1.98
	(9.494)			(-1.995)	(-1.919)		
Model 8	0.599***		-0.278**	-18.546**	-10.623**	15.50%	3.25**
	(4.979)		(-2.329)	(-2.067)	(-2.273)		

Panel C : Cross Sectional Regressions Results for the E- measures

Models	*λ0*	*λ 1*	*λ 2*	*λ 3*	*λ 4*	*Adj R2*	*F-stat*
Model 3	0.649***			-0.683**		9.30%	4.8**
	(3.983)			(-2.193)			
Model 4	0.376***				-0.044	1.00%	0.71
	(3.816)				(-0.847)		
Model 5	0.669***		-0.118	-0.447		7.40%	2.48*
	(3.465)		(-0.092)	(-0.168)			
Model 6	0.558***		0.617		-0.451**	40.00%	13.31*
	(3.585)		(1.265)		(-2.185)		
Model 7	0.582***			1.075	-0.396**	35.70%	11.26*
	(4.618)			(1.157)	(-2.105)		
Model 8	0.505***		2.806**	-4.702**	-0.46**	45.60%	11.34*
	(3.236)		(2.453)	(-2.235)	(-2.472)		

*This table reports the estimates coefficients, their t-Statistics in parenthesis, the adjusted R^2 and the Fisher-statistics issued from the cross-sectional regressions of mean return on beta ,downside beta and the orthogonalized components of downside gamma and downside delta over the models 3 to 8. The parameters are White heteroscedasticity–consistent. Pane1 A, B and C report results relative to HW, HR and E measures respectively.***, ** and * denote significance at 1%, 5% and 10% level respectively*

Panels A, B and C of Table 4 report the resulting average coefficients, statistic of Student –MacBeth, the average adjusted R^2 and the average Fisher statistics for HW, HR and E measures respectively. Although the regressions with the Fama-MacBeth methodology have slightly better explanatory power as measured by the adjusted coefficient of determination, the variables do not appear to be priced in any model except Model 7 which includes jointly the downside gamma and downside delta for whatever the approach used to measure risk. The downside gamma and delta are significant at 10 % (5%) level for HW and HR (E) measures. The results based on the Fama-MacBeth methodology support our earlier finding indicating that downside gamma and downside delta have significant explanatory power over cross-sectional variation in the Paris Bourse when they are jointly considered. However, there is a difference on the subject of the signs of the associated premium; in this case, as expected, we find a positive relation between returns and downside co-kurtosis as it is a risk enhancing and a negative relation between returns and downside coskewness.

Are Downside Co-Moments Due to Recession Market Periods?

In this study we investigate to what extent the results in previous section depend on market conditions. To test this we isolate the period of recession market times as the stock market crash of October 1987 in the last quarter of 1987, the downturns due to the deflation of dot-com bubble and the events of 11^{th} of September, 2001 covering 01/01/2001 to 31/01/2002 and finally the global financial crisis in middle 2007 to 2009.

The results are reported in Table 5 and reveal that none of the downside risk HW and HR measures is significant and the adjusted coefficient of determination is very low (expect for the E-downside gamma and downside delta when they are jointly considered). This result is expected and is in line with the findings of Post and Vliet (2006) which indicates that there is a near perfect relation between return and risk (measured by downside beta) during bad–states of the world advocating that downside risk measures are appropriate in pricing models only when the market is in decline. This result may be also due to the fact that the departure from normality becomes less pronounced when downturn periods are excluded. This is confirmed by the test of normality of returns according to the modified sample data that indicates that the skewness of the returns distribution is nearer to zero and overall kurtosis is weaker than it was for the full sample period showing that the returns distribution is less asymmetric and more peaked and thus weakens the motivation for using downside measures or higher order co-moments in pricing models.

CONCLUSION

In this study, we introduce in the CAPM downside beta, downside co-skewness and downside co-kurtosis to explain stock returns on the French market. We used the three well known measures of risk in a downside framework. In a first analysis we regressed average stock returns on the risk measures over several models. Consistent with previous studies, we find that the CAPM fails to explain the cross sectional variation in the observed returns. The empirical results also provide strong evidence in favor of using three downside co-moments to explain cross-sectional stock returns in the French market and reveal that they are complementary risk measures. Another ambiguous result is that the premium associated with downside co-moments have signs opposite expected. We argue that this result could be explained by the fact that the market is not sufficiently mature to reveal the anticipated direction of the risk-return relationship.

To investigate the sensitivity of our results to the methodology used, we repeated the study using the two pass methodology of Fama-MacBeth. The results provide further evidence to consider jointly the downside co-skewness and downside co-kurtosis in pricing models. Nevertheless we cannot really say that their role is sufficient in explaining economically and statistically cross sectional mean returns in the French market.

Finally we examined the effect of recession market periods on the results. We find that none of the considered measures of risk is priced when we exclude downturn periods that affected the French stock market. This result confirms the findings of Post and Vliet (2004) indicating that there is a near-perfect relation between returns and downside risk measure (downside beta) during bad-states of the world. We find also that the results seem to depend to some extent on the degree of the departure from normality.

Although a theoretical base and an economic and financial interpretation are in somewhat lacking, this study provides further evidence to the debate on whether systematic higher order co-moments are able to explain cross sectional security returns particularly in a downside framework for the French market. Our study is limited as it considers only a small sample of securities. Stronger evidence may be found with a larger sample.

Table 4: Fama and MacBeth Regressions Results

Panel A: Cross Sectional Regressions for the HW- measures							
Models	*λ0*	*λ 1*	*λ 2*	*λ 3*	*λ 4*	*Adj R2*	*F-stat*
Model 1	0.052*	-0.024				5.20%	4.0***
	(3.63)	(-1.21)					
Model 2	0.044*		-0.016			5.00%	3.9***
	(3.088)		(-0.789)				
Model 3	0.049*			-0.019		4.20%	4.33**
	(3.462)			(-1.006)			
Model 4	0.039*				-0.008	4.10%	4.20**
	(2.848)				(-0.481)		
Model 5	0.043*		-0.055	0.039		10.00%	5.46**
	(2.904)		(-0.932)	(0.733)			
Model 6	0.043*		-0.042		0.027	10.00%	5.51*
	(2.885)		(-1.347)		(0.898)		
Model 7	0.048*			-0.12***	0.101***	10.00%	6.25*
	(3.313)			(-1.693)	(1.708)		
Model 8	0.031*		-0.109	0.13	-0.025	17.00%	8.44*
	(15.545)		(-1.103)	(0.628)	(-0.087)		
Panel B: Cross Sectional Regressions for the HR- measures							
Models	***λ0***	***λ 1***	***λ 2***	***λ 3***	***λ 4***	***Adj R2***	***F-stat***
Model 1	0.052***	-0.024				5.20%	3.9*
	(3.63)	(-1.21)					
Model 2	0.048***		-0.024			5.00%	3.9*
	(3.37)		(-1.157)				
Model 3	0.052***			-0.021		4.70%	3.9*
	(3.66)			(-1.124)			
Model 4	0.041***				-0.01	4.10%	4.20**
	(2.982)				(-0.604)		
Model 5	0.045***		-0.057	0.038		10.00%	5.25**
	(3.073)		(-0.936)	(0.694)			
Model 6	0.05***		-0.038		0.016	10.00%	5.63*
	(3.384)		(-0.996)		(0.528)		
Model 7	0.049***			-0.112*	0.091*	10.00%	6.21*
	(3.355)			(-1.881)	(1.662)		
Model 8	0.037**		-0.11	0.117	-0.019	17.00%	8.56*
	(2.412)		(-0.721)	(0.366)	(-0.106)		
Panel C : Cross Sectional Regressions for the E- measures							
Models	***λ0***	***λ 1***	***λ 2***	***λ 3***	***λ 4***	***Adj R2***	***F-stat***
Model 1	0.052	-0.024				5.20%	4*
	(3.63***)	(-1.21)					
Model 2	0.059***		-0.024			4.70%	3.81*
	(3.384)		(-1.157)				
Model 3	0.052***			-0.02		4.50%	3.9*
	(3.326)			(-1.014)			
Model 4	0.044***				-0.014	4.10%	4.20**
	(3.1)				(-0.77)		
Model 5	0.060***		-0.056	0.03		9.70%	5.10**
	(3.192)		(-0.893)	(0.529)			
Model 6	0.063***		-0.054		0.026	9.80%	5.75***
	(3.411)		(-1. 363)		(0.825)		
Model 7	0.060***			-0.125	0.099	10.00%	6.34***
	(3.49)			(-1.967**)	(1.716***)		
Model 8	0.06		-0.06	-0.018	0.052	17.00%	10.6**
	(2.982***)		(-0.381)	(-0.052)	(0.28)		

*This table reports the mean estimates of coefficients, the Student–Fama and MacBeth statistics in parenthesis, the mean adjusted R^2 and the mean Fisher-statistics issued from the cross-sectional Fama and MacBeth regressions of mean return on estimated measures of risk over the models 1 to 8. The estimated parameters estimated are White heteroscedasticity–consistent. Pane1 A, B and C report results relative to HW, HR and E measures respectively. ***, ** and * denote significance at 1%, 5% and 10% level respectively*

Table 5: Cross-Sectional Analysis Excluding Recession Periods

Panel A : Cross Sectional Regressions for the HW- measures							
Models	***λ0***	***λ 1***	***λ 2***	***λ 3***	***λ 4***	***Adj R2***	***F-stat***
Model 1	0.531***	0.182				3.60%	1.33
	(3.548)	(1.157)					
Model 2	0.568***		0.145			2.30%	0.86
	(3.79)		(0.928)				
Model 3	0.574***			0.134		1.90%	0.7
	(3.676)			(0.837)			
Model 4	0.621***				0.079	0.00%	0.23
	(3.868)				(0.486)		
Model 5	0.536***		0.211	-0.04		0.00%	0.72
	(3.506)		(0.4593)	(-0.082)			
Model 6	0.549***		0.218		-0.065	4.00%	0.76
	(3.444)		(1.014)		(-0.28)		
Model 7	0.555***			0.409	-0.271	0.00%	0.84
	(3.466)			(1.055)	(-0.669)		
Model 8	0.664***		-1.348	2.974	-1.597		
	(3.807)		(-1.102)	(1.386)	(-1.529)	2.80%	1.35
Panel B: Cross Sectional Regressions for the HR- measures							
Models	***λ0***	***λ 1***	***λ 2***	***λ 3***	***λ 4***	***Adj R2***	***F-stat***
Model 1	0.531***	0.182				3.60%	1.33
	(3.548)	(1.157)					
Model 2	0.532***		0.18			3.50%	1.29
	(3.52)		(1.136)				
Model 3	0.549***					2.60%	0.94
	(3.471)			0.159 (0.974)			
Model 4	0.605***				0.096	0.90%	0.33
	(3.697)				(0.579)		
Model 5	0.557***		0.51	-0.361		4.80%	0.89
	(3.547)		(1.043)	(-0.717)			
Model 6	0.544***		0.31		-0.153	0.70%	1.14
	(3.303)		(1.406)		(-0.639)		
Model 7	0.524***			0.54	-0.368	2.00%	1.38
	(3.329)			(1.401)	(-0.926)		
Model 8	0.579***		-0.439	1.309	-0.754	0.10%	0.77
	(3.192)		(-0.382)	(0.671)	(-0.808)		
Panel C: Cross Sectional Regressions for the E- measures							
Models	***λ0***	***λ 1***	***λ 2***	***λ 3***	***λ 4***	***Adj R2***	***F-stat***
Model 1	0.531***	0.182				3.60%	1.33
	(3.548)	(1.157)					
Model 2	0.568***		0.145				
	(3.79)		(0.928)			2.30%	0.86
Model 3	0.631***		-0.996			0.30%	0.12
	(3.283)		(-0.358)				
Model 4	0.697***				0.013	0.00%	0
	(4.375)				(0.01)		
Model 5	0.49**		0.241	1.018		1.40%	1.26
	(2.023)		(1.537)	(0.4265)			
Model 6	0.538**		0.226		-0.746	2.30%	1.43
	(2.247)		(1.423)		(-0.714)		
Model 7	0.233			-29.249***	-12.469***	21.20%	5.97
	(1.121)			(-3.196)	(-3.393)		
Model 8	0.268		0.065	-19.904*	-8.125*	10.20%	2.4*
	(1.118)		(0.356)	(-1.761)	(-1.814)		

*This table reports the estimates coefficients, their t-Statistics in parenthesis, the adjusted R^2 and the Fisher-statistics issued from the cross-sectional regressions of mean return on beta ,downside beta and the orthogonalized components of downside gamma and downside delta over the models 1 to 8. The average returns and the estimates of risk measures considered are calculated over the sample period excluding recession periods (the crash of October 1987 on last quarter of 1987, the downturns due to the deflation of dot-com bubble and the attempt of the 11th of September spending from 01/01/2001 to 31/01/2002 and the global financial crisis in middle 2007 to 2009). The parameters are White heteroscedasticity–consistent. Pane1 A, B and C report results relative to HW, HR and E measures respectively. ***, ** and * denote significance at 1% , 5% and 10% level respectively.*

APPENDIX

The downside risk co-moments corresponding to Harlow and Rao (1989) measure are given by:

$$\beta_{im}^{(HR)} = \frac{E[(R_i-\mu_i).min(R_m-\mu_m,0)]}{E[min(R_m-\mu_m,0)]^2} \tag{3}$$

$$\gamma_{im}^{(HR)} = \frac{E\left[(R_i-\mu_i).min(R_m-\mu_m,0)^2\right]}{E[min(R_m-\mu_m,0)]^3} \tag{5}$$

$$\delta_{im}^{(HR)} = \frac{E\left[(R_i-\mu_i).min(R_m-\mu_m,0)^3\right]}{E[min(R_m-\mu_m,0)]^4} \tag{6}$$

The downside risk co-moments corresponding to Estrada (2002) measure are given by :

$$\beta_{im}^{(E)} = \frac{E[min(R_i-\mu_i,0).min(R_m-\mu_m,0)]}{E[min(R_m-\mu_m,0)]^2} \tag{7}$$

$$\gamma_{im}^{(E)} = \frac{E\left[min(R_i-\mu_i,0).min(R_m-\mu_m,0)^2\right]}{E[min(R_m-\mu_m,0)]^3} \tag{8}$$

$$\delta_{im}^{(E)} = \frac{E\left[min(R_i-\mu_i,0).min(R_m-\mu_m,0)^3\right]}{E[min(R_m-\mu_m,0)]^4} \tag{9}$$

Where R_i and R_m are the asset's and the market return respectively, μ_i and μ_m is the asset's and market mean return.

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ACKNOWLEDGEMENT

The authors wish to thank the anonymous reviewers for their excellent comments, resulting in a significant improvement in the quality of this paper.

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