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Mind Coskewness:
A Performance Measure for Prudent, Long-Term Investors

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Abstract

This study examines how negative skewness affects the behaviour of prudent investors. It also shows how the commonly used framework in the intertemporal asset pricing and the dynamic portfolio-consumption choice literature can generate negative skewness in asset reutrns. Given this impact, an extra premium is required in order to hold an asset with negatively coskewed returns. This premium was, on average, 2.09% p.a. for the UK stock market universe. Hence, a new performance measure, the intercept of the Harvey-Siddique two-factor asset pricing model is suggested for prudent, long-term investors. Using this model, the performance of UK unit trusts is examined over the period 1991-2005. Despite exhibiting significantly negative managerial ability, trust managers were successful in reaping part of this negative coskewness premium.

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1 Introduction

Most of theory of finance has been developed within a static, mean-variance framework. The main examples of this framework is the mean-variance portfolio choice by Markowitz (1952) and the Sharpe (1964)-Lintner (1965)-Mossin (1996) Capital Asset Pricing Model. These pathbreaking contributions served as an excellent first exploration of the complex world of asset prices and had an immense impact on the investment industry. Nevertheless, the limitations of this framework are numerous and crucial.

Extensive research in the time series behaviour of the stock returns showed that these exhibit a series of stylized facts, such as time-varying volatility, predictability, negative skewness and excess kurtosis. Hence, returns clearly violate the assumption of being normally or identically distributed over time. Equally importantly, there has been documented significant empirical failure of the CAPM. In a series of papers, Fama and French (1993, 1995) established that value and size strategies generate returns that cannot be explained by beta-risk loading. The momentum strategy documented by Jegadeesh and Titman (1993) is another "anomaly".

Severe criticism to the CAPM assumptions comes from utility theory too. The assumption of quadratic preferences is clearly rejected since it implies increasing absolute risk aversion (IARA). A desirable property of a utility function is that agents are averse to negative skewness and have a preference for payoffs exhibiting positive skewness. This behaviour is termed prudence (see Kimball, 1990). Interestingly, experimental evidence (see Kahneman and Tversky, 1979) showed that there is an asymmetrically higher impact on utility by losses as related to gains, leading to a class of utility functions such as the Disappointment Aversion by Gul (1991). These functions imply that agents are even more averse to negative skewness. Hence, aversion to negative skewness is a crucial feature that has been neglected in asset pricing. In this spirit, the present study employs the stochastic discount factor framework to show how that negative coskewness bears a risk premium. Harvey and

Siddique (2000) provide evidence for the existence of this premium.

Another very important limitation of the CAPM is its static nature. The recent asset pricing literature has attempted to resolve the documented "anomalies" within an intertemporal framework. The studies of Vassalou (2003), Campbell and Vuolteenaho (2004) and Petkova (2006), *inter alia*, provide characteristic examples. This approach has its origins in the Intertemporal CAPM of Merton (1973). The most important observation is that there is a set of underlying risk factors which evolve stochastically through time and affect the dynamics of asset returns. The present study takes a further step showing that the impact of these risk factors on asset returns can be represented by means of higher moments. In other words, the intertemporal risks can be interpreted as higher moments risks. Having drawn this link, it is discussed how the outperformance of the size, value and momentum strategies can be explained as risk premia due to negative coskewness.

Asset pricing models play a significant role in investment performance evaluation, hence the assumptions of these models are crucial in order to understand the incentives generated. Fund managers try to distinguish themselves from their peers on the basis of these measures. Therefore, they respond to these incentives by adopting investment strategies, which generate excess returns and help them outperform. If the employed measure, however, does not take into account all underlying risk factors, then the managers will be incentivised to load the neglected risks to their portfolios in order to reap the relevant premia and outperform.

This issue becomes of utmost importance when we deal with delegated asset management, where a series of issues related to principal-agent problems arise due to asymmetric information (see Spencer, 2000, for an analytical treatment). Closely related to the choice of a performance measure is the issue of *ex post verification*. This refers to the problem of a principal (fund shareholder) to fairly evaluate the investment outcome of the agent (fund manager). To this end, there have been suggested a series of performance measures, according to which, managers should be classified and rewarded. The most obvious reason is the necessity of having an objective way to compensate and promote managers (resolving the *ex post verification* problem).

The present study reviews the most commonly used performance measures and discusses the assumptions on which they are based. The incentives for specific investment strategies generated by the corresponding measures are discussed. In particular, mean-variance measures create the incentive to invest in assets exhibiting negative coskewness. Consequently, the Harvey-Siddique two-factor asset pricing model, which adds a negative coskewness mimicking portfolio factor, is proposed to be an appropriate framework for a long-term, prudent investor. This model takes into account the risk premia formed in capital markets due to the participants' aversion to negative skewness as well as the risk premia arising due to the desire of long-term investors to hedge against negative shocks in the underlying opportunity set. The intercept of this model, which we term as *Harvey-Siddique alpha*, is employed as a performance measure to evaluate the performance of UK unit trusts during the period 1991-2005.

In order to perform this analysis, the returns of a zero-cost coskewness spread portfolio have been calculated for the UK, showing that the average monthly return of this strategy was 2.09% p.a. over the period 1991-2005. Previewing our results, the unit trusts investing in the FTSE All Share had an average *Harvey-Siddique alpha* of -2.12% p.a., while their average *Jensen alpha* was -1.23% p.a. The regression analysis discovered that almost all of the examined trusts had a positive loading on the coskewness strategy, for the most of them being statistically significant too. Most interestingly, the trusts which had the highest Jensen alphas were those with very high loadings on negative coskewness. The nonnormality of the trusts' performance distribution can be indeed attributed to heterogeneous risk-taking, with the coskewness strategy being a main source of this heterogeneity. The subperiod analysis yielded similar results.

There are two main conclusions from this study: Firstly, long-term, prudent investors who are averse to negative skewness, should employ the *Harvey-Siddique alpha* in order to neutralize the incentives of trust managers to load this type of risk. For this type of investors, most of UK unit trusts managers exhibited a significantly negative managerial ability. Secondly, the trust managers were very succesful to reap the negative co-skewness premium priced in the market, boosting their returns and correctly responding to their incentives, since they were evaluated according to static, mean-variance measures, which regard this premium as a "free lunch".

2 Motivation

2.1 (Co)skewness in asset pricing

The central problem in Asset Pricing is to find a valid Stochastic Discount Factor (SDF) M for future payoffs. Formally, the SDF is assumed to be positive (see Harrison and Kreps, 1979), it is unique under complete markets and satisfies the following relationship:

$$P_t = E_t[M_{t+s}X_{t+s}] \tag{1}$$

where P_t is the price of an asset at time t and X_{t+s} denotes the asset payoff(s) at time $t+s$.

In a one-period ahead framework, gross returns $R_{t+1} = \frac{X_{t+1}}{P_t} = 1 + r_{t+1}$ are employed to re-write:

$$1 = E_t[M_{t+1}R_{t+1}] \tag{2}$$

It is straightforward to derive the following relationships (see Smith and Wickens, 2002 for an analytical treatment), which relate the SDF, the risky and the risk-free asset return r_t^f :

$$1 = E_t(M_{t+1})(1 + r_t^f) \Rightarrow E_t(M_{t+1}) = \frac{1}{1 + r_t^f} \tag{3}$$

and

$$E_t(R_{t+1}) = \frac{1 - Cov(M_{t+1}, R_{t+1})}{E_t(M_{t+1})} \tag{4}$$

Combining these two equations we get a central result in asset pricing theory:

$$E_t(r_{t+1}) - r_t^f = -(1 + r_t^f)Cov(M_{t+1}, r_{t+1}) \tag{5}$$

This equation implies that the excess expected return of a risky asset depends on the covariance of the SDF with this return.

A commonly used *ad hoc* assumption is that the SDF is linear in the market returns:

$$M_{t+1} = a + br_{M,t+1} \tag{6}$$

where $r_{M,t+1}$ is the return of the market portfolio, usually proxied by a stock market index.

Such a specification leads to the standard CAPM. In particular,

$$E_t(r_{t+1}) - r_t^f = -(1 + r_t^f)bCov(r_{M,t+1}, r_{t+1}) \tag{7}$$

But since this equation holds for all assets, it should also hold for the market portfolio $r_{M,t+1}$:

$$E_t(r_{m,t+1}) - r_t^f = -(1 + r_t^f)bVar(r_{M,t+1}) \Rightarrow b = -\frac{E_t(r_{m,t+1}) - r_t^f}{(1 + r_t^f)Var(r_{M,t+1})} \tag{8}$$

Replacing back this expression for b we get:

$$E_t(r_{t+1}) - r_t^f = \frac{Cov(r_{M,t+1}, r_{t+1})[E_t(r_{m,t+1}) - r_t^f]}{Var(r_{M,t+1})} = \beta[E_t(r_{m,t+1}) - r_t^f] \tag{9}$$

where $\beta \equiv \frac{Cov(r_{M,t+1}, r_{t+1})}{Var(r_{M,t+1})}$ is essentially the coefficient of regressing $(r_{t+1} - r_t^f)$ on $(r_{m,t+1} - r_t^f)$.

But is this a legitimate specification for the SDF? Harvey and Siddique (2000) use the marginal rate of substitution $\frac{U^{'}(W_{t+1})}{U^{'}(W_t)}$ as an SDF to show the implications of this linear specification. Taking a first-order Taylor series expansion of $U^{'}(W_{t+1})$ around W_t, we get

$$\begin{aligned} U^{'}(W_{t+1}) &\simeq U^{'}(W_t) + U^{''}(W_t)(W_{t+1} - W_t) \Rightarrow \\ \frac{U^{'}(W_{t+1})}{U^{'}(W_t)} &\simeq 1 + \frac{U^{''}(W_t)W_t}{U^{'}(W_t)} r_{m,t+1} = 1 - \gamma r_{m,t+1} \end{aligned} \quad (10)$$

where we have used the simple relationship $W_{t+1} = W_t(1 + r_{m,t+1})$ and the definition of the Arrow-Pratt measure of Relative Risk Aversion, $\gamma = -\frac{U^{''}(W_t)W_t}{U^{'}(W_t)}$. This implies that the ad hoc SDF (6) can be regarded as an approximation to the marginal rate of substitution, with $a = 1$ and $b = -\gamma$.

However, there is no particular reason why the truncation of the Taylor series expansion occurs at the first order. If the truncation takes place at the second order, then:

$$\begin{aligned} U^{'}(W_{t+1}) &\simeq U^{'}(W_t) + U^{''}(W_t)(W_{t+1} - W_t) + \frac{U^{'''}(W_t)(W_{t+1} - W_t)^2}{2!} \Rightarrow \\ \frac{U^{'}(W_{t+1})}{U^{'}(W_t)} &\simeq 1 + \frac{U^{''}(W_t)W_t}{U^{'}(W_t)} r_{m,t+1} + \frac{U^{'''}(W_t)W_t^2}{2U^{'}(W_t)} r_{m,t+1}^2 = \\ &= 1 - \gamma r_{m,t+1} + \frac{U^{'''}(W_t)W_t}{2U^{''}(W_t)} \frac{U^{''}(W_t)W_t}{U^{'}(W_t)} r_{m,t+1}^2 = \\ &= 1 - \gamma r_{m,t+1} + \frac{1}{2}\gamma\eta r_{m,t+1}^2 \end{aligned} \quad (11)$$

where $\eta \equiv -\frac{U^{'''}(W_t)W_t}{U^{''}(W_t)}$ is the measure of Relative Prudence defined by Kimball (1990). Furthermore, defining $c \equiv \frac{U^{'''}(W_t)W_t^2}{2U^{'}(W_t)} = \frac{1}{2}\gamma\eta r_{m,t+1}^2$, the SDF in (11) can now be written as:

$$m = 1 + br_{m,t+1} + cr^2_{m,t+1} \tag{12}$$

This is not a linear SDF any more, since the squared market returns are involved. Recalling the fundamental asset pricing equation (5) of the SDF approach, the expected excess return of an asset now depends on the covariance of this asset returns not only with the market portfolio return but also with the squared market returns. This is exactly what the coskewness measures. In the standard case of $\eta > 0 \Rightarrow c > 0$, the fundamental equation of asset pricing (5) can be written as:

$$E_t(r_{t+1}) - r^f_t = -(1 + r^f_t)bCov(r_{M,t+1,}r_{t+1}) - (1 + r^f_t)cCov(r^2_{M,t+1,}r_{t+1}) \tag{13}$$

Therefore, for given $Cov(r_{M,t+1,}r_{t+1})$, we have two cases with respect to the $Cov(r^2_{M,t+1,}r_{t+1})$.

On the one hand, if $Cov(r^2_{M,t+1,}r_{t+1}) > 0$, then $E_t(r_{t+1}) - r^f_t$ is now lower in comparison to the case of equation (7). This implies that if a risky asset has positive coskewness with the market returns, then it will bear a lower risk premium. On the other hand, if $Cov(r^2_{M,t+1,}r_{t+1}) < 0$, then $E_t(r_{t+1}) - r^f_t$ is now higher. In other words, a prudent investor seeks an extra risk premium in order to hold an asset the returns of which are characterized by negative coskewness. Therefore, if financial markets are dominated by prudent investors, expected returns should be higher for assets having negative coskewness with the market portfolio. This is a key result in our analysis.

A similar exposition would be also informative in an equilibrium model. In the Consumption CAPM the Euler equation is given by:

$$E_t[\beta \frac{U'(C_{t+1})}{U'(C_t)} R_{t+1}] = 1 \tag{14}$$

making $\beta \frac{U'(C_{t+1})}{U'(C_t)} R_{t+1} = M_{t+1}$ a valid SDF. The standard approach is to take a first-order Taylor series expansion of $U'(C_{t+1})$ around C_t and to re-write the SDF as:

$$\beta \frac{U'(C_{t+1})}{U'(C_t)} \simeq \beta(1 - \gamma \Delta \ln(C_{t+1})) \tag{15}$$

As it has been mentioned, there is no theoretical reason why the Taylor-series expansion should be truncated in the first order. If we take a second-order expansion of $U'(C_{t+1})$ around C_t, we get the following approximation:

$$\begin{aligned} \beta \frac{U'(C_{t+1})}{U'(C_t)} &\simeq \beta[1 - \gamma \Delta \ln(C_{t+1}) + \frac{1}{2} \frac{U'''(C_t)}{U'(C_t)} (C_{t+1} - C_t)^2] = \\ &= \beta[1 - \gamma \Delta \ln(C_{t+1}) + \frac{1}{2} \frac{U'''(C_t) C_t}{U''(C_t)} \frac{U''(C_t) C_t}{U'(C_t)} \frac{(C_{t+1} - C_t)^2}{C_t^2}] = \\ &\simeq \beta[1 - \gamma \Delta \ln(C_{t+1}) + \frac{1}{2} \eta \gamma (\Delta \ln(C_{t+1}))^2] \end{aligned} \tag{16}$$

Even though the tidy linear form is abandoned, the advantage of expression (16) is that another important term appears now, which involves the quadratic change in the consumption level. This essentially implies that the volatility of the consumption change is an important factor in asset pricing. Neglecting this volatility we may ignore important information. A similar argument can be found in Brav et al. (2002) in a model with multiple agents and incomplete consumption insurance. They argue that the cross-sectional properties of the variance and skewness of consumption growth rates are important in asset pricing even though they do not explicitly incorporate prudence in their analysis.

2.2 (Co)skewness in preferences

Examining the impact of coskewness on asset pricing, the assumption of positivity for the term $\frac{U'''(W_t)}{U'(W_t)}$ was made. It is important to explain how this assumption is derived. In particular, the current analysis deals with utility functions which share the following properties:

i) Monotonicity $U'(W_t) > 0$

ii) Concavity, i.e. the idnividuals are risk averse and $U''(W_t) < 0$.

Furthermore, a desirable property of a utility function is to exhibit Decreasing Absolute Risk Aversion (DARA). This property implies that the wealthier an investor is, the less risk averse he must be over a specific amount of investment. Since the coefficient of Absolute Risk Aversion (ARA) is given by:

$$ARA = -\frac{U''(W)}{U'(W)} \tag{17}$$

for this to be decreasing in wealth it should hold:

$$\frac{\vartheta(ARA)}{\vartheta W} < 0 \Rightarrow -\frac{U'''(W)}{U'(W)} + (\frac{U''(W)}{U'(W)})^2 < 0 \Rightarrow -\frac{U'''(W)}{U'(W)} < 0 \Rightarrow U'''(W) > 0 \tag{18}$$

due to the properties previously stated. The positivity of the third derivative of the utility function can be also interpreted as *prudence*. Leland (1968) and Sandmo (1970) argue that this behaviour is associated with the motive for precautionary savings in the face of future income/consumption uncertainty. In general, prudence could be characterized as the sensitivity of the optimal choice for a decision variable with respect to its variability (see Kimball, 1990 for an analytical treatment). It is important to note that this behaviour is distinct from risk aversion. In particular, under quadratic utility, $U(W) = aW + bW^2$, the individual, has zero measure of prudence, even though he is risk averse when $b < 0$.

Extending the previous analysis, it is very informative to examine the interplay between returns' distributions and preferences. It is expected that a risk-averse and prudent investor has a preference over positively skewed payoffs and an aversion towards negatively skewed ones. In other words, a negatively skewed distribution implies higher downside risk provoking aversion to investors. There is significant actual evidence in the markets supporting this argument. The very popular portfolio insurance products are protecting investors against downside risk. Moreover, most of modern risk management is based on the avoidance of extreme negative retuns. The most characteristic example is the Value-at-Risk (VaR) measurement.

Further evidence is provided by the option-implied distribution, which is constructed by option prices across different strike prices on an underlying asset over a specific period and it is a very powerful tool to illustrate this behaviour. Option-implied distributions, after the 1987 crash, are typically negatively-skewed. In particular, deep out-of-the-money puts, which are popular instruments for portfolio insurance, have quite high prices relatively to the ones implied by the Black and Scholes (1973) model. This creates the smirk in the implied volatility-strike price graph, in contrast to the constant volatility assumption of Black-Scholes. This feature of option prices has been termed *crashophobia* (see Jackwerth, 2004, for analytical discussion). On the other hand, preference for positive skewness is evident in lotteries. Agents are willing to participate in lotteries with positive skewness (see for example, Golec and Tamarkin, 1998), even though these have negative expected values (unfair games). It is worth mentioning that participation in such unfair games increases as positive skewness increases (e.g. jackpots in lotteries).

In order to examine more formally the impact of skewness on expected utility, it proves useful to perform a Taylor series expansion around the mean level of wealth $\overline{W}$. Then, the expected utility at time t over wealth at time $t+1$ is given by:

$$E_t[U(W_{t+1})] = E_t[\sum_{k=0}^{\infty} \frac{U^{(k)}(\overline{W}_{t+1})(W_{t+1} - \overline{W}_{t+1})^k}{k!}] \tag{19}$$

Equation (19) can be re-written, under mild assumptions, as:[1]

$$E_t[U(W_{t+1})] = \sum_{k=0}^{\infty} \frac{U^{(k)}(\overline{W}_{t+1})}{k!} E_t[(W_{t+1} - \overline{W}_{t+1})^k] \tag{20}$$

In a portfolio choice context, the case of $k = 2$ corresponds to the familiar mean-variance analysis, *à la Markowitz*. If we truncate the Taylor series expansion at order $k = 3$, the third moment of the wealth distribution is taken into account, i.e.:

$$E_t[U(W_{t+1})] \simeq U(\overline{W}_{t+1}) + \frac{U^{(2)}(\overline{W}_{t+1})}{2!} E_t[(W_{t+1} - \overline{W}_{t+1})^2] + \frac{U^{(3)}(\overline{W}_{t+1})}{3!} E_t[(W_{t+1} - \overline{W}_{t+1})^3] \tag{21}$$

The expansion of the expected utility shows the importance of asymmetries in the risky asset distributions. If we have a symmetric distribution, then the last term vanishes and is irrelevant for the portfolio choice, even if the agent is prudent. Since most of asset returns are characterized by negative skewness, it becomes evident that the mean-variance *Weltanschauung* is only a restrictive case of the general problem.

Interestingly, the impact of skewness is often examined under the assumption of a CRRA utility, such as the power utility function, $U(W) = \frac{W^{1-\gamma}}{1-\gamma}$. The main characteristic of this function is that it treats symmetrically utility gains and losses due to a wealth change of the same magnitude. Actually, this is also a property of the mean-variance analysis. It assumes that individuals do not distinguish between volatility and downside risk.

Nevertheless, there is significant experimental evidence that agents are mainly averse to losses, not just to volatility. The Loss Aversion Theory of

[1] Lhabitant (1998) argues that if the Taylor series is uniformly convergent, then we also have pointwise convergence and the infinite series ($\sum_{k=0}^{\infty} \frac{U^{(k)}(\overline{W})}{k!}$) can be integrated out of the expectation term-by-term. Lhabitant's assumtpions depend on the choice of the utility function. In the case of power utility function, convergence occurs for wealth levels in the range of $[0, 2\overline{W}]$, which is not such a restrictive range.

Kahnemann and Tversky (1979) as well the Disappointment Aversion framework of Gul (1991) imply that investors maintain an asymmetric attitude towards losses as compared to gains. In other words, investors are more averse to negative skewness in comparison to CRRA agents. The non-paticipation in capital markets is a consequence of these preferences. In particular, mean-variance theory predicts that even agents who are extremely risk averse, should hold a portion of their portfolio in the risky asset which bears a positive risk premium. Nevertheless, actual data show that a large proportion of households have zero holdings in risky assets (see e.g. Haliassos and Bertaut, 1995).

Ang et al. (2005) provide a very detailed treatment of the portfolio choice problem under Disappointment Aversion. In particular, the preferences of the agent can be approximated by the following utility function:

$$U(W, A, s) = \frac{1}{K}\left(\int_{-\infty}^{s} U(W)dF(W) + A\int_{s}^{+\infty} U(W)dF(W)\right) \qquad (22)$$

where $A \leq 1$, $K = \Pr(W \leq s) + A\Pr(W > s)$ and s is the certainty equivalent of wealth. If $A = 1$ then $K = 1$ and we get back the standard utility specification. For $A < 1$ the investors are averse to losses or disappointment averse. Such a specification essentially implies a transformation of the probabilities assigned to various realizations of the wealth distribution. In particular, realizations of wealth levels below s are assigned a higher weight than the corresponding realizations above s. In other words, agents are more averse to negative skewness in comparison to power utility agents. Interestingly, from equation (21) one can observe that even if the distribution is symmetric, the higher moments would still be important for the portfolio choice problem due to the asymmetric impact of returns on preferences.

There is a number of regulatory, legal and psychological issues related with the aversion towards negative skewness. Moreover, pension funds and insurance companies usually face legal obligations to pay out fixed or quasifixed amounts. The same holds for households with legal obligations over mortgages, loan installments or fees. Habit formation is another example of anchoring one's preferences around a reference point and being reluctant to accept any wealth level below that. This mixture of obligations and preferences make pension funds, insurance companies and individuals willing to hedge against large negative movements in asset prices.

2.3 (Co)skewness, market "anomalies" and intertemporal risks

The previous section exhibited that negative (co)skewness plays a significant role in asset pricing and portfolio choice. Consequently, ignoring the risk premia assigned to negative coskewness can lead to inefficient investment policies as well as inappropriate performance evaluation. It is argued in this subsection that the documented asset pricing "anomalies" which are currently being explained as premia for intertemporal risks are directly linked to negative coskewness.

Among the most often cited failures of the CAPM is the outperformance of size and value strategies. Fama and French (1993, p.55) questioned whether "...specific fundamentals [can] be identified as state variables that lead to common variation in returns that is independent of the market and carries a different premium than general market risk". This conjecture motivated significant research effort to relate the returns of Fama-French portfolios with specific economic and financial variables. Liew and Vassalou (2000) argued that size and value returns have predictive ability for future GDP growth for a series of markets. Extending these results, Vassalou (2003) creates a mimicking portfolio, which proxies news to future GDP growth and argues that this can explain the cross-section behaviour of the Fama-French portfolios.

On the other hand, Brennan et al. (2004) use as intertemporal risk factors the real interest rate and the Sharpe Ratio. Petkova (2006) devises an asset pricing model using the financial variables that have been employed to predict future stock returns (dividend yield, term spread, default spread and the short term rate). Showing the superior explanatory ability of the shocks to these variables in comparison to the Fama-French portfolios, she establishes a link between the cross-section and the time-series behaviour of the stock returns. Campbell and Vuolteenaho (2004) suggest a two-beta model, explicitly specifying the cash flows and the discount rate as risk factors in an intertemporal asset pricing model.

Summarizing, there have been several promising attempts to rationalize the Fama-French anomalies within an intertemporal framework. All these studies essentially assume the existence of a set of risk factors, which vary stochastically and their innovations are correlated with the innovations to the stock returns. Such a setup generates intertemporal risk premia, as shown in Merton (1973). It is argued here that these intertemporal risk premia can be statically represented in terms of skewness and kurtosis. To show that formally, let us fix a probability space $(\Omega, \mathcal{F}, P)$ and the information filtration $(\mathcal{F}_t) = \{\mathcal{F}_t : t \geq 0\}$. Let S_t be the stock price and X_t the underlying risk factor at time t. The processes $(S_t,\ X_t)$ form jointly a Markov process in the state space $D \epsilon R^2$ and they obey the following stochastic differential equations:

$$\frac{dS_t}{S_t} = \mu dt + \sigma_s \sqrt{X} dW_{St} \tag{23}$$

$$dX_t = k(\theta - X)dt + \sigma_x \sqrt{X} dW_{Xt} \tag{24}$$

where $dW = (dW_S, dW_X)'$ is a vector of standard Brownian motions adapted to $(\mathcal{F}_t)$ and the two Brownian motions have correlation coefficient $(dW_S)(dW_X) = \rho_{sx} dt$. An important observation is that even though the processes (S_t, X_t) are jointly Markovian, the process of the risky asset price (S_t) is not necessarily Markovian. In other words, the entire history of observations could provide important information for the future stock price movements.

In order to find the moments of the the stock returns given the presence of the underlying stochastic factor X, it is most convenient to derive the joint conditional characteristic function of the processes $(S_t,\ X_t)$ and to work out the unconditional characteristic function of the risky asset returns $\Delta s_{t+1} = s_{t+1} - s_t$, where $s_t = \ln S_t$.

The joint conditional characteristic function is given by:

$$\varphi(u_1, u_2; S_{t+\tau}, X_{t+\tau}|S_t, X_t) = E[\exp(iu_1 S_{t+\tau} + iu_2 X_{t+\tau})|S_t, X_t] \tag{25}$$

and satisfies the following Kolmogorov equation:

$$E\{\frac{\vartheta\varphi}{\vartheta S}dS+\frac{\vartheta\varphi}{\vartheta X}dX+\frac{1}{2}\frac{\vartheta^2\varphi}{\vartheta S^2}(dS)^2+\frac{1}{2}\frac{\vartheta^2\varphi}{\vartheta X^2}(dX)^2+\frac{\vartheta^2\varphi}{\vartheta X\vartheta S}(dS)(dX)+\frac{\vartheta\varphi}{\vartheta t}dt\} = 0 \tag{26}$$

Due to affine structure of the processes (see Duffie et al., 2000), we conjecture the trial form for the characteristic function to be:

$$\varphi(u_1, u_2; S_{t+\tau}, X_{t+\tau}|S_t, X_t) = \exp\{C(\tau; u_1, u_2)+D_1(\tau; u_1, u_2)S_t+D_2(\tau; u_1, u_2)X_t\} \tag{27}$$

with the terminal conditions: $C(0; u_1, u_2) = 0$, $D_1(0; u_1, u_2) = iu_1$, $D_2(0; u_1, u_2) = iu_2$.

Replacing this trial form into the Kolmogorov equation and simplifiying we get:

$$\begin{aligned} D_1\mu + D_2 k(\theta - X) + \frac{1}{2}(D_1)^2\sigma_s^2 X + \frac{1}{2}(D_2)^2\sigma_x^2 X + D_1 D_2 \sigma_s \sigma_x \rho_{sx} X = \\ = \frac{\vartheta C}{\vartheta\tau} + \frac{\vartheta D_1}{\vartheta\tau}S + \frac{\vartheta D_2}{\vartheta\tau}X \end{aligned} \tag{28}$$

A separation of variables argument yields the following ODEs:

$$\frac{\vartheta D_1}{\vartheta \tau} = 0 \Rightarrow D_1 = iu_1 \tag{29}$$

$$\frac{\vartheta C}{\vartheta \tau} = (D_1)\mu + (D_2)k\theta = iu_1\mu + (D_2)k\theta \tag{30}$$

$$\begin{aligned}\frac{\vartheta D_2}{\vartheta \tau} &= \frac{1}{2}(D_1)^2\sigma_s^2 + \frac{1}{2}(D_2)^2\sigma_x^2 - D_2 k + D_1 D_2 \sigma_s \sigma_x \rho_{sx} = \\ &= -\frac{1}{2}u_1^2\sigma_S^2 + \frac{1}{2}(D_2)^2\sigma_x^2 + D_2(iu_1\sigma_s\sigma_x\rho_{sx} - k) \end{aligned} \tag{31}$$

with the terminal conditions previously defined. This is a system of ODEs. In particular, we get:

$$D_1 = iu_1 \tag{32}$$

The ODE with respect to $D_2(\tau)$ is of *Riccati* type and can be solved analytically. In particular, defining $a = iu_1\sigma_S\sigma_X\rho_{SX} - k$, $b = \frac{1}{2}\sigma_X^2$, $c = -\frac{1}{2}u_1^2\sigma_S^2$, $\psi = \sqrt{a^2 - 4bc}$, the solution is given by:

$$D_2(\tau) = -\frac{2(\exp(\psi\tau) - 1)}{(a+\psi)(\exp(\psi\tau) - 1) + 2\psi}c + iu_2\tau \tag{33}$$

Consequently, $C(\tau)$ is given by:

$$C(\tau) = iu_1\mu\tau + iu_2k\theta\tau -$$
$$-2ck\theta[\frac{2\ln[a(\exp(\psi\tau) - 1) + \psi(\exp(\psi\tau) + 1)] - 2\ln(2\psi) - (a+\psi)\tau}{(\psi + a)(\psi - a)}]$$

Using Lemmas 2 and 3 of Jiang and Knight (2002), given the joint conditional characteristic function, we can derive the unconditional characteristic function of Δs_{t+1} by:

$$\varphi(u_1, u_2; \Delta s_{t+1}) = \exp\{C(1; u_1, 0)\}\psi(D_2(1; u_1, 0); X_0) \tag{34}$$

where $\psi(D2(1; u_1, 0); X_0)$ is the characteristic function of X_0. This follows a Gamma distribution with mean θ and variance $\frac{\theta\sigma_x^2}{2k}$. Given the solutions to the ODEs and since X_t follows a Gamma distribution,

$$
\begin{aligned}
&\varphi(u_1, u_2; \Delta s_{t+1}) = \\
&= \exp\{iu_1\mu - 2ck\theta[\frac{2\ln[a(\exp(\psi) - 1) + \psi(\exp(\psi) + 1)] - 2\ln(2\psi) - (a + \psi)}{(\psi + a)(\psi - a)}]\} \\
&(1 - (D_2(1; u_1, 0))\frac{\sigma_x^2}{2k})^{-\frac{2k\theta}{\sigma_x^2}} = \\
&= \exp\{iu_1\mu - 2ck\theta[\frac{2\ln[a(\exp(\psi) - 1) + \psi(\exp(\psi) + 1)] - 2\ln(2\psi) - (a + \psi)}{(\psi + a)(\psi - a)}]\} \\
&(1 + \frac{2(\exp(\psi) - 1)}{(a + \psi)(\exp(\psi) - 1) + 2\psi} c\frac{\sigma_x^2}{2k})^{-\frac{2k\theta}{\sigma_x^2}}
\end{aligned} \tag{35}
$$

Given this characteristic function, we can find the moments of the returns process:

$$E(\Delta s) = \mu \tag{36}$$

$$E(\Delta s - E(\Delta s))^2 = \sigma_s^2\theta \tag{37}$$

$$E(\Delta s - E(\Delta s))^3 = \frac{3}{k^2}(e^{-k} + k - 1)\theta\sigma_s\sigma_x\rho_{sx} \tag{38}$$

$$E(\Delta s - E(\Delta s))^4 = 3E(\Delta s - E(\Delta s))^2 + (3/k^3)(e^{-k} + k - 1 + 4((2 + k)e^{-k} + k - 2)\rho_{sx}^2)\sigma_s^2\sigma_x^2\theta \tag{39}$$

We see that the skewness of the returns' distribution crucially depends on the sign of the correlation of the shocks. Trivially, if there is zero correlation, then the returns distribution is symmetric. If the correlation is negative, then the returns' distribution is negatively skewed. Interestingly, there is a series of studies in the dynamic asset allocation literature, which report a negative correlation between the shocks to the risky assets and the shocks to the underlying risk factor. We refer *inter alia* to Brennan *et al.* (1997), who use the dividend yield, the short and the long rate as the stochastic factors, Campbell and Viceira (1999) and Barberis (2000), who use the dividend yield and Wachter (2002), who uses the Sharpe ratio. This negative correlation, which would be equivalent to negative skewness in the asset returns according to the previous setup, gives rise to a hedging demand component in the optimal portfolio choice of the long-term, risk-averse investor. Consequently, risky assets incorporate a hedging value with respect to intertemporal risks, which are shown to be equivalent to negative skewness risk within this framework.

Since intertemporal risks can be statically reflected by means of higher moments, it is argued that the Fama-French factors essentially proxy negative skewness or excess kurtosis. Confining ourselves to negative skewness, the study of Harvey and Siddique (2000) establishes such a link. They show that the excess returns generated by the value, size and momentum portfolios can be partly explained by the fact that these portfolios are negatively coskewed with the market returns. Consequently, the implementation of these strategies is essentially adding negative skewness to the portfolios, so the excess returns generated by these strategies are due to the assumption of skewness risk. As they comment (p. 1283): "HML and SMB [portfolios], to some extent, capture information similar to that captured by skewness". A direct consequence of the previous analysis is that the two approaches to asset pricing -intertemporal risk premia and higher moments risk premia- are essentially equivalent. It is important to note that it is not necessary for the value and small stock returns to be negatively skewed, but rather that they are less positively skewed in comparison to the growth and big size stock returns correspondingly.

Examining further this link, stocks with high book to value ratios and small size are dominated by cash-flows (earnings) risk, as argued in Campbell and Vuolteenaho (2004). An earnings shock has an irreversible effect through time, while an interest rate shock has a partly reversible effect, because interest rates determine the rates of returns apart from discounting future cash flows. If investors are forward looking and price these intertemporal risks, a shock to the cash flow will have a higher impact on prices today, while an interest rate shock is expected to have a lower impact due to its reversibility through time.

This is sufficient to argue that assets with high earnings risk are expected to incorporate a higher risk premium. In terms of moments, this argument essentially implies that small size and value stocks are expected to have higher cokurtosis, because a shock to earnings will have a larger impact on their prices, in comparison to big size and growth stocks, which are mainly characterized by interest rate risk. However, bearing in mind that negative shocks (news) typically have a stronger impact than positive shocks (news), see Conrad et al. (2002), as well as the asymmetric impact of gains and losses on preferences, this feature leads to negative coskewness.

Providing further reasoning for the small size stock anomaly, it is claimed that small size stocks are expected to have higher negative skewness in comparison to the big size stocks because they have lower survival probability rates. Small size stocks are thought to be more vulnerable to negative shocks because they are mainly new companies with lower capital capacity and they have higher probabilities of ceasing operations.

Regarding the ouperformance of the momentum strategy, there has not been any successful intertemporal framework to provide an explanation of its outperformance. As Campbell and Vuolteenaho (2004) remark (p. 1270): "We are pessimistic about the two-beta model's ability to explain average returns on portfolios formed on past one-year stock returns". The explanation we put forward is related to the limited liability property of the assets. If there is a hypothetical range of values for the asset, past losers are thought to have shifted closer to the left end of this interval, so the downside risk over the next periods is thought now to be much lower in comparison to past winners who have shifted to the right end. Since asset values essentially have a left truncated distribution, the closer the asset price is to this left end, the more positively coskewed with the market returns it will be.

3 Performance measures and incentives in fund management

3.1 Raw returns

Since the work of Markowitz (1952), it has been understood that there exists a direct positive relationship between risk and return. However, managers and funds are still often ranked according to their raw returns. The new breed of funds appearing as "absolute-return" seeking funds reflects the lack of understanding of the notions of risk and return. Using raw returns as a performance measure essentially means that the investor is indifferent to risk, i.e. his utility is not decreasing in volatility/risk. Hence risk premia are thought to be a "free lunch". Evaluating a manager's performance using such a measure, he will be incentivised to undertake the highest possible risk.

3.2 Sharpe ratio

On the other hand, most of the academic literature has been evaluating investment strategies according to their risk-adjusted returns. One of the most commonly used measures of risk-adjusted performance is the Sharpe ratio due to Sharpe (1966):

$$SR = \frac{R_p - r^f}{\sigma_p} \tag{40}$$

where R_p is the fund's return, r^f is the risk-free rate and σ_p is the standard deviation of the returns. Using this measure, fund managers do not have the incentive to invest in more volatile assets, since higher volatility essentially penalizes their excess returns.

The Sharpe ratio is, however, a purely mean-variance measure, neglecting higher moments. Nevertheless, these higher moments bear risk premia in a market with prudent, long-term investors, as it was previously discussed. Consequently, the rational response of the fund managers is to invest in assets that exhibit negative skewness and excess kurtosis in order to reap the corresponding risk premia. For example, a manager could shift from an asset class to another one with the same volatility, but higher negative skewness and, as a result, higher expected returns. This will create a higher Sharpe ratio and the manager will be classified as a Winner.[2]

There is a series of examples documenting the existence of these strategies. Investing in emerging countries' and junk bonds is a straightforward case. These bonds have higher probability of default in comparison to investment grade bonds. As a result, their returns are more negatively skewed and they provide higher yields. If a manager matches bonds with the same volatility but with different degrees of skewness, he can substitute the ones with low skewness for the ones with higher negative skewness in order to have a higher Sharpe ratio- until the default occurs.

Goetzmann et al. (2007) analyze methods of maximizing a portfolio's Sharpe ratio using derivatives. Shorting different fractions of out-of-the-money puts and calls creates a negatively skewed distribution of returns and leads to the maximal Sharpe ratio. Their example also shows that hedge funds and other investment vehicles which use derivative assets can manipulate their Sharpe ratio. Leland (1999) provides an example of a dynamic strategy of cash and stocks as well as static strategies using options, which

[2] Fund management practice shows that managers try to find and exploit patterns in stock returns in order to generate portfolios that beat the measures according to which they are evaluated. Therefore, a negative coskewness strategy does not necessarily mean that the manager consciously picks stocks with this characteristic, but that the strategies he implements actually mimick this statistical characteristic.

generate negative skewness and outperform in terms of Sharpe ratio. Therefore, such funds should not be evaluated by mean-variance measures.

The inappropriateness of the Sharpe ratio for skewed returns is also mentioned in Ziemba (2005), who provides a modification of the Sharpe ratio to emphasize the importance of the downside risk. The Symmetric Downside-Risk Sharpe ratio is given by:

$$SR_{-} = \frac{\mu - r^f}{\sqrt{2(\sigma_{-}^2)}} \tag{41}$$

where

$$\sigma_{-}^2 = [1/(T-1)] \sum_{t=1}^{T} (r_t - E(r))_{-}^2 \tag{42}$$

where the returns (r_t) used are those below $E(r)$. This measure essentially replaces the upside deviation by the downside risk, using the semi-variance instead of using the variance to adjust the excess returns.

3.3 Jensen Alpha and Treynor Ratio

Within the CAPM framework, Jensen (1968) introduced the intercept of the regression as a measure for the fund manager's ability:

$$r_{p,t} = \alpha_{Jensen} + \beta_p r_{M,t} + \epsilon_t \tag{43}$$

where $r_{p,t}$ is the excess returns of the trust, r_M is the excess return of a suitable market index and β_p is the CAPM beta of the excess fund's returns.

The intercept (α_{Jensen}) shows whether the manager has added any value over and above the return justified by the risk he had undertaken. The concept of risk here is summarized in the CAPM beta factor, which depends on the covariance of the portfolio with the market returns, since this is the only non-diversifiable risk according to the CAPM theory.

Closely related is the measure proposed by Treynor (1965):

$$TR = \frac{R_p - R_f}{\beta_p} \tag{44}$$

Following the spirit of the Sharpe ratio, the Treynor ratio adjusts excess returns for the corresponding CAPM beta risk (β_p).

As it has been analytically discussed, the CAPM provides a poor approximation of reality. The CAPM is a mean-variance static measure, neglecting all other sources of risk, in particular those arising due to the higher moments and the stochastic evolution of the underlying risk factors affecting the asset returns. Consequently, if evaluated by the CAPM, managers are incentivised to employ portfolio strategies, which load intertemporal and higher comoments risks in the portfolios. It is known that fund managers construct portfolio strategies which exploit patterns such as the size, value and momentum anomalies to add value to their portfolios. Temporary success of these strategies generates a positive Jensen alpha classifying the manager as a Winner. These portfolio strategies have zero CAPM beta risk but they are not necessarily riskless.

3.4 Carhart Alpha

The basic doctrine of financial theory is that "free lunches" in the spirit of Harrison and Kreps (1979) should be ruled out.[3] Furthermore, since the Fama-French and momentum strategies are very simple to construct and implement, these returns cannot be regarded as genuinely added value. Reflecting these arguments, Carhart (1997) suggested a measure, the *Carhart alpha*, which is the intercept of the four-factor model:

$$r_{p,t} = \alpha_{Carhart} + \beta_p r_{M,t} + \beta_1 SMB + \beta_2 HML + \beta_3 MOM + \epsilon_t \tag{45}$$

[3] Accepting "free lunches" would be equivalent to discarding asset allocation. If there exist strategies which add value to portfolios without undertaking any further risk, then the optimal portfolio choice collapses to an infinite demand schedule for these strategies.

The Carhart regression (45) essentially attributes the fund returns generated by the size (SMB), value (HML) and momentum (MOM) strategies to the corresponding risk factors. The intercept of this regression ($\alpha_{Carhart}$) shows the value the manager has added to his portfolio above what the beta risk could justify and these known strategies could generate. The importance of this measure is that it neutralizes the incentives to adopt these strategies, since these are recognized as risk factors.

Despite the significance of this measure, managers would still try to find patterns in stock returns in order to outperform even this measure. Even though the Carhart model reduces the possible opportunities, there exist other such strategies which load other types of risks, in order to outperform. The need for a more general measure capturing all these kinds of risks is obvious.

4 Data and Methodology

As it has been already discussed in the previous section, tactical asset allocation schemes will always find patterns to generate returns which will not be captured by the previously presented measures. Therefore, it is argued that instead of using mimicking portfolios for specific strategies, an appropriate measure should employ a portfolio mimicking the underlying risk factor.

We follow the methodology of Harvey and Siddique (2000) to construct this portfolio. Using 60 months of returns, we regress the market model for each individual stock

$$r_{it} = a + br_{M,t} + \varepsilon_t \tag{46}$$

extracting the residuals ε_t, which by definition are orthogonal to the market returns r_M. Therefore, these residuals are net of the systematic risk as this is measured by the covariance of the stock returns with the market portfolio. However, these residuals incorporate the coskewness risk. Therefore, we can get a measure of the standardized coskewness of each stock with the market return. This is given by:

$$\beta_{SKD} = \frac{E[\varepsilon_{i,t}\varepsilon_{M,t}^2]}{\sqrt{E[\varepsilon_{i,t}^2]}E[\varepsilon_{M,t}^2]} \tag{47}$$

and represents the contribution of a security to the skewness of a broader portfolio.

Ranking the stocks according to this coskewness measure, we can form a value-weighted portfolio of the 30% most positively coskewed stocks (S^+), while the 30% most negatively coskewed stocks form another portfolio (S^-). The next step is to find their returns on the 61st month. The spread of these two portfolios returns ($S^- - S^+$) will yield the return generated by the self-financing strategy of buying stocks with high negative coskewness and selling stocks with positive coskewness.

Consequently, an investment strategy should be evaluated using the following model:

$$r_t = a_{HS} + br_{M,t} + c(S^- - S^+)_t + \varepsilon_t \tag{48}$$

The intercept of this model, (a_{HS}), termed as the *Harvey-Siddique alpha*, will give us the value added by the manager over and above the covariance and negative coskewness risks. As Harvey and Siddique (2000, p. 1276), this asset pricing model has two main advantages over a model which would include the squared market returns as a factor (see Kraus-Litzenberger, 1976): Firstly, the direct coskewness is constructed by residuals, so it is by construction independent of the market return and, secondly, b is similar to the standard CAPM beta. Moreover, standardized coskewness is unit free and analogous to a factor loading. Apart from the parsimony in comparison to the Carhart (1997) measure, the suggested measure is also more general since it will capture the excess returns from any possible strategy that loads negative skewness to the portfolio.

To construct the coskewness measure β_{SKD} we employ data for monthly returns and market values of all stocks, being listed in the FTSE All Share Index during the period 1986-2005 which had at least 61 observations. The number of stocks utilized to create the coskewness portfolios varied from 413 (with market value of £339,404 mil.) in December 1991 to 581 in January 2004, (with market value of £1,045,331 mil.). The risk-free rate was the interbank monthly rate and the market returns were the returns of the FTSE All Share Index. The source for the data and the FTSE All Share Index listings was Thomson Datastream and Worldscope. The coskewness portfolios returns were constructed for the period January 1991 to December 2005 using the methodology described above. Table 1 presents the average returns of the zero-cost coskewness spread portfolio ($S^{-} - S^{+}$) and the market excess returns for various periods. A striking feature of the zero-cost portfolio is that it yielded, on average, a return of 2.09% *p.a.*, over the period 1971-2005, having a very low standard deviation. Figure 1 shows these returns along with the excess market returns. The subperiod analysis showed that negative coskewness was more significantly priced in the last subperiod, 2001-2005.

With respect to the Fama-French strategies, we approximate the Size strategy as the difference between the monthly returns of the Hoare Govett Small Cap and the FTSE 100 index and the Value strategy as the spread between the monthly returns of the MSCI UK Growth and the MSCI UK Value indices. As Table 1 shows these strategies yielded significant positive returns only during the subperiod 2001-2005. To provide evidence for the argument that the size and value strategies may mimick negative coskewness, we explore the properties of their returns during this subperiod. Figure 2 and Firgure 3 plot the densities of the monthly returns of the size and value strategies, correspondingly, during this period.[4] As it is evident, the

[4]These and the distributions in the following figures were smoothed using a kernel density estimator. We employed a Gaussian kernel function and the corresponding optimal bandwith (see Silverman, 1986, for an analytical treatment).

returns of these strategies exhibited negative skewness. Furthermore, the coefficients of standardized coskewness for the period Jan 2001- Dec 2005 were $\beta_{SKD}^{SMB} = -0.257$ for the Size (SMB) strategy and $\beta_{SKD}^{HML} = -0.107$ for the Value (HML) strategy, demonstrating that these two strategies had negatively coskewed returns indeed. Hence, a trust manager who followed these strategies was loading negative skewness to his portfolio, extracting the corresponding premium.

For the UK unit trusts[5], the Lipper Fund Database was used to acquire Net Asset Values (NAV) on a monthly basis. We selected the unit trusts which are marked for sale in the UK and they have domicile either in UK or overseas. The performance study refers to unit trusts which had as a fund manager benchmark in the Lipper Database the FTSE All Share Index, hence the returns of this index were used as a proxy for market returns. To alleviate the problem of survivorship bias, the database we employ includes unit trusts which have ceased operations before 2005. To have a meaningful performance study, only trusts with more than 61 observations of NAVs were employed.

This selection left us with 273 unit trusts having more than 60 monthly returns for the period January 1991- December 2005. The minimum number of trusts of our database was 150 trusts in 1991 and the maximum number was 273 trusts in 2004. Table 2 shows the number of trusts for each subperiod as well as their average returns.

5 Unit trust performance

5.1 Jensen alpha

The benchmark measure is the Jensen's alpha given by the intercept of equation (43). Over the period 1991-2005, the average Jensen's alpha of the ex-

[5]The term "unit trust" corresponds to the most common in US term "open-ended mutual fund". Henceforth, the two terms will be interchangeably used.

amined trusts was -1.23% *p.a.* This result implies that the average fund manager had negative managerial ability, achieving lower returns than what the exposure to the market risk would justify. Figure 4 shows the distribution of the trusts' alphas over during this period. It is evident that the majority of the trusts have negative alphas, but the distribution exhibits positive skewness and fat tails. This implies that there are a few trusts who have quite high positive alphas. Having ranked the trusts according to their alphas, Table 3 shows the corresponding values for various percentiles of the distribution. The upper 25% of the trusts had a positive alpha, though very few of these estimates were statistically significant. On the other side of the distribution, the bottom 45% of the trusts exhibited alphas of less than -2%.

The common practice of ranking trusts according to the alpha point estimates can be misleading, since the standard error of the estimate is not taken into account. It has been suggested (see Kosowski et al., 2006) that ranking trusts according to their t-statistics is more appropriate, since this adjusts the point estimate for its in-sample variability (standard error). Table 5 presents such a ranking, according to the t-OLS values. Using a 95% confidence interval, only 5% of the trusts exhibit significantly positive managerial ability. On the other hand, more than 30% exhibited significantly negative managerial ability.

An immediate conclusion from the shape of the distribution is that, according to this static, mean-variance measure, significant managerial ability existed, but only for a very small portion of the trust managers. Furthermore, the mean-variance investors who chose the bottom 30% trusts would have been significantly better off if they had invested in low-cost index funds. Since we deal with net returns, high expenses and management fees could well be a reason for the significant underperformance of many trusts. The nonnormality of the alphas' distribution[6] can be explained by two main hy-

[6]The Kolmogorov-Smirnov test was employed to formally test the hypothesis of normality for the standardized alphas. The hypothesis of normality was rejected at levels

potheses: Firstly, that trust managers exhibit heterogeneous abilities with a few managers being highly skillful and secondly that they adopted heterogeneous risk-taking strategies. The next subsections investigate further these hypotheses.

5.2 Harvey-Siddique alpha

This subsection presents the results of the unit trusts' evaluation using the Harvey-Siddique asset pricing model of equation (48). Interestingly, the average Harvey-Siddique (H-S) alpha was -2.12 *p.a.* This is much lower than the average Jensen's alpha. Figure 4 plots the distribution of the alphas according to these two asset pricing models. It is evident that the whole distribution of the Harvey-Siddique alphas is shifted to the left. The main explanation for this difference is that trust managers followed coskewness strategies indeed, earning positive returns, which were regarded as "abnormal returns" according to Jensen's alpha. If a manager had genuinely added value to his portfolio without adding negative coskewness, then there should be no significant difference between these two measures. To verify this conjecture, it is interesting to note that 263 out of the total 273 trusts during the examined period had a positive loading (coefficient) on the coskewness portfolio and this positive loading was statistically significant at a 95% level for 175 funds. Figure 5 plots the density of these coefficient estimates, showing that the 95% of the trusts had a positive coefficient estimate and more than the 50% of the trusts had an estimate of more than 0.25. This finding confirms that the majority of the funds were employing strategies which essentially loaded negative coskewness to the funds, though it does not mean that they consciously followed the specific coskewness spread strategy we analyzed in Section 4.

Ranking the trusts according to their Harvey-Siddique alphas, Table 3 reports their estimates for various percentiles of this distribution. It is striking

even lower than 1%.

to observe that only the 16% of the trusts had positive alphas. On the other hand, the 55% of the funds had an alpha of less than -2%. In particular, the median trust had a negative alpha of -2.36% *p.a.* Ranking trusts according to the t-value of these alphas, the results are equivalent. Only 3 funds had significantly positive alphas at a 95% level, while 41% had significantly negative alpha estimates at the 95% level. With respect to the distribution of the alphas, this is now closer to normality,[7] since it exhibits less positive skewness in comparison to the Jensen's alphas distribution. Interestingly, the two trusts with the highest Jensen's alphas (15.5% and 13.71% *p.a.* correspondingly), which account for the extreme positive tail of the distribution, are the trusts with the 2nd and 8th (out of 273) highest loadings of the coskewness strategy (with factor estimates 1.53 and 0.98 correspondingly). Hence, the heterogeneity risk-taking conjecture of the previous subsection can be supported and part of this heterogeneity is due to the coskewness risk.

There are two main conclusions from these results: The first is that prudent and long-term investors, who are averse to skewness and should use the Harvey-Siddique alpha to evaluate their trust managers, would have been better off by investing in a low-cost index fund as compared to more than 80% of the available trusts over the period 1991-2005. The second conclusion is that managers were very successful in reaping the negative coskewness premium, presenting it as "added value"- higher Jensen's alpha, due to the static, mean-variance nature of the measure employed to evaluate them. Figure 6 presents in a scatterplot the estimate of Jensen alpha for each trust against the coefficient estimate on the coskewness portfolio, demonstrating this positive relationship.[8] In other words, unit trusts would have been useful investment vehicles for agents with quadratic preferences, who regard the coskewness premium as "free lunch".

[7] The null hypothesis of normality is marginally rejected at a 5% level using the Kolmogorov-Smirnov test.

[8] The Pearson correlation coefficient of these two series is 0.45.

5.3 Subperiod analysis

Due to the high turnover of trust managers as well as the different market phases they face, it is interesting to examine whether the previous findings are robust for shorter time periods. Therefore, the total period is split into 3 subperiods of 5 years each. Table 2 gives the average returns the trusts achieved as well as their average Jensen and Harvey-Siddique alpha. With respect to average returns, there has been a significant improvement in comparison to the initial period of 1991-1995, when trusts underperformed the market by more than 400 *bps*.

There are three possible explanations for this improvement: The first is that there may have been a decrease in the expenses of the industry due to higher competition caused by the entry of new trusts, passing more of their managerial ability to the individual shareholder.[9] The second is that the trusts were more exposed to market risk from 1995 onwards. This hypothesis cannot be supported by the data, since the average beta of the trusts remained relatively stable and close to 0.93 for all three subperiods. The third explanation is that managers added part of the coskewness premium to their portfolios during the two last subperiods.

As Table 1 presents, the coskewness spread strategy, yielded significant positive returns only after 1996. These returns were as high as 3.39% *p.a.* during 2001-2005. Interestingly, the number of funds having positive loadings to the coskewness risk increased as this premium was increasing. While during the period 1991-1995 there were 113 trusts out of total 150 having a positive loading (and only 26 of them being statistically significant at a 5% level), during 1996-2000 there 167 out of 197 trusts with positive loadings (now 46 of them being significant) while during 2001-2005, as many as 252 out of total 263 trusts were loading negative coskewness (with 160 of these coefficients being statistically significant). This is actually the period that

[9] This hypothesis is not testable, since no data on UK unit trusts' expenses were available.

the Value and the Size strategies yielded high positive returns. Concluding, trust managers responded very quickly to the existence of this premium, employing strategies that mimicked negative coskewness and correctly acted according to their incentives, since the most of them were evaluated either through their raw returns or through mean-variance measures.

The previous analysis explains the significant improvement in trusts' Jensen alphas over the subperiods presented in Table 4, where the median trust started from an alpha of -4.1% *p.a.* during 1991-1995, this being significantly improved to -2.01% *p.a.* and -1.4% *p.a.* the next subperiods. Hence, this provides further evidence that the trusts were successful in reaping the negative coskewness premium, actually increasing their exposure to this risk during the period its premium was at its highest levels. While this strategy would have yielded a significant gain for a quadratic investor, it does not for a prudent one, because at the same time it loads the negative skewness risk that he is averse to.

To examine the evolution of managerial ability for a prudent, long-term investor, Table 4 presents the Harvey-Siddique alphas and their t-statistics for the three subperiods across various percentiles of the distribution. With respect to the point estimates, in all three periods less than 30% of the trusts had positive alphas. The median trust severely underperformed during the period 1991-1995 having a H-S alpha of -4.25% *p.a.* This performance was significantly improved in 1996-2000, but the median trust still had an alpha of -2.43% *p.a.*. Nevertheless, this improvement was not continued in 2001-2005, since the median fund achieved a H-S alpha of -2.68% *p.a.* Figure 7 plots the distributions of the trusts' alphas for each of the subperiods. While the distribution of alphas in 1996-2000 was shifted to the right in comparison to the previous subperiod, it was then shifted to the left during the period 2001-2005, exhibiting a large concentration of values around the mean. Ranking trusts according to the t-values of their H-S alphas, it is surprising to see than in the second and the third subperiod, apart from the top two trusts, there was no other with significant positive alpha. On the other hand, in all three subperiods, more than 30% of the trusts had significantly negative H-S alphas.

5.4 Bootstrap analysis

The previous subsections relied on standard t-statistics to examine the significance of the performance estimates, which is a valid procedure under the assumption of normality for the regressions' residuals. Nevertheless, the nonnormality of the alphas' distribution and the evidence of heterogeneous risk-taking casts doubts on the validity of the normality assumption, especially for the trusts with extreme alphas. In other words, if the residuals are not normally distributed, then the t-statistics may lead to spurious results and the extreme alpha estimates may be due to sampling variability, i.e. luck. In order to control for the sampling variability, this susbsection employs a simple bootstrap methodology (see Hall, 1992, for an introduction).

In particular, we employ a procedure similar to the one suggested by Kosowski et al. (2006), adjusted for the Harvey-Siddique asset pricing model.[10] Using the saved residuals $\{\hat{\epsilon}_{i,t}, t = T_{i0}, ..., T_{i1}\}$ for each trust i from the OLS regression

$$r_t = \hat{a}_{HS} + \hat{b} r_{M,t} + \hat{c}(S^- - S^+)_t + \hat{\epsilon}_t \tag{49}$$

we draw a sample with replacement for each of the trusts and create a pseudo-time series of resampled residuals $\{\hat{\epsilon}^b_{i,t_\varepsilon}, t_\varepsilon = s^b_{T_{i0}}, ..., s^b_{T_{i1}}\}$, where b is an index for the bootstrap number and where each of the time series indices $s^b_{T_{i0}}, ..., s^b_{T_{i1}}$ are drawn randomly from $[T_{i0}, ..., T_{i1}]$. Using this pseudo-time series of resampled residuals, we construct for each trust i a time-series of pseudo-mothly excess returns for each fund, under the null hypothesis that $\hat{a}_{HS,i} = 0$:

[10] Cuthbertson et al. (2006) employ a bootstrap methodology to evaluate UK unit trusts for a series of commonly used performance measures.

$$r_t^b = \hat{b} r_{M,t} + \hat{c}(S^- - S^+)_t + \hat{\epsilon}_{i,t_\varepsilon}^b \tag{50}$$

for $t = T_{i0}, ..., T_{i1}$ and $t_\varepsilon = s_{T_{i0}}^b, ..., s_{T_{i1}}^b$. These pseudo-returns are subsequently regressed again for each bootstrap sample b, as in equation (48), extracting an alpha estimate $\{\hat{a}_{HS}^b\}$. Repeating the previous methodology 1,000 times, we have a distribution of 1,000 alpha estimates for each fund i. Performing the same methodology for all funds $i = 1, ...N$, we can derive a cross-section of bootstrapped alphas as well as their bootstrapped t-statistics. These alphas and t-statistics result purely due to sampling variation, having imposed the null hypothesis of a zero intercept (no managerial ability).

This methodology may be used for a series of robustness checks (see Kosowski et al., 2006 for numerous examples). The focus of this subsection is to examine the bootstrapped alphas for each of the funds in Table 3, i.e. for different percentiles of the Harvey-Siddique alpha distribution for the entire period. If the actual alpha estimate of a trust is higher (lower) than the 95% of the bootstrapped alpha estimates under the null hypothesis of zero alpha, this means that the trust exhibited genuine positive (negative) managerial skill beyond luck due to sampling variability.

The last line in Table 3 shows the bootstrapped p-values for the trusts examined in the previous subsections. Almost for all funds below the median, the negative managerial ability is genuine and not due to (bad) luck. On the other hand, we identify that for a few top trusts the positive managerial ability is again genuine, at least at a 10% confidence level. In general, the qualitative conclusions were not different from the previous inference analysis.

Controlling for the impact of sampling variation is more crucial when the residuals' distribution is quite asymmetric. However, as it can be seen from Figure 8, the derived bootstrapped alphas' distributions for a series of funds are relatively symmetric, hence there is no significant difference with respect to the parametric case. This is a quite interesting result, contrasting the skewed bootstrapped alphas' distributions derived in Kosowski et al. (2006).

The explanation we put forward is that the inclusion of a coskewness factor considerably contributes to the symmetry of the residuals' distribution, since it attributes highly skewed returns to the corresponding risk factor, unlike mean-variance measures which would regard them as residuals.

6 Conclusion

Higher moments in asset returns is a relatively neglected issue in financial theory and investment performance evaluation. This study shows how aversion to negative skewness is built in commonly used utility functions and how these preferences generate premia in capital markets. This issue becomes even more important if one takes into account the experimental evidence that negative returns affect utility asymmetrically more in comparison to positive returns. Hence, a prudent investor should not use mean-variance measures to evaluate his investments, because they neglect his actual preferences and regard the negative coskewness premium as a "free lunch". In the case of delegated asset management this issue is even more crucial, since the fund manager judged by mean-variance measures will falsely interpret that the fund shareholder has no preferences over skewness and he will be incentivised to follow mechanical strategies that load this type of risk in order to reap the corresponding premium. Clearly, this creates a mismatching of objectives and outcome, leading to erroneous conclusions with respect to the *ex post verification* of the fund management performance.

Moreover, the same problem arises due to the static nature of the commonly used measures. There is sufficient evidence that intertemporal risks are priced too in capital markets, hence a long-term investor should take them into account when evaluating his investment performance. The present study utilizes a standard dynamic setup, where there is an underlying stochastic factor affecting the dynamics of the risky asset returns and shows how intertemporal risks can be translated as a negative skewness risk. In particular, the hedging value of the asset returns against intertemporal risks can be regarded as a premium for holding stocks with negative skewness.

The limitations of the static, mean-variance measures motivate the adoption of a performance that adjusts for the negative coskewness premium. The Harvey-Siddique two-factor asset pricing model is qualified to be appropriate for a prudent, long-term investor. The intercept of this model, which we term as the *Harvey-Siddique alpha*, will reveal the genuine outperformance for such an investor, resolving the *ex post verification problem*.

This measure is employed for the evaluation of UK unit trusts for the period 1991-2005. In order to perform this evaluation, the returns of the coskewness spread portfolio in the UK stock universe are calculated. This portfolio yielded a significant positive return, especially in the last subperiod of our sample. With respect to trust managers, the most of them had a negative Harvey-Siddique alpha, significantly undeperforming their benchmark. Actually, the median underperformance of the trusts (-2.12%) for prudent investors was even higher than the current average expense ratio they charge (*circa* 1.6%).

Interestingly, the most of the trusts loaded negative coskewness to their portfolios, capturing part of the corresponding premium, correctly responding to their incentives, since they were evaluated by mean-variance measures. This finding shows how a prudent investor would misinterpret this premium for genuinely added value if he was using such a measure. Hence, the call for the shift of interest from outperforming to matching investors' preferences and objectives becomes even more important reflecting the advice of Charles Ellis (2005, p. 115) not to play "the Loser's Game of trying to "beat the market"- a game that almost every investor will eventually lose".

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Appendix

Table 1				
Periods	Average Market Excess Returns	Average Size Strategy Returns (SMB)	Average Value Strategy Returns (HML)	Average Coskewness Spread Returns (S^-)-(S^+)
1991-1995	8.75%	-0.96%	1.11%	0.25%
1996-2000	7.66%	-0.08%	0.07%	2.63%
2001-2005	-1.11%	7.35%	5.32%	3.39%
1991-2005	5.10%	2.11%	2.16%	2.09%

Table 2				
Periods	Number of trusts ≥ 60	Trusts' Average Excess Returns	Average Jensen's alpha (Pct/Year)	Average Harvey-Siddique alpha (Pct/Year)
1991-1995	150	4.61%	-3.65%	-3.81%
1996-2000	197	5.76%	-1.30%	-1.91%
2001-2005	265	-2.01%	-0.98%	-2.33%
1991-2005	273	2.93%	-1.23%	-2.12%

Table 3

	Top	1%	5%	10%	30%	median	70%	90%	95%	99%	Bottom
Jensen alpha	15.51%	9.05%	4.57%	2.31%	-0.37%	-1.77%	-2.96%	-4.32%	-4.89%	-6.08%	-15.67%
t-stat	1.97	1.96	2.31	1.35	-0.27	-0.97	-3.59	-3.38	-2.62	-3.89	-3.97
p-value	0.03	0.03	0.01	0.09	0.37	0.25	<0.01	<0.01	0.01	<0.01	<0.01
H-S alpha	11.20%	6.45%	2.87%	0.88%	-1.20%	-2.36%	-3.69%	-4.97%	-5.68%	-6.94%	-17.07%
t-stat	1.43	1.84	1.01	0.49	-0.88	-2.34	-3.53	-3.61	-2.37	-4.27	-4.28
p-value	0.14	0.08	0.21	0.35	0.29	0.01	<0.01	<0.01	0.01	<0.01	<0.01
boots. p-value	0.07	0.03	0.15	0.28	0.18	0.01	<0.01	<0.01	0.01	<0.01	<0.01

Table 4: Alpha Rankings

	Top	1%	5%	10%	30%	median	70%	90%	95%	99%	Bottom
Panel A: 1991-1995											
Jensen alpha	14.83%	7.13%	3.01%	1.48%	-2.41%	-4.10%	-5.44%	-7.21%	-8.31%	-14.79%	-15.05%
t-stat	2.88	2.18	1.45	0.27	-1.86	-2.86	-3.58	-2.62	-2.77	-3.16	-3.49
p-value	<0.01	0.04	0.14	0.38	0.07	<0.01	<0.01	0.01	<0.01	<0.01	<0.01
H-S alpha	14.23%	6.50%	2.71%	0.97%	-2.58%	-4.25%	-5.49%	-7.33%	-8.70%	-15.12%	-15.25%
t-stat	2.82	2.14	1.35	0.18	-1.50	-1.44	-3.58	-1.25	-2.98	-3.23	-3.51
p-value	<0.01	0.04	0.16	0.39	0.13	0.14	<0.01	0.18	<0.01	<0.01	<0.01
Panel B: 1996-2000											
Jensen alpha	19.97%	13.76%	6.44%	3.05%	-0.51%	-2.01%	-3.11%	-4.98%	-6.02%	-7.65%	-9.03%
t-stat	1.93	1.75	1.66	1.34	-0.12	-1.27	-0.44	-1.94	-1.95	-2.25	-3.48
p-value	0.06	0.09	0.1	0.16	0.39	0.17	0.36	0.06	0.06	0.03	<0.01
H-S alpha	14.19%	11.11%	4.36%	1.95%	-0.72%	-2.43%	-3.54%	-5.36%	-6.81%	-8.21%	-10.13%
t-stat	1.48	1.43	1.21	0.41	-0.28	-1.03	-1.94	-2.11	-3.32	-2.44	-4.01
p-value	0.13	0.14	0.19	0.36	0.38	0.23	0.06	<0.03	<0.01	0.01	<0.01
Panel C: 2001-2005											
Jensen alpha	11.11%	10.02%	5.32%	2.73%	-0.04%	-1.40%	-2.73%	-3.93%	-5.07%	-11.69%	-20.78%
t-stat	2.24	2.24	1.27	1.03	-0.01	-0.78	-1.47	-2.39	-2.84	-2.54	-2.06
p-value	0.03	0.03	0.17	0.23	0.4	0.29	0.13	0.02	<0.01	0.01	0.05
H-S alpha	8.97%	8.01%	3.13%	0.76%	-1.35%	-2.68%	-3.65%	-4.86%	-5.87%	-11.94%	-26.24%
t-stat	2.01	2.07	0.82	0.21	-0.82	-0.96	-2.61	-1.47	-2.02	-2.50	-2.61
p-value	0.05	0.04	0.28	0.38	0.28	0.25	0.01	0.14	0.05	0.01	<0.01

Table 5: t-stat Rankings

	Top	1%	5%	10%	30%	median	70%	90%	95%	99%	Bottom
t-Jensen alpha	2.81	2.61	1.91	0.85	-0.18	-1.14	-2.05	-3.59	-4.18	-4.80	-6.96
Jensen alpha	13.71%	6.99%	6.05%	1.73%	-0.40%	-1.32%	-3.24%	-5.21%	-3.28%	-6.07%	-3.25%
p-value	<0.01	0.01	0.07	0.27	0.39	0.21	0.05	<0.01	<0.01	<0.01	<0.01
t-H-S alpha	2.20	1.98	1.31	0.40	-0.71	-1.54	-2.60	-3.90	-4.58	-5.33	-6.70
H-S alpha	5.85%	9.55%	6.12%	1.41%	-1.45%	-1.55%	-4.17%	-4.82%	-4.46%	-4.70%	-3.21%
p-value	0.01	0.03	0.09	0.37	0.25	0.08	0.01	<0.01	<0.01	<0.01	<0.01

Table 6: t-stat Rankings

	Top	1%	5%	10%	30%	median	70%	90%	95%	99%	Bottom
Panel A: 1991-1995											
t-Jensen	2.88	2.18	1.14	0.27	-0.98	-1.86	-2.70	-3.18	-3.56	-4.63	-4.74
Jensen alpha	14.83%	7.13%	2.23%	1.48%	-2.06%	-2.41%	-6.29%	-6.92%	-8.76%	-8.89%	-9.84%
p-value	<0.01	0.04	0.21	0.38	0.25	0.07	0.01	<0.01	<0.01	<0.01	<0.01
t-H-S	2.81	2.14	1.08	0.18	-1.00	-1.86	-2.71	-3.24	-3.68	-4.69	-4.74
H-S alpha	14.23%	6.50%	2.43%	0.97%	-4.56%	-2.43%	-5.80%	-6.25%	-5.75%	-9.84%	-9.06%
p-value	<0.01	0.04	0.22	0.39	0.24	0.07	0.01	<0.01	<0.01	<0.01	<0.01
Panel B: 1996-2000											
t-Jensen	2.38	1.94	1.35	0.77	-0.20	-0.78	-1.49	-2.27	-2.52	-3.45	-4.85
Jensen alpha	11.78%	19.97%	3.05%	4.56%	-0.73%	-2.46%	-2.58%	-3.09%	-3.99%	-6.93%	-3.07%
p-value	0.02	0.06	0.16	0.29	0.39	0.29	0.13	0.03	0.02	<0.01	<0.01
t-H-S	2.16	1.65	1.13	0.63	-0.29	-0.96	-1.64	-2.31	-2.77	-3.49	-4.73
H-S alpha	10.83%	7.90%	2.59%	5.94%	-0.70%	-2.44%	-5.36%	-5.02%	-4.87%	-6.19%	-3.06%
p-value	0.04	0.1	0.21	0.32	0.38	0.25	0.1	0.03	<0.01	<0.01	<0.01
Panel C: 2001-2005											
t-Jensen	2.74	2.27	1.70	0.96	-0.02	-0.72	-1.46	-2.29	-2.63	-4.43	-5.30
Jensen alpha	10.97%	9.78%	8.58%	4.39%	-0.03%	-1.53%	-3.24%	-4.93%	-3.58%	-3.21%	-2.95%
p-value	<0.01	0.03	0.09	0.25	0.40	0.31	0.14	0.03	0.01	<0.01	<0.01
t-H-S	2.07	1.77	0.99	0.27	-0.62	-1.27	-2.00	-2.85	-3.02	-4.21	-5.69
H-S alpha	8.01%	4.32%	3.96%	0.89%	-2.88%	-3.30%	-3.97%	-4.81%	-3.60%	-3.17%	-3.80%
p-value	0.05	0.08	0.24	0.38	0.33	0.18	0.05	<0.01	<0.01	<0.01	<0.01

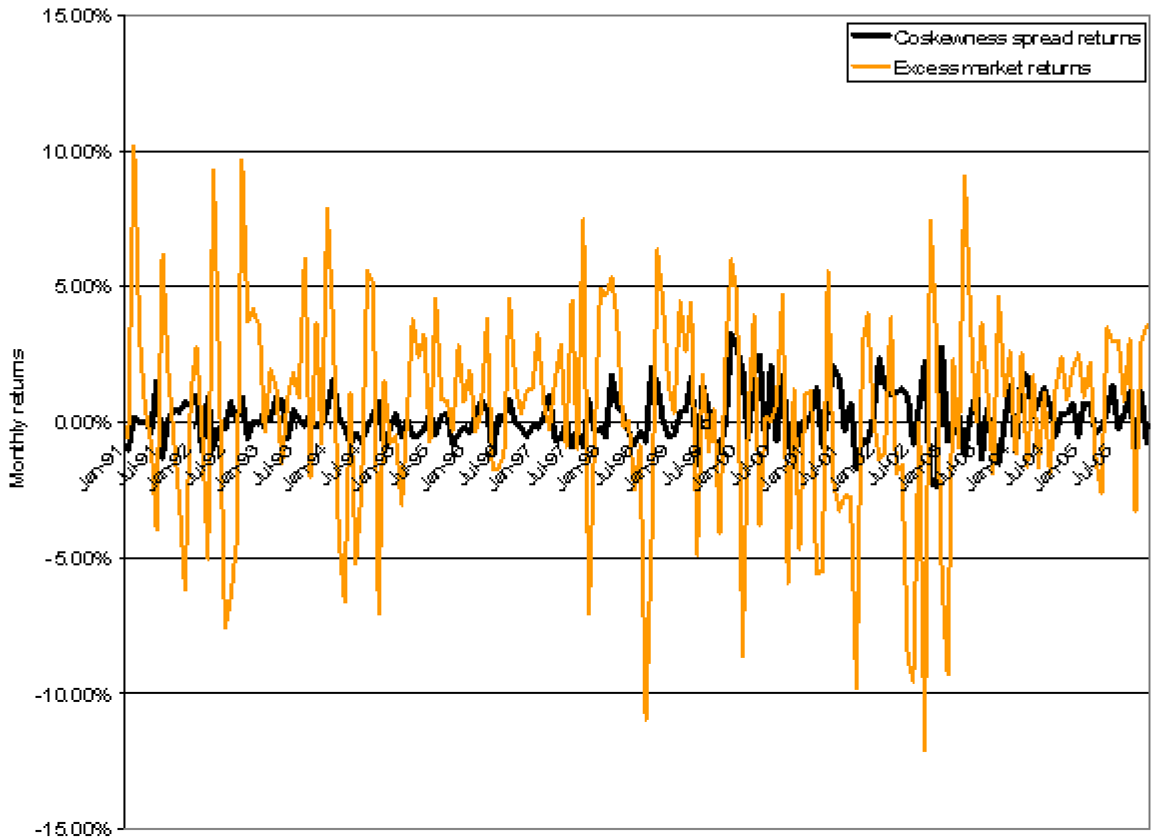

Figure 1: This Figure shows the Excess returns of the FTSE All Share Index (orange line) and the returns of the zero-cost Coskewness spread strategy (black line) as defined in Section 4, during the period Jan 1991- Dec 2005.

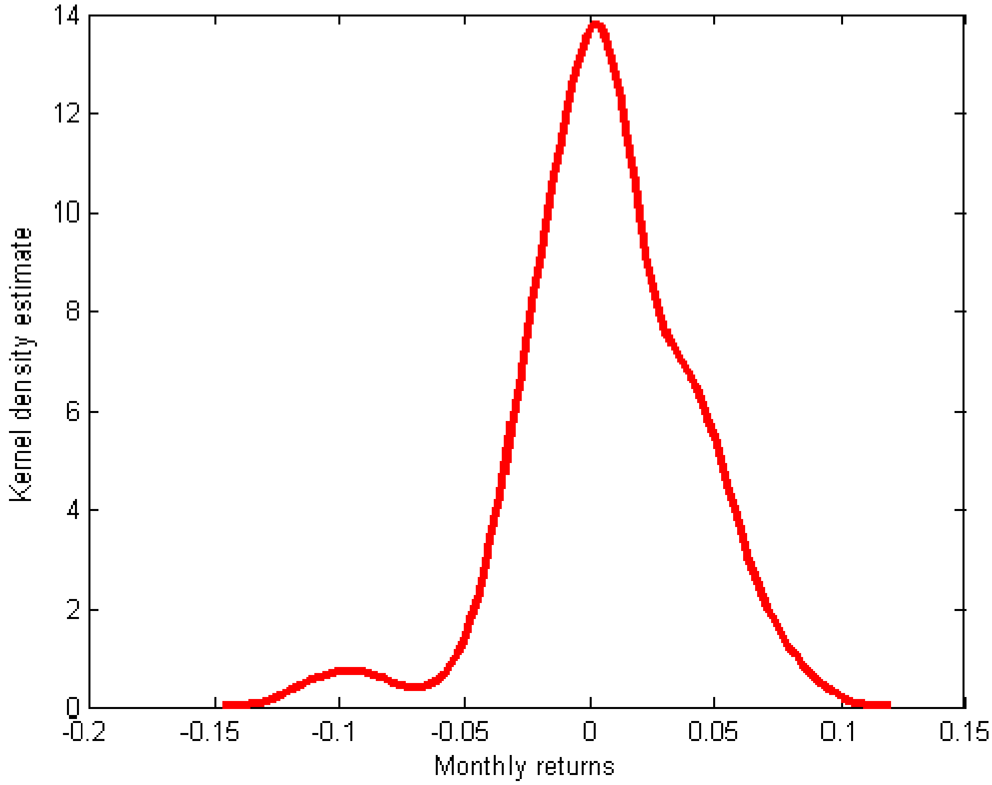

Figure 2: This Figure shows the smoothed density of the Size (SMB) strategy returns, as defined in Section 4, for the period Jan 2001- Dec 2005.

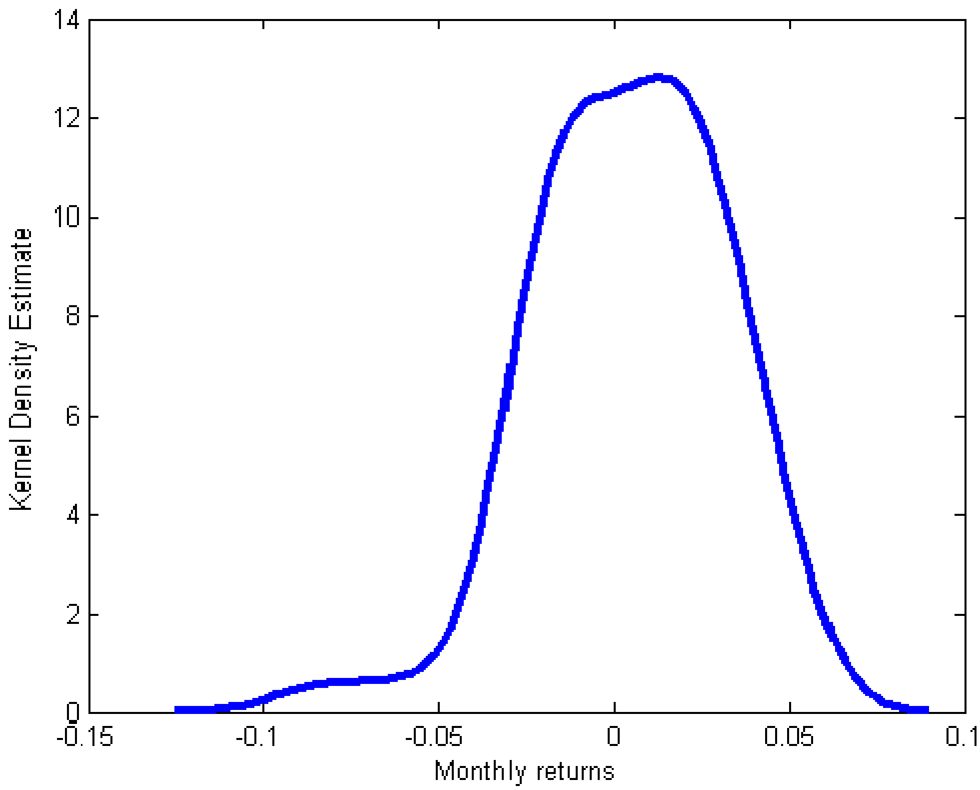

Figure 3: This Figure shows the smoothed density of the Value (HML) strategy returns, as defined in Section 4, for the period Jan 2001- Dec 2005.

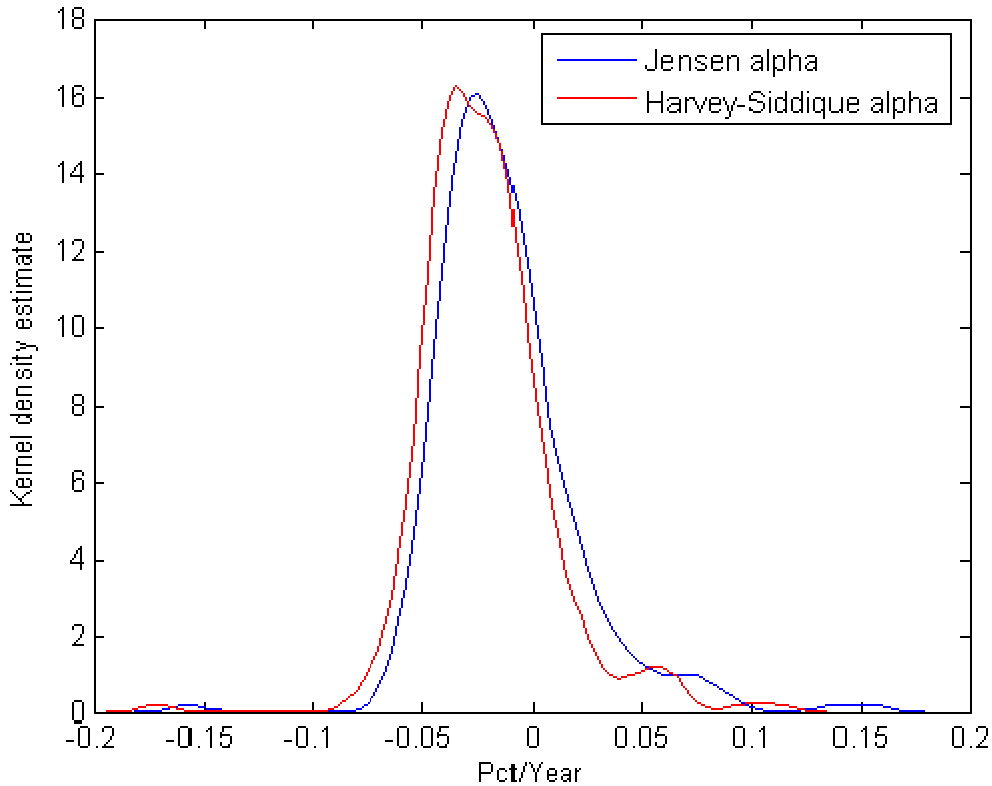

Figure 4: This Figure shows the distribution of the trusts' Jensen alphas (blue line) and the distribution of the trusts' Harvey-Siddique alphas (red line) during the period Jan 1991- Dec 2005.

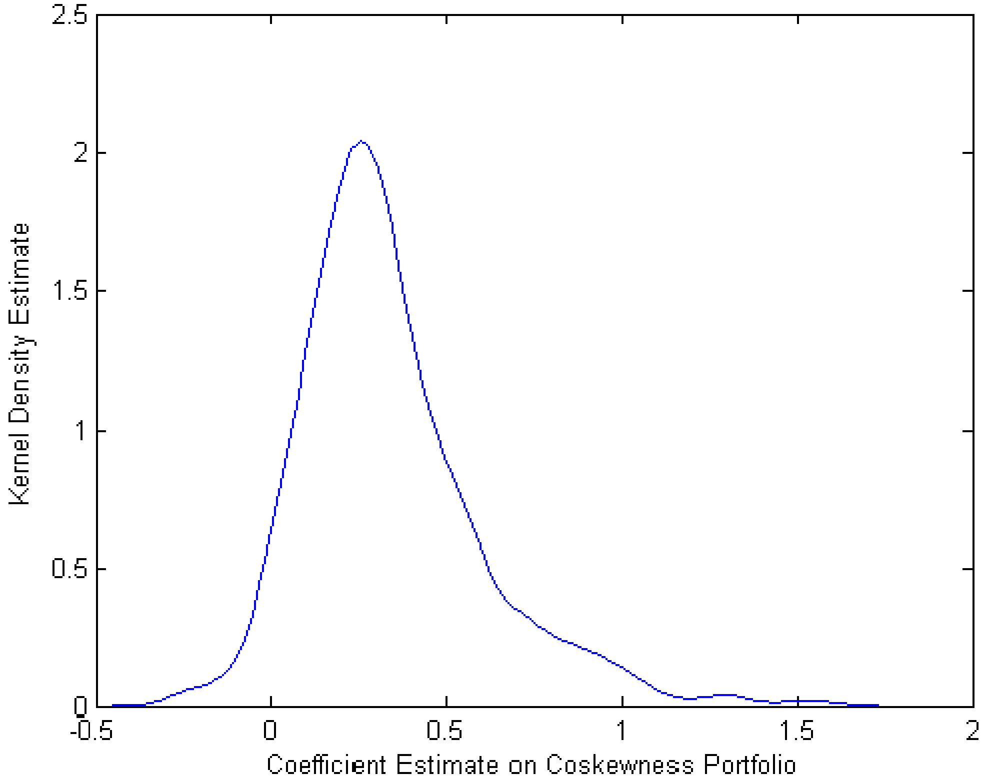

Figure 5: This Figure plots the density of the coefficient estimates (c) on the coskewness strategy for each trust from equation (48) for the period Jan 1991- Dec 2005.

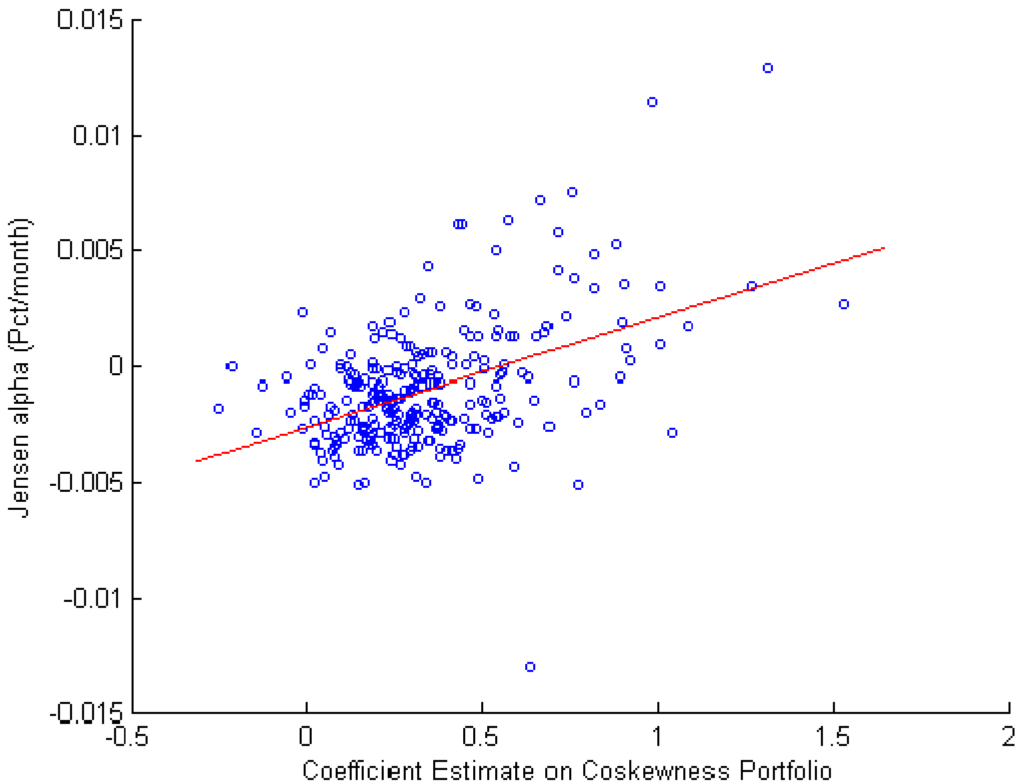

Figure 6: This Figure presents the scatterplot of Jensen alpha estimates from equation (43) versus the coefficient estimates (c) on the coskewness strategy from equation (48) for each trust for the period Jan 1991- Dec 2005. It also plots the fitted values from a standard OLS regression for the same period.

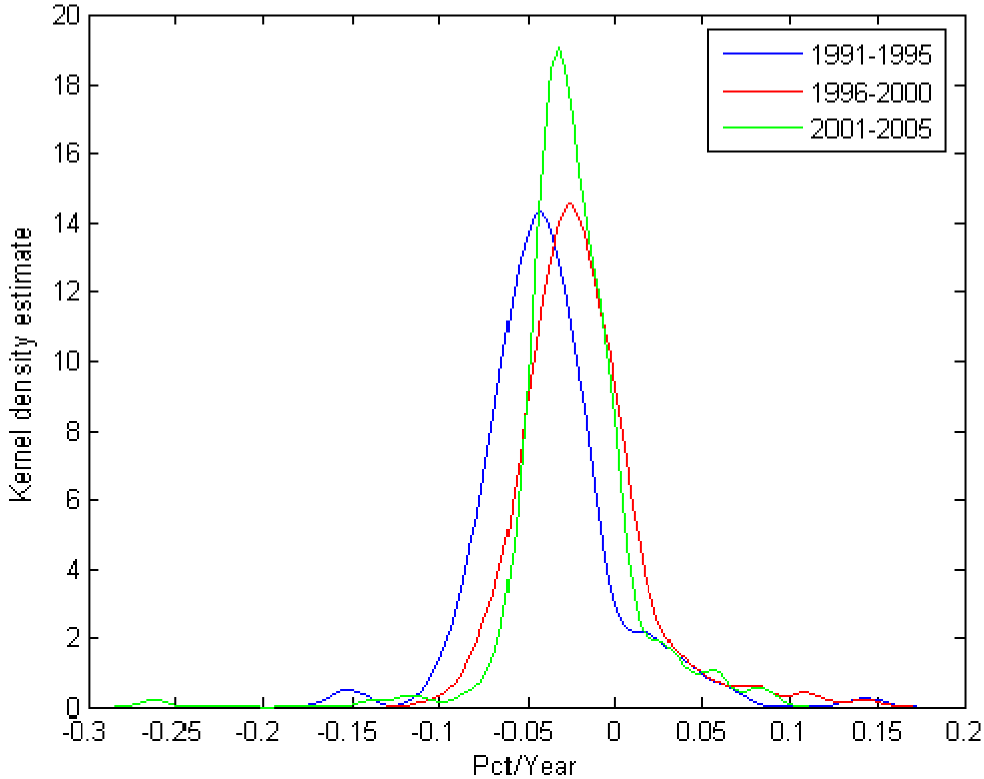

Figure 7: This Figure shows the distribution of trusts' Harvey-Siddique alphas for the periods: Jan 1991- Dec 1995 (blue line), Jan 1996- Dec 2000 (red line) and Jan 2001- Dec 2005 (green line).

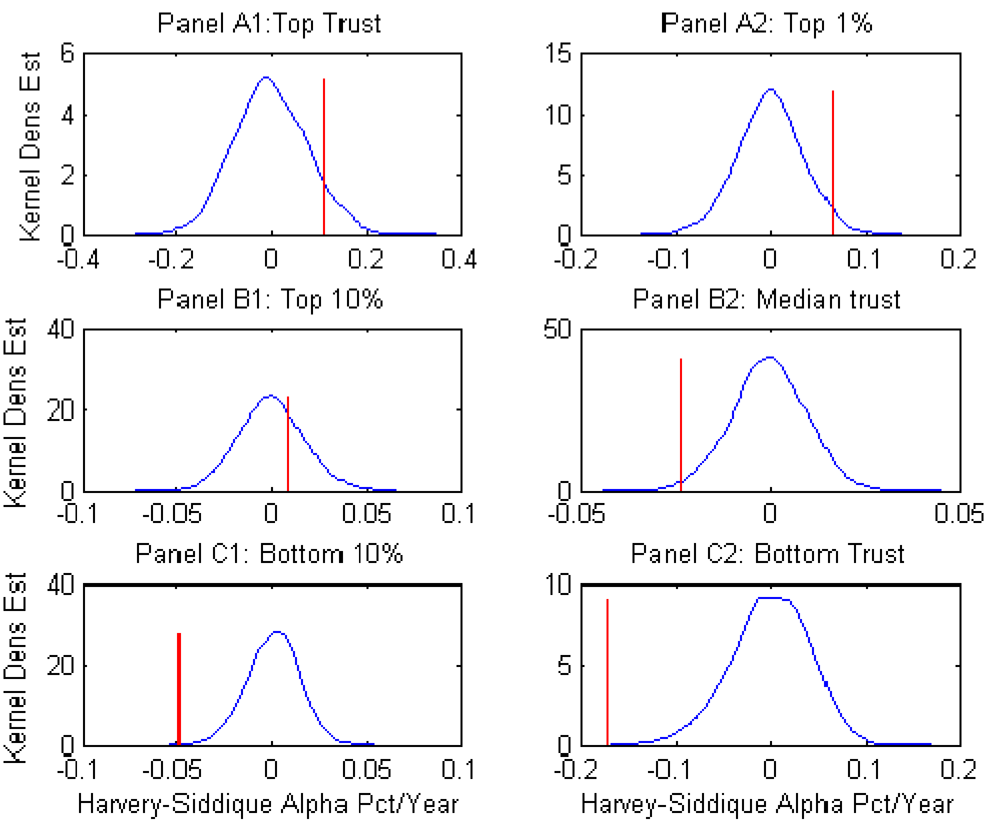

Figure 8: This Figure shows the density of the bootstrapped Harvey-Siddique alphas under the null hypothesis of no managerial ability (blue line) and the actual estimate of the H-S alpha (red line) for various rankings of the trusts according to this estimate for the period Jan 1991- Dec 2005.