Performance evaluation considering the coskewness

A stochastic discount factor framework

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Abstract

Purpose The paper aims to examine the performance of Spanish mutual funds between 1999 and 2003.

Design/methodology/approach The methodolgy uses the stochastic discount factor (SDF) framework across a variety of models developed in the recent asset pricing literature. This approach is a fairly recent innovation in the evaluation of investment performance.

Findings The present work complements the research of Farnworth *et al.* and Fletcher and Forbes, adding a new issue to the SDF, the third co moment of asset returns. Recent asset pricing studies show the relevance of the component of an asset's skewness related to the market portfolio's skewness, the coskewness, and how it helps to explain the time variation of ex ante market risk premiums. It is found that the effects of adding coskewness to evaluate the performance is significant even when factors based on size, book to market and momentum are included.

Practical implications The omission of a coskewness factor may lead to erroneous evaluations of a fund's performance, and therefore, issues such as the persistence of performance should be revised.

Originality/value This paper explores, for the first time, the effects of incorporating a coskewness factor in the analysis of investment performance, both in an unconditional and a conditional framework using SDF models.

Keywords Spain, Fund management, Capital asset pricing model

Paper type Research paper

1. Introduction

The evaluation of the performance of portfolio managers is a very common issue in the empirical financial literature. The question is important because of its implications. Thus, if managers can beat the market it has implications for the efficiency of financial markets. If they underperform it has implications for the fund management industry. Moreover, given the development of this industry, the investors need to choose from a large range of investment alternatives. For all these reasons and in spite of its long history, measuring the performance of mutual funds continues to be an interesting research topic.

The earliest studies of performance measures were developed under the CAPM framework. Among these, we can highlight, for example, Jensen's Alpha (Jensen, 1968) from the CAPM, Sharpe's Ratio (Sharpe, 1966) and the Treynor measure (Treynor, 1965). The Jensen's Alpha approach to evaluate a portfolio manager's performance has been generalized to multifactor models. Basically, the idea is to have a reference model that correctly explains the asset's mean returns. In this sense, it is essential to consider the characteristics of the assets in which the evaluated fund invests. For this reason, it

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is important to include characteristics that represent added risk factors, or alternatively, indexes that incorporate the influence of, not only stocks, but also bonds. For example, Elton *et al.* (1996a) propose a performance model based on the work by Fama and French (1993), Carhart (1997) includes a momentum factor and Basarrate and Rubio (1999) incorporate a long term bond index and a short term bond index.

However, multifactor models do not consider the public information available in each moment of time. The models use unconditional expected returns and assume that the investor generates the expectations without taking into account the state of the economy. Furthermore, unconditional measures are bias when managers react to market indicators or consider dynamic investment strategies. Chen and Knez (1996) and Ferson and Schadt (1996) advocate conditional performance evaluation using time varying expected returns and betas in spite of the traditional unconditional moments[1].

In this paper, we examine the performance of Spanish mutual funds between 1999 and 2003 using the stochastic discount factor (SDF) approach across a wide variety of models developed in the recent asset pricing literature. The SDF method has received wide attention in the theoretical and empirical asset pricing literature. As Jagannathan and Wang (2002) point out, the main attraction of this method is its generality. It provides a unified framework for asset pricing analysis of both linear and nonlinear asset pricing models. The approach is a fairly recent innovation in the evaluation of investment performance. Farnsworth *et al.* (2002) and Fletcher and Forbes (2004) use SDF models to evaluate performance in a sample of US equity mutual funds and UK unit trusts respectively. Our work complements them, adding a new issue to the SDF, the coskewness. Harvey and Siddique (2000) show the relevance of the component of an asset's skewness related to the market portfolio's skewness in the asset pricing relation, and how it helps to explain the time variation of ex ante market risk premiums. We study the effects of adding coskewness to performance evaluation. Moreover, to the best of our knowledge, there is no prior study that evaluates Spanish mutual fund performance within the SDF approach. Our study seeks to fill this gap in the literature.

This article is organized as follows. Section 2 describes the performance measure under the stochastic discount factor framework and presents the different discount factors that we use. Section 3 describes our database of mutual funds and the construction of the main variables needed to estimate the models. Section 4 provides the results. Section 5 concludes the article.

2. The stochastic discount factor and the performance measure

Virtually all asset pricing theories, whether statements of general equilibrium or the law of one price, can be represented as an stochastic discount factor (SDF), which is a random variable M_t such that all asset prices satisfy the pricing equation

$$E_{t-1}\left[M_t\tilde{R}_{it}\right] = 1 \tag{1}$$

where E_{t-1} means conditional expectation on the investor's time $t-1$ information and $\tilde{R}_{it}$ is one plus the return of asset i between $t-1$ and t (gross return). It is common in the SDF literature to model M_t as a linear function of factors[2] f_t. Let, $F_t' = [1, f_t']$ and $b' = [b_0, b']$ the vector of parameters. Thus,

$$M_t = b'F_t = b_0 + b'f_t \tag{2}$$

where f_t is the vector of the $K \times 1$ factor vector and b is the $K \times 1$ coefficient vector. The parameter vector b provides the information about whether a factor is an important determinant of the SDF. Expressing the models through (1) and (2) is known as the SDF representation[3].

If we assume that the expected returns and risks depend on the available information set it seems reasonable to model the relation between them. Thus, Jagannathan and Wang (1996) developed a conditional version of the static CAPM, considering changes in the available information. It is straightforward to generalize the idea to whichever factor model. Thus, the SDF representation of these conditional models will be:

$$M_t = b_0 + b'f_t + b'_Z Z_{t-1} \tag{3}$$

Cochrane (1996) indicates that one way to incorporate the variables in the information set is to allow the SDF parameters to vary over time with the state of the economy. So if we allow them to vary with an element Z_{t-1} we find that the SDF depends on the state variables, the risk factors and its product with the lagged information.

$$\begin{aligned} M_t &= b'(Z_{t-1})F_t \\ &= \left(b_{0,1} + b_{0,2}Z_{t-1}\right) + \left[b'_{1,1} + \left(b_{1,2}Z_{t-1}\right)'\right]f_t \\ &= b_{0,1} + b_{0,2}Z_{t-1} + b'_{1,1}f_t + b'_{1,2}f_tZ_{t-1}\,. \end{aligned} \tag{4}$$

We must note that the specification of the SDF in (4) differs from (3) only in the additional risk sources generated by the interaction between the risk factors and the variables determining the state of the economy.

For the unconditional models we set $Z_{t-1} = 1$. For conditional models, we use dividend yield to track the business cycle. Furthermore, recent literature (Hodrick and Zhang, 2001; Wang and Zhang, 2004) is concerned with the test of conditional linear factor models using the SDF framework and the no arbitrage restriction. The SDFs of these models might take negative values and thus assign inappropriate values to dynamic trading strategies. This is especially true for models with highly volatile factors such as conditional models. Moreover, Wang and Zhang (2004) show that allowing factor prices b to depend on conditional information tends to make the parameter estimates unstable. To avoid this concern, we only allow the coefficient of the constant factor (intercept element) to vary with Z_{t-1} and restrict other elements of b being constant. This is the same as incorporating the information as do Jagannathan and Wang (1996).

2.1. *Measuring performance*

For a given M_t we may define a fund's conditional SDF alpha following Chen and Knez (1996) and Jagannathan and Wang (2002) as

$$\alpha_{p,t-1} \equiv E_{t-1}\left[M_t\tilde{R}_{p,t}\right] \quad 1, \tag{5}$$

where $\tilde{R}_{pt}$ is the gross return of the fund in time t.

Jensen's alpha measures the deviation of the vector of excess returns from what the corresponding object should be according to the pricing model. Here, if the SDF prices the primitive assets, $\alpha_{p,t-1}$ will be zero when the fund forms a portfolio of primitive assets. The SDF performance measure depends on the model for the M_t, and given that the SDF is not unique unless markets are complete, different SDFs produce different measures of performance. This mirrors the classical approaches to performance evaluation, where performance is sensitive to the benchmark in the beta pricing context. The inferences are valid if the candidate SDF satisfies the restrictions in equation (1) for a set of N primitive assets.

While $\alpha_{p,t-1}$ is, in general, a function of the set of information used to form expectations, it is simpler following Ferson (2003) to discuss the estimation of $\alpha_p = E(\alpha_{p,t-1})$. Thus, if we examine the average abnormal performance of a fund, a useful approach is to form a system of equations as follows:

$$\begin{aligned} &E\left[M_t\tilde{R}_{it} \quad 1\right] = 0 \quad \text{for} \quad i = 1, \ldots, N \\ &E[\alpha_p \quad M_t\tilde{R}_{pt} + 1] = 0 \end{aligned} \tag{6}$$

where the N first moment conditions are the average pricing errors for the primitive assets. Under the null hypothesis of no abnormal performances, alpha should equal zero.

We can use the generalized method of moments (GMM) to simultaneously estimate the parameters of the SDF model and the fund's SDF alpha. The system of equations (6) can be estimated using a two step approach, where the parameters of the model for M_t are estimated in the first step and the fitted SDF is used to estimate alphas in the second step. Farnsworth *et al.* (2002) found that simultaneous estimation was dramatically more efficient. However a potential problem with the simultaneous approach is that the number of moment conditions grows significantly if several funds are evaluated. They also showed that we can estimate the joint system separately for each fund without loss of generality. Estimating a version of system (6) for one fund at a time is equivalent to estimating simultaneously a system with many funds. The estimates of alpha and the standard errors for any subset of funds are invariant to the presence of another subset of funds in the system.

To asses the performance of the candidate SDFs to correctly price the primitive assets we use the Hansen and Jagannathan (1997) distance (HJ distance hereafter) measure for each model. The HJ distance measure is equivalent to $(g'Wg)^{1/2}$, where g is the simple mean vector of moment conditions and $W = [E(R_tR_t')]^{-1}$ is the inverse of the second moment matrix of asset returns. The magnitude of the HJ distance can be directly compared across models as a maximum pricing error of a portfolio of the primitive assets with unit norm for a given model. If the model is correct, the HJ distance measures should be zero[4].

2.2 The SDFs

We evaluate the performance of a set of Spanish mutual funds using six expressions of the SDF and using both unconditional and conditional approaches.

The CAPM is the first, most famous and most widely used model in asset pricing. It ties the discount factor M_t to the returns on the wealth portfolio. The function is linear

$$M_t = b_0 + b_1 r_{mt}, \tag{7}$$

where r_{mt} is the excess return on the market portfolio[5].

The conditional version of the CAPM is given by[6]:

$$M_t = b_0 + b_1 r_{mt} + b_2 dy_{t-1}. \tag{8}$$

The most popular higher moment asset pricing is the three moment CAPM (3MCAPM hereafter) of Kraus and Litzenberger (1976) which includes preferences over the systematic skewness. Skewness matters since investors with non increasing risk aversion have a preference for positive skewness and an aversion to negative skewness. The SDF that is consistent with the 3MCAPM[7] is a quadratic function in the return on the market portfolio.

$$M_t = b_0 + b_1 r_{mt} + b_2 r_{mt}^2 \tag{9}$$

The conditional version of the 3MCAPM is given by:

$$M_t = b_0 + b_1 r_{mt} + b_2 r_{mt}^2 + b_3 dy_{t-1}. \tag{10}$$

In the research of the factors explaining the systematic risk of assets, Fama and French (1993) proposed a model where expected returns are related to three different risk factors arising from the empirical evidence of cross section asset pricing evaluation. These risk factors are the excess return of a market portfolio and two mimic factors of size and book to market. Under this three factor model (FF3 hereafter), the SDF is:

$$M_t = b_0 + b_1 r_{mt} + b_2 SMB_t + b_3 HML_t, \tag{11}$$

where SMB_t is the size factor and HML_t the factor linked to book to market[8]. The conditional version of this model is given by:

$$M_t = b_0 + b_1 r_{mt} + b_2 SMB_t + b_3 HML_t + b_4 dy_{t-1}, \tag{12}$$

Harvey and Siddique (2000) test the three moment CAPM's implication that stocks with large negative coskewness with the market will earn higher risk premium by constructing a coskewness factor following the methodology used by Fama and French (1993) when constructing the *SMB* and *HML* factors. They find that some of the empirical usefulness of *SMB* and *HML* is because they proxy for the coskewness factor. Smith (2004) also finds support for this but indicates that not all of the explanatory capacity of them is due to the fact they proxy for coskewness.

To analyse the effect of the coskewness factor on performance evaluation we use the following stochastic discount factor model (FF3 + CSK hereafter)[9]

$$M_t = b_0 + b_1 r_{mt} + b_2 SMB_t + b_3 HML_t + b_4 CSK_t, \tag{13}$$

The conditional version of this model is given by

$$M_t = b_0 + b_1 r_{mt} + b_2 SMB_t + b_3 HML_t + b_4 CSK_t, + b_5 dy_{t-1} \tag{14}$$

The fourth model is a four factor model based on Carhart (1997). The model incorporates a momentum (WML) factor with respect to the three factor model of Fama and French (1993). So the model (FF4 hereafter) is,

$$M_t = b_0 + b_1 r_{mt} + b_2 SMB_t + b_3 HML_t + b_4 WML_t, \tag{15}$$

The conditional version of the FF4 is given by

$$M_t = b_0 + b_1 r_{mt} + b_2 SMB_t + b_3 HML_t + b_4 WML_t + b_5 dy_{t-1}. \tag{16}$$

The last SDF model incorporates the five factors mentioned above (FF4 + CSK hereafter)

$$M_t = b_0 + b_1 r_{mt} + b_2 SMB_t + b_3 HML_t + b_4 CSK_t + b_5 WML_t, \tag{17}$$

The conditional version of the model is given by:

$$M_t = b_0 + b_1 r_{mt} + b_2 SMB_t + b_3 HML_t + b_4 CSK_t + b_5 WML_t + b_6 dy_{t-1.} \tag{18}$$

3. Data base

3.1. Mutual funds

The database used comprises weekly returns of 370 equity mutual funds from the Spanish market, between January 1999 and January 2003. The database covers approximately 80 per cent of the entire Spanish mutual fund market (for this time period there existed 470 equity funds)[10]. These mutual funds are classified in four different groups: Equity Funds, Equity Income Funds, Equity Euro Funds and Global Funds. These categories were established by the CNMV (*National Security Exchange Commission*) and INVERCO (*Spanish Association of Collective Investments Institutions*) in June 1999, and constitute the current and official classification[11]. It must be highlighted that the Spanish mutual funds market has grown surprisingly in the last decade, thus, at the moment Spain is the third highest ranking country in a number of mutual funds in Europe and the seventh in the world [12].

Table I provides a complete description (economical and statistical) of the database. We present, in columns, for each category: the annualized mean return, the risk, measured as the standard deviation, the kurtosis, the minimum and maximum weekly return during the entire sample, the number of mutual funds in each category and the

	Mean	Std dev.	Kurtosis	Max. losses
Equity	10.33	22.1	4.01	5.62
Equity Income	5.20	12.2	3.87	3.02
Equity Euro	11.58	22.3	4.49	5.41
Global	4.63	12.9	4.29	3.25
	Max. returns	N	*Representativity (per cent)*	*Normality*
Equity	4.23	76	83	97.37
Equity Income	2.45	160	85	60.63
Equity Euro	4.41	72	77	98.61
Global	2.61	62	64	69.35

Note: The table reports some summary statistics of mutual funds in the database: the annualized mean return, the standard deviation, the kurtosis, the 5 per cent highest profits and losses for the last three years, the number of mutual funds (N) in each category and the percentage that our data represents of the total number of mutual funds in the Spanish market. The last column represents the percentage of funds for which the null hypothesis of normality of a Jarque Bera test is rejected at a ten percent level of significance percentage of the total number of funds in the Spanish market that our data represents. We also show the percentage of funds for which the null hypothesis of normality, from a Jarque Bera test, is rejected at a 10 per cent significance level.

As we can see from Table I, for each category of mutual funds we use more than 60 per cent of mutual funds that exist in Spain for that time period. Furthermore, we can observe how the kurtosis is on average higher than three (a value under the null of a normal distribution) and we reject the null hypothesis of normality for approximately 80 per cent of mutual funds (97.37 per cent in Equity Funds, 60.63 per cent in Equity Income Funds, 98.61 per cent in Equity Euro Funds and 69.35 per cent in Global Funds)[13]. According to this result the use of a performance measure based on normality should be rejected.

3.2 Risk factors

To compute the proxy of coskewness and the risk factors of the models we use weekly returns on 133 common stocks listed on the Spanish continuous market[14] from January 1998 to January 2003. As a measure of size for each company we use the logarithm of market capitalization calculated by multiplying the number of shares of each firm in December of the previous year by their price at the end of every week. To compute the book to market ratio for each firm, we employ the accounts information from the balance sheets of each firm at the end of every year[15]. The book value for any firm remains constant from January to December. The market value is given by total capitalization of each company in the previous week. The return on the stock market index is based on the IBEX35 Spanish index which is a value weighted index comprising of the 35 most traded stocks on the exchange market. This is a very popular index since it is the index taken as the reference underlying asset in the Spanish derivatives market. As a risk free asset we use the return on the six month Spanish T bills.

The SMB and HML factors are constructed from six portfolios of securities formed on the basis of size and book to market values as in Fama and French (1993)[16]. Also, we construct the WML factor in a similar manner to Carhart (1997)[17].

To compute the *CSK* factor we use the standardized unconditional coskewness,

$$S_i = \frac{E(\varepsilon_{i,t+1}\varepsilon_{M,t+1}^2)}{\sqrt{E(\varepsilon_{i,t+1}^2)E(\varepsilon_{M,t+1}^2)}} \tag{19}$$

where $\varepsilon_{i,t+1} = r_{i,t+1} \quad a_i \quad b_i r_{M,t+1}$ are the residuals from the regression of the excess return on the contemporaneous market excess return and $\varepsilon_{M,t+1}$ are the residuals of the market return over its mean. S_i represents the contribution of a security to the skewness of a broader portfolio. A negative measure means that the security is adding negative skewness. Therefore, a stock with negative coskewness should have a higher expected return.

Using weekly data from the six months of returns and following Harvey and Siddique (2000), we compute the standardized unconditional coskewness for each one of the stocks in the continuous market of our Spanish data. We then rank the stocks based on their past coskewness and form three equally weighted portfolios: the 30 per cent with the most negative coskewness, which we call S^-; the middle 40 per cent, which is called S^0; and the 30 per cent with the most positive coskewness, S^+.

The post ranking excess returns on S^- and S^+ are then used as proxies for the coskewness factor.

3.3 Primitive assets

Primitive assets should reflect the returns available to investors and fund managers. For this study, we consider the following primitive assets: a short term risk free security; the DJ STOXX 50 index and stock portfolios that mimic large cap, small cap, value, growth, momentum, and contrarian investment strategies. Following Farnsworth *et al.* (2002) we form the last five primitive assets from common stock portfolios. For each semester we group the common stocks into thirds according to each of three independent criteria, producing 27 portfolio return series. The grouping criteria are the past return, the equity market capitalization and the book to market ratio. We form a small cap portfolio by equally weighting the nine portfolios with the lowest market capitalization. For the momentum (contrarian) strategy, we use an equally weighted average of the nine portfolios with the highest (lowest) returns. For the value (growth) strategy we use an equally weighted average of the nine portfolios with the highest (lowest) book to market ratio. In Table II we present summary statistics of the primitive assets returns and the lagged instrument.

3.4 Instruments

The vector of instruments $Z_{t-1,}$ formed by predetermined variables which help to predict future economic conditions, includes the typical set of variables employed in literature. We use the dividend yield of the Spanish market[18]. The Spanish dividend yield is given, on a monthly basis, by Morgan Stanley. In order to obtain the weekly dividend yield, we observed the yield at the end of a given month. Since we have the price index level, we are able to obtain the global dividend amount paid per share in the market. Using the price index level for each week, and assuming that during a given month the amount of the global dividend is the same, we can infer the weekly dividend yield[19].

4. Empirical results

4.1 The skewness evidence

This section analyses the relevance of the systematic skewness in Spanish mutual funds returns. The systematic skewness is a measure of the asset's coskewness risk,

	Mean	Median	Minimum	Maximum	Std dev.	ρ_1
Primitive assets rates of return (weekly per cent)						
IBEX35	0.249	0.4781	12.3438	8.9268	3.2578	0.029
T bill (annual per cent)	0.0298	0.0293	0.0246	0.0354	0.00322	0.983
Momentum	0.0562	0.0193	7.2509	3.8168	1.5269	0.100
Contrarian	0.2848	0.2992	8.9451	8.4435	2.5188	0.171
Value	0.0847	0.00308	7.5386	6.6148	1.8776	0.216
Growth	0.2561	0.1531	6.3577	3.9674	1.7869	0.178
Small cap	0.1869	0.201	6.4221	6.716	1.835	0.186
STOXX 50	0.2017	0.2351	9.3464	6.5003	3.0534	0.065
Lagged Instrument (annual per cent)						
Dividend yield	1.911	1.743	1.379	3.231	0.429	0.951

Note: The data are weekly from January 1999 through January 2003, a total of 207 observations and is defined as the ratio of the coskewness of that asset's return with the market to the market's skewness. Therefore, we are interested in the coskewness of an asset with the investment portfolio. It is particularly important in the Spanish case, where there is no empirical evidence of asymmetry in the distribution of returns in the market portfolio[20] (see Sánchez Torres and Sentana, 1998; Peiró, 1999).

For robustness tests, we adopt two different measures for coskewness used in Harvey and Siddique (2000). The first one is the standardized unconditional coskewness, S_i, which represents the contribution of a security to the skewness of a broader portfolio. A negative measure means that the security is adding negative skewness. Therefore, a stock with negative coskewness should have a higher expected return. The other measure of coskewness is based on the sensitivity to a coskewness hedge portfolio (in much the same way Fama and French construct factor loadings on SMB and HML). We compute the measure of coskewness by regressing the fund's excess return on the spread between the returns on the ($S^{-}\ S^{+}$) portfolios, and denominated it as $\beta^{S\ -S^{+}}$.

Table III reports some summary statistics that compare the above measures across the four categories of funds analysed in this paper. In Panel A we also show the unconditional skewness, computed as the third central moment around the mean. The

	Equity	Equity Income	Equity Euro	Global
Panel A: Unconditional skewness				
Mean	0.554	0.373	0.408	0.420
Median	0.546	0.381	0.409	0.468
Min.	0.936	1.083	0.864	1.094
Max.	0.048	0.384	0.022	0.277
Positive and Sign. At 5 per cent	0.000	0.000	0.000	0.000
Negative and Sign. At 5 per cent	86.842	44.375	51.389	62.903
Panel B: Unconditional coskewness				
Mean	0.141	0.101	0.134	0.095
Median	0.159	0.104	0.129	0.096
Min.	0.381	0.370	0.362	0.349
Max.	0.283	0.408	0.109	0.248
Positive and Sign. At 5 per cent	1.316	1.250	0.000	3.226
Negative and Sign. At 5 per cent	23.684	16.250	18.056	27.419
Panel C: $\beta^{S\ \ S^{+}}$				
Mean	0.501	0.288	0.615	0.281
Median	0.525	0.281	0.636	0.244
Min.	0.074	0.012	0.005	0.046
Max.	0.662	0.572	1.210	1.056
Positive and Sign. At 5 per cent	97.368	96.875	94.444	79.032
Negative and Sign. At 5 per cent	0.000	0.000	0.000	0.000
t statistic	3.179	3.214	3.642	2.692

Notes: The unconditional skewness is computed as the third central moment around the mean. The unconditional coskewness is defined as $E(\varepsilon_{i,t+1}\varepsilon^{2}_{M,t+1})/\sqrt{E(\varepsilon^{2}_{i,t+1})E(\varepsilon_{M,t+1}{}^{2})}$, where $\varepsilon_{i,t+1}$ is the residual from the regression of the excess return on the contemporaneous market excess return and $\varepsilon_{M,t+1}$ is the residual of the market return over its mean. $\beta^{S\ \ S^{+}}$ is calculated regressing the fund excess return on the spread between the returns on the ($S\ \ S^{+}$) portfolios. Significance levels for unconditional skewness and coskewness are computed following Harvey and Siddique (2000) and Lin and Jerry (2003) results show that a high percentage of the funds have a negative skewness, significant at the 5 per cent level[21]. These percentages are 87, 44, 51 and 63 per cent, respectively. We also find zero funds with significant positive skewness. Panel B shows the unconditional coskewness S_i, which is a "direct" measure of coskewness, whereas the measure in Panel C is based on the sensitivity to coskewness. The results for the unconditional coskewness show that the percentage of funds with negative and significant coskewness is between 16 and 27 per cent.

The factor loadings on (S^{-} S^{+}) presented in Panel C are positive, implying that positive premiums on the systematic skewness risk exist for these funds. The betas are, in general, significantly different from zero with percentages between 79 and 97 per cent, as can be seen from the mean of the *t* statistic, showing the sensitivity of mutual funds to this coskewness factor.

Therefore, the statistics suggest that coskewness plays an important role in explaining the performance evaluation of mutual funds and implies that a disregard for this factor will create a bias (perhaps a significant bias) in assessing performance evaluation. We test this hypothesis in the following sections.

4.1. Estimating the SDF models

This section evaluates the fit of the SDF models in the sample of primitive assets. The models are estimated using weekly data for the period January 1999 to January 2003. The first row of Table IV reports the result of a constant discount factor model, in which the SDF is assumed to be fixed over time and equal to the inverse of the sample mean of the *t* bill's gross return. A constant SDF model can be motivated by risk

Model	E (M)	SD (M)	Min (M)	Max (M)	Num (M < 0)	*p* value	HJ
Constant discount factor	0.9997	0	0.9997	0.9997	0	0.033	0.244
Panel A: Unconditional models							
CAPM	0.9997	0.0860	0.6805	1.2419	0	0.066	0.2286
3MCAPM	1.0010	0.2173	0.8469	2.2051	0	0.058	0.2257
FF3	1.0004	0.3839	0.1650	2.7117	3	0.243	0.1378
FF4	0.9997	0.3698	0.0845	2.4961	1	0.552	0.1071
FF3 + CSK	0.9997	0.4116	0.0367	2.5539	3	0.157	0.1325
FF4 + CSK	0.9999	0.4007	0.0995	2.3181	1	0.396	0.0984
Panel C: Conditional models (Z dy)							
CAPM	1.0891	0.4349	0.2354	1.7066	4	0.079	0.4274
3MCAPM	1.0701	0.4107	0.1606	2.4100	3	0.124	0.4197
FF3	1.0900	0.5865	0.8027	2.9898	10	0.449	0.2469
FF4	1.0369	0.4244	0.3964	2.6246	3	0.212	0.2319
FF3 + CSK	1.1041	0.6749	0.9859	3.0522	14	0.362	0.2186
FF4 + CSK	1.0900	0.6974	2.6001	3.0101	13	0.152	0.2186

Notes: The table reports the sample descriptive statistics of the estimated stochastic discount factors. The primitive assets used in estimating the models are the IBEX35, the *t* bill and five portfolios grouped as described in the text, according to lagged return (momentum, contrarian), book to market ratios (value, growth) and market capitalization (small stocks), and the Euro Stoxx index. HJ is the Hansen Jagannathan (1997) measure of misspecification. The lagged instruments are the dividend yield and the *t* bill. *p* value is the *p* value of the specification test neutrality. For our purposes this provides a simple point of comparison for the performance of the rest of the models.

Table IV presents the summary statistics for the time series of the fitted SDFs. The means of most of the SDFs are close to the inverse of the mean of the gross T bill return, which is the value for the constant SDF model. Thus, including the *t* bill as primitive asset is generally effective in controlling the mean of the SDF. Farnsworth *et al.* (2002) point out that as the complexity of the models increases (more factors are used, or we move from an unconditional to a conditional model), the standard deviation of the fitted SDF generally increases[22]. Our results confirm this fact. Moreover, this may be the reason for a mean for the SDF above one in the conditional models. Hansen and Jagannathan (1991) showed that the minimum variance of an SDF increases when the number of assets increases, because the mean variance frontier can only expand as more assets are included. Thus, it makes sense that the conditional SDF models could have larger standard deviations.

The SDFs have more negative values when more factors are used. The conditional models also have more negative values. More frequent negative values are expected, other things equal, as the SDF becomes more volatile. However, negative values mean the SDF assigns positive prices to negative payoffs at some points in time. While a larger variance of an SDF is useful, according to the equity premium puzzle of Mehra and Prescott (1985), a more volatile SDF implies a lower capacity to detect abnormal performance and this will be critical in mutual funds performance evaluation.

The HJ distance is a summary of the mean pricing errors across a group of assets[23]. The measure may be interpreted as the distance between the candidate SDF and one that would correctly price the primitive assets. All the unconditional models have smaller pricing errors than would be obtained by the constant SDF model, discounting the returns at a fixed risk free rate. The unconditional Fama and French models has a smaller distance measure than the CAPM. We must highlight that adding coskewness always reduces the HJ distance. The conditional models produce larger HJ distances than their unconditional model counterparts. In attempting to price the dynamic strategies implied by the lagged instruments, the conditional models sacrifice some accuracy on the primitive returns (this is consistent with Farnsworth *et al.* (2002)). The Fama and French four factor model plus coskewness always attains the smallest HJ distance measure.

4.2. Evidence on mutual funds performance

We use the SDF models to measure performance in our sample of Spanish mutual funds. The candidate stochastic discount factor models are estimated between January 1999 and January 2003. The results are reported in Tables V VIII (one for each category of mutual funds). Each table includes the average fund's performance (α, expressed in a monthly frequency and per cent), mean absolute performance ($|\alpha|$), average *t* statistic (of α), and minimum and maximum performance. For all the models *N* is the number of funds with positive (+) and negative ( ) performance. The total number of funds for each category is 76 for the Equity Funds, 160 for the Equity Income Funds, 72 for the Equity Euro Funds, and 62 for the Global Funds. Panel A of each of the tables reports the unconditional models and Panel B the conditional models.

We find that under an unconditional framework the majority of alphas are positive. Thus, on average, approximately between 59 and 72 per cent of mutual funds show a positive risk adjusted investment performance. If we use public information through conditional asset pricing models, there is no a relevant change, the majority of

Model	α	$\lvert\alpha\rvert$	Min (α)	Max (α)	N+	N	t stat
Panel A: Unconditional models							
CAPM	0.135	0.461	1.882	1.418	25	51	0.228
3MCAPM	0.151	0.477	1.440	1.282	24	52	0.216
FF3	0.336	0.448	3.682	1.479	71	5	0.144
FF4	0.084	0.228	1.680	0.950	44	32	0.029
FF3+CSK	0.244	0.308	1.542	0.922	66	10	0.036
FF4+CSK	0.176	0.267	1.603	0.848	61	15	0.032
Panel B: Conditional models (dy)							
CAPM	0.060	0.245	2.830	0.825	49	27	0.002
3MCAPM	0.061	0.246	2.811	0.829	49	27	0.002
FF3	0.026	0.238	2.662	0.904	44	32	0.002
FF4	0.039	0.223	2.780	0.848	45	31	0.002
FF3+CSK	0.084	0.239	2.913	0.813	55	21	0.002
FF4+CSK	0.071	0.232	3.014	0.840	50	26	0.003

Notes: The candidate stochastic discount factor models are estimated between January 1999 and January 2003. The table reports summary statistics of Equity Mutual Funds performance. This includes the average (α) performance (monthly per cent), mean absolute performance ($\lvert\alpha\rvert$), average t statistic (of α), and minimum and maximum performance. N is the number of funds with positive (+) and negative ( ) performance. 76 equity funds were studied

fund managers obtains positive alphas, the figures range between 52 and 66 per cent. We must note that these results are radically different than in a traditional linear regression framework where conditional models make the average performance look better than unconditional ones shifting the distribution of alphas to the right. Thus, in our SDF framework the distributions of the alphas are not highly sensitive to the

Model	α	$\lvert\alpha\rvert$	Min (α)	Max (α)	N+	N	t stat
Panel A: Unconditional models							
CAPM	0.092	0.307	1.013	1.244	49	111	0.171
3MCAPM	0.110	0.336	0.844	1.420	45	115	0.181
FF3	0.374	0.387	0.306	1.363	153	7	0.132
FF4	0.056	0.191	0.708	0.752	94	66	0.025
FF3+CSK	0.122	0.203	0.510	1.163	111	49	0.024
FF4+CSK	0.109	0.188	0.552	1.000	111	49	0.023
Panel B: Conditional models (dy)							
CAPM	0.011	0.183	0.662	0.818	77	83	0.002
3MCAPM	0.014	0.184	0.663	0.818	76	84	0.002
FF3	0.012	0.171	0.663	0.857	80	80	0.001
FF4	0.012	0.165	0.627	0.784	82	78	0.001
FF3+CSK	0.033	0.166	0.590	0.771	92	68	0.002
FF4+CSK	0.022	0.157	0.604	0.716	94	66	0.002

Notes: The candidate stochastic discount factor models are estimated between January 1999 and January 2003. The table reports summary statistics of Equity Income Mutual Funds performance. This includes the average (α) performance (monthly per cent), mean absolute performance ($\lvert\alpha\rvert$), average t statistic (of α), and minimum and maximum performance. N is the number of funds with positive (+) and negative ( ) performance. 160 equity income funds were studied

Model	α	$\lvert\alpha\rvert$	Min (α)	Max (α)	N+	N	t stat
Panel A: Unconditional models							
CAPM	0.364	0.565	1.038	2.117	50	22	0.271
3MCAPM	0.252	0.506	0.656	2.097	45	27	0.206
FF3	0.329	0.428	0.723	1.815	60	12	0.136
FF4	0.178	0.313	0.585	1.121	51	21	0.04
FF3+CSK	0.226	0.302	0.418	1.196	57	15	0.036
FF4+CSK	0.169	0.271	0.498	1.185	49	23	0.033
Panel B: Conditional models (dy)							
CAPM	0.160	0.364	0.602	2.187	47	25	0.003
3MCAPM	0.150	0.355	0.601	2.152	47	25	0.003
FF3	0.200	0.333	0.437	1.759	50	22	0.002
FF4	0.115	0.293	0.497	1.340	47	25	0.003
FF3+CSK	0.152	0.312	0.585	1.623	48	24	0.003
FF4+CSK	0.119	0.302	0.592	1.324	45	27	0.003

Notes: The candidate stochastic discount factor models are estimated between January 1999 and January 2003. The table reports summary statistics of Equity Euro Mutual Funds performance. This includes the average (α) performance (monthly per cent), mean absolute performance ($\lvert\alpha\rvert$), average t statistic (of α), and minimum and maximum performance. N is the number of funds with positive (+) and negative ( ) performance. 72 equity Euro funds were studied

conditional models[24]. Moreover, in a traditional linear regression framework the majority of mutual funds alphas are negatives under an unconditional perspective (see Moreno and Rodriguez, 2004). However, when we estimate the conditional FF3 and FF4 models with and without coskewness, the number of positive alphas decreases for all categories. This is consistent with the idea that incorporating public information managers who trade mechanically in response to these variables get no credit.

Model	α	$\lvert\alpha\rvert$	Min (α)	Max (α)	N+	N	t stat
Panel A: Unconditional models							
CAPM	0.087	0.338	0.938	1.997	31	31	0.179
3MCAPM	0.027	0.333	0.798	1.097	29	33	0.132
FF3	0.403	0.470	0.468	1.036	52	10	0.159
FF4	0.068	0.320	0.942	1.159	37	25	0.042
FF3+CSK	0.066	0.305	0.790	0.861	39	23	0.037
FF4+CSK	0.081	0.257	0.793	0.930	39	23	0.037
Panel B: Conditional models (dy)							
CAPM	0.022	0.280	1.372	0.941	33	29	0.002
3MCAPM	0.017	0.282	1.366	0.939	33	29	0.002
FF3	0.070	0.299	1.409	1.066	35	27	0.002
FF4	0.042	0.271	1.228	0.935	33	29	0.003
FF3+CSK	0.035	0.266	1.043	0.940	33	29	0.003
FF4+CSK	0.027	0.260	0.89	0.846	33	29	0.003

Notes: The candidate stochastic discount factor models are estimated between January 1999 and January 2003. The table reports summary statistics of Global Mutual Funds performance. This includes the average (α) performance (monthly per cent), mean absolute performance ($\lvert\alpha\rvert$), average t statistic (of α), and minimum and maximum performance. N is the number of funds with positive (+) and negative ( ) performance. 62 global funds were studied

In order to analyse whether or not the coskewness can significantly change the distribution of the alphas, we look at the models with and without this new factor. If we incorporate the coskewness factor to the Fama and French three factor model, or we consider the three moment CAPM instead of the CAPM, the number of funds with positive alphas decreases slightly. Thus, a small percentage of mutual funds that were earlier evaluated as producing a positive performance when coskewness is taken into account, result in negative mean performance. In this sense, if we compute the performance of fund managers from an unconditional model and without considering the coskewness, we are making the fund managers, on average, look better than they are.

This last effect is not so clear when the coskewness factor is added in a model that incorporates the momentum factor or if the models are dependent upon public information. In these cases the results are mixed, sometimes the positive alphas increase (for example if we use the Fama and French model for the Equity Funds category and we add coskewness in a conditional framework), other times decreases (for example if we use the Fama and French model for the Equity Euro Funds category and we add coskewness in a conditional framework) and also is invariant (for example if we use the Fama and French plus momentum model for the Global Funds category and we add coskewness in a conditional framework).

We can not check if these results are maintained when we observe the alphas that are statistically different from zero. In Tables V VIII we can observe that the average absolute *t* statistic is unable to reject the null hypothesis that the performance measures are equal to zero for all the categories of funds. Furthermore, as the complexity of the models increases (more factors are used, or we move from an unconditional to a conditional model) the estimated alpha is less significative because the standard error is larger. This presents a problem in the choice between the conditional and unconditional models and the incorporation of additional factors in a SDF framework. Conditional models allow us to capture better the dynamic strategies of mutual fund managers but at the cost of larger variances of the pricing errors that potentially presents the managers as managers without ability[25].

It would be interesting to study whether not obtaining alphas significantly different from zero is due to the fact that we are working with data net of fees. We could think that maybe the average mutual fund manager has ability to obtain an extra return, but once we take into account the management fees the ability disappears. To check quickly this fact we add back a 2.65 per cent annual to the return of the fund to cover the maximum total annual fees (it is composed by the management fees and custody fees) and estimate again all the models[26]. Again, the average alphas are equal to zero. In summary, the overall impression is that the average mutual fund performance is consistent with the null hypothesis of no ability.

5. Conclusions

Recent asset pricing studies have shown that systematic skewness is important, and helps to explain the time variation of risk premiums. This paper explores, for the first time, the effects of incorporating a coskewness factor in the analysis of investment performance, both in an unconditional and a conditional framework using SDF models. We examine a sample of 370 equity mutual funds in the Spanish market between January 1999 and January 2003.

The HJ distance demonstrates that the unconditional models have smaller pricing errors than a constant SDF model. The unconditional Fama and French models has a smaller distance measure that the CAPM. The conditional models produce larger HJ distances than their unconditional model counterparts. In attempting to price the dynamic strategies implied by the lagged instruments, the conditional models sacrifice some accuracy on the primitive returns.

The results demonstrate that both the unconditional and conditional estimations reduce the HJ distance when a coskewness factor is used as an additional variable. The coskewness factor is relevant even when factors based on size and book to market are included. Therefore, a failure to consider the systematic skewness will create a potential problem of specification that could bias the risk adjusted return obtained by mutual funds and provide investors with erroneous information about past performance of mutual fund managers.

Unlike the evidence provided by linear regression multifactor models, the SDF framework indicates that the choice between conditional and unconditional models presents a trade off. Conditional models capture better dynamic strategies of fund managers but at cost of larger variances in pricing errors on the primitive assets of the model. While a larger variance of an SDF is useful, according to the equity premium puzzle of Mehra and Prescott (1985) a more volatile SDF implies a lower power to detect abnormal performance. As a result, when we evaluate the models, the average mutual fund performance is consistent with the null hypothesis of no ability.

Notes

1. See Ferson and Quian, 2004 for a survey on Conditional Performance Evaluation.
2. The Intertemporal CAPM generates linear discount factor models in which the factors are state variables for the investor's consumption portfolio decision. Also, if a set of asset returns are generated by a linear factor model, there is a stochastic discount factor linear in the factors.
3. The vast majority of the empirical research on asset pricing models involves expressions for expected returns, stated in terms of beta coefficients relative to one or more portfolios or factors. Multi beta models can be derived as a special case of the SDF representation, when the factors capture the relevant systematic risks. For a proof see Ferson and Jagannathan (1996).
4. The HJ distance also offers a specification test. Jagannathan and Wang (1996) derive the asymptotic null distribution for the HJ distance.
5. See Cochrane (2001) to derive the CAPM from the consumption based model.
6. We rewrite the parameters to simplify the notation. The coefficient of dy is b_{02} in (4).
7. The multibeta expression of the 3M CAPM is $E_{t\ 1}(r_{it}) \quad \gamma_1\beta_{it}^M + \gamma_2\beta_{it}^s$, where β_{it}^M is the beta risk, β_{it}^s is the systematic skewness, and the gammas are the prices of the risk. Just as the beta of an asset is the ratio of the covariance of that asset's returns with the market to the variance of market returns, β_{it}^s is defined as the ratio of the coskewness of that asset's return with the market, to the market skewness.
8. See Fama and French (1993) for the construction of the factors.
9. If we write the multi beta specification of this SDF model $E_{t\ 1}(r_{it}) \quad \gamma_1\beta_{it}^M + \gamma_2\beta_{it}^{SMB} + \gamma_3\beta_{it}^{HML} + \gamma_4\beta_{it}^{S\quad S^+}$ the beta of the coskewness factor would indicate the sensitivity to coskewness hedge portfolio (the covariance between the return of the fund and the factor, divided by the variance of the factor). It must be noted this is not exactly the same as systematic skewness β_{it}^s.
10. An important characteristic of this database is that it is almost free of survivorship bias (see Brown *et al.*, 1992 for more details), given that for the time period considered only two mutual funds were dropped out of the categories of mutual funds here considered, so the results found here are free of survivorship bias.

11. It must be noted that the vast majority of papers studying Spanish mutual funds are not based on this classification; therefore these studies could use a larger sample size data. However, the new classification supposes a change in the number and type of funds in each category, and the underlying relations in the data could shift during the sample. For this reason, we decide to use the latest one.
12. According to the *Mutual Fund Fact Book* (44th ed., 2004) published by the Investment Company Institute.
13. The rest of funds are not used because: (i) it was a very young fund, having less than two year's data, or (ii) there were a high proportion of weekly erroneous observations.
14. The authors thank Mikel Tapia for his help in obtaining price data.
15. Information provided by the CNMV.
16. Beginning in January 1999, all stocks are ranked in ascending order on the basis of their market value. The securities are split into two portfolios (small (S) and big (B)). Within each size portfolio, the stocks are ranked on their book to market ratio and grouped into three portfolios (high (H), medium (M) and low (L)). This gives six size/book to market portfolios (S/L S/M S/H B/L B/M B/H). we estimate the weekly returns over the next six months on the six portfolios. This process is repeated for the following semesters. The SMB factor is the difference in the weekly returns of the three small firm portfolios and the mean return of three large portfolios. The HML factor is the difference in the mean return of the two high book to market portfolios and the mean return of the two low book to market portfolios.
17. Beginning in January 1999, all securities are ranked on the basis of their cumulative return over the past six months. Three portfolios are formed with the intersections with the two size portfolios, we obtain six portfolios. The WML factor is the difference in the weekly returns of the two portfolios with the highest past returns and the two portfolios with the lowest past returns.
18. We have also used the returns of the six month T bill, but results are similar.
19. In all cases following Basarrate and Rubio (1999) we use two week lagged values of the instruments rather than just one week lag. This seems to be more reasonable when employing weekly data.
20. Sanchez Torres and Sentana (1998) show that the extension of the CAPM, which adds the coskewness of an asset with the market portfolio as an explanatory factor for risk premium (3MCAPM), does not require any assumption regarding the asymmetry in the distribution of returns on the market portfolio.
21. Significance levels for unconditional skewness and coskewness are computed, as in Harvey and Siddique (2000) and Lin and Jerry (2003).
22. Recall that for the linear factor models, a conditional model is equivalent to an unconditional model fit to the primitive asset returns, and also to the "dynamic strategy" returns obtained by multiplying the primitive returns by the lagged instruments.
23. The measure may be interpreted, analogous to Hotelling's T^2 statistic, as the maximum t ratio of pricing errors for portfolios of the primitive assets. Its advantage in our setting is that the standard error of the t ratio in question is not affected by the estimation error in the SDF, as it depends only on the test asset returns. Thus, there is no penalty or advantage to a volatile SDF.
24. This result is in accordance with Farnsworth *et al.* (2002) for a sample of 188 US mutual funds.
25. The same dataset of funds was used by Moreno and Rodriguez (2004) to estimate the performance with different multifactor models under the traditional lineal regression framework. Approximately 3 per cent of funds reached significative alphas. The above section showed that as the complexity of the model increases the volatility of the SDF

also increases producing imprecise estimators of alpha and lower *t* statistics. To test this we have estimated the performance with a constant SDF model, where the volatility is zero (see Table IV). The percentage of funds with alphas statistically higher or lower than zero at 5 per cent is 40 per cent, and the *t* average is 2.01.

26. Gil Bazo and Martinez (2004), in a study about the mutual fund fees, point out the maximum total annual fee for the Spanish Equity mutual funds is established in 2.65 per cent. This total annual fee is formed by the management fees (which maximum legal is 2.25 per cent of assets under management by the mutual fund) and the custody fees (which maximum legal is established in 0.40 per cent of assets under management).

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