Evaluating the Performance of Hedge Funds Using the Stochastic Discount Factor

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Abstract

We evaluate the performance of hedge funds using the stochastic discount factor (SDF) approach and imposing no arbitrage restriction and conditional framework. This approach has been proposed as hedge fund returns are mostly the results of the derivatives and dynamic trading strategies, which may make traditional parametric performance measure not applicable to this asset class. Furthermore, the SDF approach has additional advantages for the evaluation of hedge funds by avoiding model specification error and not depending on returns' distribution. The results show that hedge funds returns have positive risk-adjusted excess returns. And our results show that the conditional NA (no arbitrage) performance measure reflects business cycle related time-varying risk premia *and* satisfies no arbitrage restriction, while other performance measures do not. Those indicate that the conditional NA measure is the best appropriate benchmark for the evaluation of hedge funds.

JEL classifications: G12; G23

Keywords: hedge fund performance; stochastic discount factors; no arbitrage restriction;

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1. Introduction

Recently, hedge funds have attracted investor's concerns as they are less regulated than mutual funds, thereby they can develop trading strategies which bear high risk and high return. Although hedge funds seem to generate much higher cumulated returns than mutual funds, investors should cautiously pay attention to high risk embedded in hedge funds when evaluating the performance. Asset pricing theory says that any asset which has high risk should give high return. Therefore we need to investigate whether hedge funds give positive *risk-adjusted* return after accounting risk premium.

In this paper, we provide an empirical analysis of hedge funds performance evaluation using the stochastic discount factor (SDF) approach. As elegantly demonstrated by Cochrane (2001), the SDF approach provides a unified framework for asset pricing analysis and has been widely used to study equities, bonds, options, trading strategies, and mutual funds.[1] Also the SDF approach has desirable advantages especially for the evaluation of hedge funds for the following reasons.

First, the SDF approach naturally incorporates the no arbitrage restriction (that is, the SDF has to be positive to avoid arbitrage opportunities) since SDF approach basically belong to the relative pricing framework. This restriction has been applied to asset pricing in modern financial studies. As hedge funds use heavily the derivatives, which are priced by arbitrage-free requirement, this restriction is particularly important for the evaluation of hedge funds. On the other hand, it is extremely difficult to impose no arbitrage restriction in a linear regression framework (parametric performance

[1] See, for example, Jagannathan and Wang (1996), Hodrick and Zhang (2001), Buraschi and Jackwerth (2001), Coval and Shumway (2001), Ahn, Conard, and Dittmar (2003), Chen and Knez (1996), and Farnsworth et all (2002).

measure) commonly used with standard linear asset pricing models.[2] Therefore, existing performance measures such as the Sharpe ratio and the Jensen's alpha are inappropriate for hedge funds. For example, Goetzmann, Ingersoll, Spiegel, and Welch (2003) show that the Sharpe ratio can easily be manipulated by investing in derivatives. Grinblatt and Titman (1989) show that a manager selling a call option on the index will be incorrectly classified as displaying superior performance by an investor using the Jensen's alpha.

Second, the SDF approach can easily incorporate conditional information, thereby allowing risk premia to be time varying. Despite rich evidence of time variation in expected returns [e.g., Gibbons and Ferson (1985), Ferson and Harvey (1991), Conrad and Kaul (1988), and Evans (1994)], previous studies of hedge funds performance use an unconditional framework and compare the performance of hedge funds against buy and hold strategies.[3] As discussed by Ferson and Schadt (1996), the use of an unconditional model can result in biased estimates of performance if investment opportunity sets are time varying. Extant evidence shows that recognition of the time-varying nature of risk premia is important. Ferson and Schadt (1996) develop conditional performance measures that account for time-varying risk premia. They find no evidence of abnormal mutual fund performance, in contrast to studies documenting unconditional abnormal performance. Given the importance of time-varying risk premia, and particular characteristics of hedge funds which use dynamic trading strategies heavily, a natural question is whether abnormal performance of hedge funds can be explained as an artifact of time-varying risk premia.

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[2] See also Dybvig and Ingersoll (1982)

[3] See Fung and Hsieh (1997), Liang (1999), Agarwal and Naik (2001), and Brown et. Al. (1999).

Third, as an alternative to specifying a particular parametric model of benchmark returns, the SDF approach is a non-parametric, or “model free” approach. Previous studies which examine the risk-adjusted performance of hedge funds rely on the parametric model to measure risk, and therefore abnormal returns. For instance, the Jensen’s alpha and the Treynor’s ratio specify the risk factor (or SDF) as the covariance between market index return and fund return. However, if these pricing models are misspecified, then the abnormal performance which follows from their use is misspecified as well. That is, as Fama (1998) points out, these studies are potentially plagued by a “bad model” problem. Since it is impossible to directly measure the specification error in a parametric model for benchmark returns, the bad model problem is insurmountable in this framework. The SDF approach for the evaluation of performance, first proposed by Chen and Knez (1996), extracts a set of discount factors from a group of basis assets employed in the analysis, and then by using this SDF we can price other assets (i,e., test assets). Therefore, the SDF approach also generates benchmark return, but so does based on minimal conditions such as the law of one price (LOP) or no arbitrage (NA) conditions rather than a model’s prespecified risk factor(s). Thus, relative to parametric approaches, this approach investigates whether abnormal performance of hedge funds can be explained with the minimal restriction of equilibrium in securities markets.[4]

And lastly the SDF approach does not require strong assumptions on the distribution of hedge fund returns. Previous studies noted that the return distribution of hedge funds is not normal distribution.[5] Following this observation, hedge funds

[4] Ahn, Conrad, and Dittmar (2003) address this point.
[5] See Kat (2003)

performance literature have focused on how to improve existing measures such as the Sharpe ratio and Value at Risk to incorporate non-normal distribution: negative skewness and positive kurtosis.[6] However, the SDF approach needs not to suffer from considering characteristics of return distribution.

The only other studies that we are aware of that adopt SDF approach in the performance of hedge funds are Kazemi and Schneeweis (2003) and Bailey, Li, and Zhang (2004). Kazemi and Schneeweis (2003) also use the method of Chen and Knez (1996), but they do not impose no arbitrage restriction, which is most important restriction for the hedge funds. Their results indicate that surprisingly abnormal performances of hedge funds using the SDF approach are not significantly different from those using the traditional parametric performance measures. However, in our studies, those two different approaches give totally different results. The study of Bailey, Li, and Zhang (2004) is different from ours as they use the Hansen and Jagannathan (1997) distance measure instead of Chen and Knez (1996).

Using the hedge funds index data during the period 1994 – 2006, we reexamine the abnormal performance of hedge funds. There are three main empirical findings. First, we find significant abnormal performance of hedge funds using either the parametric or non-parametric benchmarks. Second, the conditional non-parametric measures reflect business cycle related time-varying risk premia and its direction is counter-cyclical. Therefore, the funds that give high returns when economic condition is bad and low returns when economic condition is good so that investors can smooth their consumption are evaluated to the high price (i,e., high positive abnormal performance). Finally, only the extracted SDF based on no arbitrage condition has no negative values

[6] See Dowd (1999), Favre and Galeano (2002), and Mahdavi (2004)

while the other benchmarks have negative values frequently. Based on those empirical findings, we argue that that the conditional NA measure is the best appropriate benchmark for the evaluation of hedge funds.

The remainder of this paper is organized as follows. Section 2 discusses the measurement of abnormal performance and compares the parametric and non-parametric approaches. Section 3 discusses the data. Section 4 reports our empirical results. We conclude in section 5 with a summary of our results.

2. Performance Measurement

When we evaluate the performance of hedge funds, the proper specification of "normal return" is important. We consider two approaches. First, we employ the traditional parametric performance measures (i,e., linear regression framework). The parametric performance measures specify the risk which characterizes the "normal return". Specifically, if we use the capital asset pricing model (CAPM) benchmark, the performance measure is determined by the covariance of market portfolio and hedge fund. On the other hand, if we choose the Fama-French (1993) three factor model as benchmark return, the risk is specified differently. However, there is considerable evidence that the extant asset pricing model is misspecified [See Hodrick and Zhang (2001)]. Therefore, when we get risk-adjusted return by using the parametric performance measures, we cannot identify whether it is true abnormal return or it comes from model misspecification error. Furthermore, it is hard to impose the no arbitrage restriction when we use the parametric performance measures [See Dybvig and Ingersoll (1982). As hedge funds use derivatives and dynamic trading strategy heavily, the no arbitrage restriction is important for the evaluation of the hedge funds.

To avoid those problems, we employ a SDF approach which is nonparametric. Unlike parametric performance measures, which adopt candidate stochastic discount factor implied by particular asset pricing models, nonparametric performance measures attempt to recover a set of admissible stochastic discount factors based on minimal conditions such as the law of one price or no arbitrage conditions. Especially the NA performance measure is important for the evaluation of the hedge funds as it incorporates the no arbitrage condition by construction.

2.1 Parametric Performance Measure

The traditional parametric performance measure is to estimate Jensen's alpha. In this paper, we use two asset pricing models. First, we evaluate the performance measure using the capital asset pricing model (CAPM)

$$r_{i,t} - r_{f,t} = \alpha + \beta_i (r_{M,t} - r_{f,t}) + \varepsilon_{i,t}.$$

$r_{i,t}$ is the return on the hedge funds, $r_{M,t} - r_{f,t}$ is the return on the market portfolio in excess of the riskless rate. As a lot of previous studies suggest that the CAPM does not hold [e.g., MacKinlay (1987), Fama and French (1992)], we explore alternative benchmarks. Second, we evaluate hedge funds performance using the Fama-French (1993) three factor model to adjust for risk. Thus the following model is estimated:

$$r_{i,t} - r_{f,t} = \alpha + \beta_{i,MRP} R_{MRP,t} + \beta_{i,SMB} R_{SMB,t} + \beta_{i,HML} R_{HML,t} + \varepsilon_{i,t}, \qquad (1)$$

where $R_{MRP,t}$ is the excess return on the market proxy, $R_{SMB,t}$ is the return on a zero-cost portfolio that buys large-capitalization firms and sells small-capitalization firms, and $R_{HML,t}$ is the return on another zero-cost portfolio that buys high book-to-market and sells low book-to-market firms.

2.2 Non-parametric Performance Measure

The stochastic discount factor (SDF) approach has its roots in the modern asset pricing models and contingent valuation models (See Cochrane (2001) for reviews). Under the law of one price (LOP), there exists a stochastic discount factor m_{t+1} such that

$$E_t[m_{t+1}R_{t+1}] = 1 .$$

The pricing equation should hold for all assets in the economy. We refer to the N-vector of gross returns R_{t+1} (bold notation indicates vectors) as basis assets. Hansen and Jagannathan (1991) show that a valid SDF can be formed from basis assets $m_{t+1}^{LOP} = b'R_{t+1}$ with $b = E[R_{t+1}R'_{t+1}]^{-1}1$. With N basis assets to be priced and N parameters, this system is exactly identified. This SDF m_{t+1} can perfectly price the basis assets by construction

$$E[R_{t+1}m_{t+1}] = E[R_{t+1}R'_{t+1}E[R_{t+1}R'_{t+1}]^{-1}1] = 1 .$$

To evaluate the performance of hedge fund returns, we want to check if the SDF also correctly prices the hedge fund returns. Following Chen and Knez (1996), define the LOP measure α^{LOP} of abnormal performance as follows:

$$\alpha^{LOP} = E[R_{h,t+1}m_{t+1}^{LOP}] - 1$$

, where $R_{h,t+1}$: hedge fund's gross return
m_{t+1}^{LOP} : the LOP SDF

It measures the abnormal performance as the difference between the fair price and the market price (normalized to one).

This leads to the following set of moment conditions for the GMM estimation

$$E\begin{bmatrix} 1-R_{t+1}R'_{t+1}b \\ 1-R_{h,t+1}R'_{t+1}b-\alpha^{LOP} \end{bmatrix}=\begin{bmatrix} 0 \\ 0 \end{bmatrix}.$$

By including the parameter α^{LOP} in the last moment condition, the system is just identified with N+1 parameters and N+1 moment conditions.

This measure is similar to other abnormal performance measures such as Jensen's (1968) alpha. However, unlike the Jensen measure, the LOP measure does not rely on the existence of a particular asset pricing model.

Although the LOP measure is simple to implement, it has serious disadvantage. It cannot preclude arbitrage opportunity. This implies SDF can have negative values for some states. Equivalently, it assigns negative price to certain assets which have only positive payoff(s). Therefore, we need a restriction that SDF should be non-negative. We can implement this by using $m_{t+1}^{NA}=\max(b'R_{t+1},0)$. Using this NA SDF, we can define the NA performance measure as follows:

$$\alpha^{NA}=E[R_{h,t+1}m_{t+1}^{NA}]-1$$

$$,where\ R_{h,t+1}: hedge\ fund's\ gross\ return$$
$$m_{t+1}^{NA}: the\ NA\ SDF$$

2.3 Incorporating Conditioning Information

Unconditional models arise from one-period static models. As Chen and Knez (1996) and Ferson and Schadt (1996) note, unconditional models presumes a simple buy-and-hold trading strategy. If expected returns and risk premia, however, are time-varying, performance evaluation should incorporate dynamic trading strategies as well. Otherwise, unconditional performance measure may simply captures gains or losses of dynamic trading strategies.

To incorporate time-varying expected returns for the parametric measure, we consider a conditional version of the CAPM model and the Fama and French (1993) model. The conditional approach requires the conditioning variables which act as instruments for changes in the investment opportunity set. We scale factors by conditioning variables for the conditional parametric measures. Specifically for the case of the Fama and French (1993) model, we replace the three factors in (1) with $(R_{MRP,t}) \otimes z_{t-1}$, $(R_{SMB,t}) \otimes z_{t-1}$, and $(R_{HML,t}) \otimes z_{t-1}$, where z_{t-1} is a set of conditioning variables known at time t-1. We use a constant and one instrument as conditioning variables, so the three factor model becomes a six factor model.

For a conditional version of the non-parametric performance measures, following the convention in Ferson (1989), we augment the payoff space by scaling the conditioning variables to the basis asset. As discussed by Cochrane (1996), we can interpret $R_t \otimes z_{t-1}$ as dynamically managed portfolios which are based on conditioning information. Specifically for the case of the Fama-French 6 portfolio and one month risk free rate as basis assets, as we use 7 basis assets from the unconditional analysis along with two conditioning variables (including a constant), total 14 basis assets are used as basis assets in the conditional analysis.

3. Data

The sample for our analysis consists of 153 monthly observations from April 1994 through December 2006.[7] Our data consist of the returns on hedge funds, the basis assets' returns, the Fama and French (1993) factors, and conditioning variable. We discuss these data below.

3.1. Hedge Fund

In this study, we evaluate the performance of hedge funds using monthly net-of-fee returns of live and dead hedge funds reported in the hedge fund databases; namely, CSFB/Tremont database. The CSFB/Tremont indexes are asset-weighted indexes of funds with a minimum $10 million of assets under management, a minimum one-year track record, and current audited financial statement. An aggregate index is computed from this hedge fund universe, and 10 sub indexes based on the investment style are also computed using a similar method.

3.2 Model Factors

To implement the CAPM model, we use the return on the CRSP value-weighted index as the market portfolio return. For the Fama and French (1993) model we obtain the three factors described in Fama and French (1993). Here the factors are excess market return which we subtract the one-month T-bill return from the market return, the return differentials between small and large caps (SMB), and the return differentials between high and low book-to-market stocks (HML). Summary statistics for these variables are in Panel A of Table 2.

Basis assets should reflect the returns available to investors and hedge fund managers. Of course, it is not practical to measure the entire investment opportunity set.

[7] Data covered from January 1994 to March 1994 is missing from the original data source.

In this paper, we use the 6 Fama and French portfolios formed on size and book-to-market, in addition to the monthly return to the one month T-bill.[8] These portfolios capture a large cross-section of average returns and standard deviations and are widely considered to be appropriate portfolios for spanning the payoff space.

The summary statistics including mean and standard deviation of basis assets are reported in Panel B of Table 2. Overall, the patterns across the six portfolios are consistent with twenty five Fama and French (1993) portfolios formed on size and book-to-market. Average returns tend to increase in book-to-market and decrease with size. Volatility tends to decrease with both book-to-market and size.

3.3 Conditioning Variables

We consider default spread DEF to capture time variation in expected return. The default spread is defined as the difference between Moody's BAA rated corporate bond yield and the AAA rated corporate bond. The conditioning variable is known as of the start of period t. Fama and French (1989) show that DEF displays a business cycle related pattern, rising in troughs and falling in peaks. Therefore, DEF picks the variation related to the NBER-designated recessions. The DEF is widely used in conditional asset pricing tests [e.g., Ferson and Harvey (1991)] and have been found to be good predictors of future returns. Panel C of Table 2 shows the summary statistics for DEF variables. Figure 5 shows the time series of the DEF variable.

[8] We also consider 25 Fama and French portfolios as basis assets. However, if we use a conditional framework, the number of moment conditions (51) are relatively high with respect to the number of observations (153). In this case, GMM estimates can give biased estimate results (See Cochrane (2001))

4. Empirical Results

We evaluate the hedge funds returns by using four benchmarks: the CAPM model, the Fama-French model, the LOP measure, and the NA measure. For each approach, we perform both unconditional and conditional versions of the tests.

4.1 Unconditional Performance Measures

The main results in the paper are the estimation of the hedge funds performance using the four different benchmarks. Table 3 contains the unconditional estimates of α along with t-statistics for the test of $\alpha = 0$. For most of hedge funds, all four benchmarks indicate that hedge funds have positive risk-adjusted return. For a convenience of comparison, we graph the alphas for each different performance measures in Figure 1.

There is a difference between the parametric and non-parametric measures. However, performance measures in each category have close relationship. Comparing the results between the CAPM benchmark and Fama-French model benchmark we can see how close the reported alphas are. The risk-adjusted returns using the Fama-French model benchmark are generally lower than those estimated using the CAPM benchmark. This reflects that the Fama-French model captures more risk than CAPM model. Also, the LOP and the NA performance measures have similar characteristics. To see this, we present the time series behavior of the unconditional SDF which is extracted from the Fama-French six portfolios in Figure 2. The unconditional LOP and NA SDFs are highly correlated (correlation coefficient is 0.92), but note that the NA SDF have no negative values. Due to the similar values of the unconditional LOP and NA SDFs, the results of performance based on non-parametric model are similar. We now check to whether above results change or not when we allow investment opportunity set to be time-varying.

4.2 Conditional Performance Measures

Table 4 repeats the analysis in Table 3, but now using the conditional version of the performance measures. We also present the alphas in Figure 3 for a convenience of comparison. While the parametric performance measures change slightly from unconditional to conditional framework, the non-parametric performance measures change dramatically.

We first address the issue whether conditional performance measures reflect the time-varying risk premia. To answer this, we compare the extracted (implied) unconditional SDFs, conditional SDFs, and conditioning variable – default spread (shown in Figure 5) which is known to be negatively correlated with business cycle. As expected, the unconditional SDFs have little relationship with default spread (correlation coefficients are 0.01 and 0.10 for the LOP and NA SDF respectively). However, the conditional SDFs are strongly positively correlated with default spread (correlation coefficients are 0.54 and 0.45 for the LOP and NA SDF respectively), which implies the *conditional* non-parametric measures reflect business cycle related time-varying risk premia and its direction is counter-cyclical.

Next, we address the significant difference between the LOP and NA measure. To investigate the difference between them, we present the time series behavior of the (implied) conditional SDFs in Figure 4. They have significant different features each other. Though they have same mean value which is equal to the inverse of the gross return of the risk free asset, the NA SDF have higher volatility than the LOP SDF due to its nature of positive restriction.[9]

Most importantly, the LOP SDF has many negative values especially when the economic condition is good. Generally, the SDF (or marginal value of wealth) should be low when the economic state is good and high when the economic state is bad as investors feel more happiness for the additional wealth when they are "hungry". In consistent with economic theory, we found above that (implied) SDFs vary counter cyclically with business condition. However, the SDF (or marginal value of wealth) should not be negative as economic theory assumes that economy agents have positive marginal utility. Therefore conditional LOP SDF is consistent with investor's characteristics of risk averseness, but is *not* consistent with positive marginal utility.[10] The lack of positive restriction of discount factor (equivalently no arbitrage restriction) can be serious disadvantage for the evaluation of the hedge funds as it allows arbitrage opportunity.

In contrast to the conditional LOP SDF, the conditional NA SDF satisfies *both* restrictions: risk averseness and no arbitrage restriction. The conditional NA SDF has low values, but not negative values when the economic state is good, and has higher values than the LOP SDF when the economic state is bad. By weighting more preferences to the "bad times" satisfying the no arbitrage restriction, the NA SDF adjusts risk better reflecting business conditions than the LOP SDF. In this context, we argue that the NA pricing kernel is the most appropriate performance measure to adjust risk especially for the evaluation of hedge funds.

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[9] 1 = E[mR] implies E[m]= 1/ Rf. We impose this restriction when estimating SDFs

[10] As we noted above, the *unconditional* LOP SDF satisfies *neither* risk averseness nor positive restriction as it does not reflect time-varying risk premia.

4. Summary and concluding remarks

In this paper, we apply the stochastic discount factor (SDF) methodology of Chen and Knez (1996) for the evaluation of hedge funds. The difference with previous studies in hedge funds is that we use the SDF approach, which explicitly takes into account the no arbitrage restriction and time-varying risk premia. As a result, our approach ensures appropriate valuation of derivatives and dynamic trading strategies. This is especially important for evaluating the performance of hedge funds that are often heavily involved in these practices. In contrast, it is much more difficult to impose same restriction in a traditional linear regression framework (i,e., parametric measures), and results on hedge funds performance based on Jensen's alpha can be difficult to interpret.

Our main empirical findings are as follows.

First, we find significant abnormal performance of hedge funds using either the parametric or non-parametric benchmarks.

Second, only the NA SDF has no negative values while the other benchmarks have negative values frequently. Economic theory says that the SDF (equivalently the price of Arrow-Debreu security) should be non-negative. Otherwise, there can be an arbitragy opportunity in the economy (See Harrison and Kreps (1979)). No arbitrage restriction is particularly important for evaluating hedge funds performance due to its heavy use of derivative securities as derivative securities can be priced by no arbitrage condition (relative pricing) rather than equilibrium pricing.

Fianlly, the conditional non-parametric measures reflect business cycle related time-varying risk premia and its direction is counter-cyclical. Therefore, the funds which make investors smooth their consumption by giving high returns when they are "hungry" and low returns when the economic state is good are evaluated to the high abnormal performance.

As conditional measure incorporates dynamic trading strategies, it is also important for evaluating hedge funds performance due to its use of dynamic trading strategies.

According to above findings, we argue that the *conditional NA measure* is the best appropriate performance benchmark for the evaluation of hedge funds.

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Table 2. Summary Statistics for Model Factors, Basis Assets, and the Conditioning Variable

Means, standard deviations, skewness, kurtosis, and autocorrelations for data used in the analysis. All data are expressed as percentage and are monthly from April 1994 to December 2006, a total of 153 observations.

	Mean	Std Dev	Skewness	Kurtosis	Autocorr
Panel A: Model Factors					
MKT	0.6765	4.2524	-0.8081	4.0903	0.0372
SMB	0.1726	3.9806	0.8352	9.7612	-0.0728
HML	0.4265	3.5952	0.0314	5.5463	0.0494
Panel B: Basis Assets					
Small Growth	0.8093	8.5666	0.5985	6.5021	0.1215
Small Neutral	1.5627	5.1189	-0.2022	5.0841	0.1920
Small Value	1.8854	4.9980	-0.1684	4.7652	0.2590
Big Growth	0.9914	5.6831	-0.5604	4.2600	0.0512
Big Neutral	1.2677	4.4484	-0.5907	5.4731	0.1060
Big Value	1.2681	4.2220	-0.4888	4.7820	0.0824
T-bill rate	0.3210	0.1407	-0.5638	1.9290	0.9571
Panel C: Conditioning Variable					
DEF	0.8144	0.2126	1.0622	3.3640	0.9552

Table 3: Unconditional Performance Measures

Estimation results for the performance of hedge funds. The table reports performance measure with the associated t-statistics. Results are based on unconditional performance evaluation using four benchmarks: CAPM uses the Capital Asset Pricing Model; FF uses the Fama and French (1993) model; LOP is the law of one price measure, which is a non-parametric method based on the 6 size and book/market portfolios and one month T-bill as basis assets; NA is the no arbitrage measure, similar to LOP but with the added restriction that the stochastic discount factor be non-negative. Data are monthly from April 1994 to December 2006, a total of 153 observations.

	Parametric		Non-parametric	
	CAPM	FF 3	LOP	NA
Convertible Arbitrage	0.397%	0.319%	0.178%	0.165%
	3.73	2.98	0.79	0.67
Dedicated Short Bias	0.193%	0.127%	0.425%	0.515%
	0.87	0.61	1.51	1.62
Emerging Markets	0.116%	0.008%	-0.217%	-0.257%
	0.37	0.02	-0.44	-0.47
Equity Market Neutral	0.454%	0.440%	0.426%	0.443%
	7.39	6.88	5.46	5.75
Event Driven	0.473%	0.355%	0.187%	0.107%
	4.57	3.68	0.95	0.53
Fixed Income Arbitrage	0.229%	0.189%	0.001%	-0.039%
	2.72	2.19	0.01	-0.19
Global Macro	0.760%	0.653%	0.518%	0.496%
	3.13	2.60	1.33	1.15
Long/Short Equity	0.403%	0.444%	0.151%	0.027%
	2.43	3.11	0.57	0.09
Managed Futures	0.318%	0.244%	0.519%	0.588%
	1.13	0.83	1.32	1.41
Multi-Strategy	0.438%	0.388%	0.370%	0.337%
	4.36	3.80	3.09	2.69

Table 4: Conditional Performance Measures

Estimation results for the performance of hedge funds. The table reports performance measure with the associated t-statistics. Results are based on conditional performance evaluation using four benchmarks: CAPM uses the Capital Asset Pricing Model; FF uses the Fama and French (1993) model; LOP is the law of one price measure, which is a non-parametric method based on the 6 size and book/market portfolios and one month T-bill as basis assets; NA is the no arbitrage measure, similar to LOP but with the added restriction that the stochastic discount factor be non-negative. Data are monthly from April 1994 to December 2006, a total of 153 observations.

`	Parametric		Non-parametric	
	CAPM	FF 3	LOP	NA
Convertible Arbitrage	0.395%	0.299%	0.528%	0.557%
	3.68	2.79	2.66	3.6733
Dedicated Short Bias	0.233%	0.173%	0.121%	0.229%
	1.07	0.84	0.32	0.4984
Emerging Markets	0.069%	-0.047%	0.520%	0.636%
	0.22	-0.15	1.09	1.23
Equity Market Neutral	0.440%	0.415%	0.554%	0.589%
	7.37	6.64	6.06	7.76
Event Driven	0.458%	0.327%	0.297%	0.334%
	4.47	3.42	1.65	1.74
Fixed Income Arbitrage	0.222%	0.182%	0.227%	0.281%
	2.63	2.08	1.62	2.56
Global Macro	0.717%	0.577%	0.567%	0.656%
	3.00	2.32	1.46	1.87
Long/Short Equity	0.357%	0.414%	0.307%	0.152%
	2.25	3.17	0.90	0.36
Managed Futures	0.277%	0.163%	0.730%	0.329%
	0.99	0.55	1.56	0.61
Multi-Strategy	0.450%	0.394%	0.490%	0.449%
	4.50	3.82	3.84	3.98

Table 5. Correlation Matrix

Correlation matrix between the (implied) pricing kernels and DEF variable. Panel A reports results when the pricing kernels are extracted in the unconditional framework. Panel B reports results when the pricing kernels are extracted in the conditional framework. The LOP is the law of one price measure; The NA is the no arbitrage measure; The DEF is default spread which is defined as as the difference between Moody's BAA rated corporate bond yield and the AAA rated corporate bond. Data are monthly from April 1994 to December 2006, a total of 153 observations.

Panel A: Unconditional framework			
	LOP	NA	DEF
LOP	1.00		
NA	0.92	1.00	
DEF	0.01	0.10	1.00
Panel B: Conditional framework			
	LOP	NA	DEF
LOP	1.00		
NA	0.86	1.00	
DEF	0.54	0.45	1.00

Figure 1. Unconditional Performance Measures

Unconditional performance measures for the hedge funds as reported in Table 3. For each hedge funds, the figure shows the abnormal performance estimate from the CAPM measure, the Fama and French (1993) measure, the LOP (law of one price) measure, and the NA (no arbitrage) measure. The measures are expressed in percentage per month. Data are monthly from April 1994 to December 2006, a total of 153 observations.

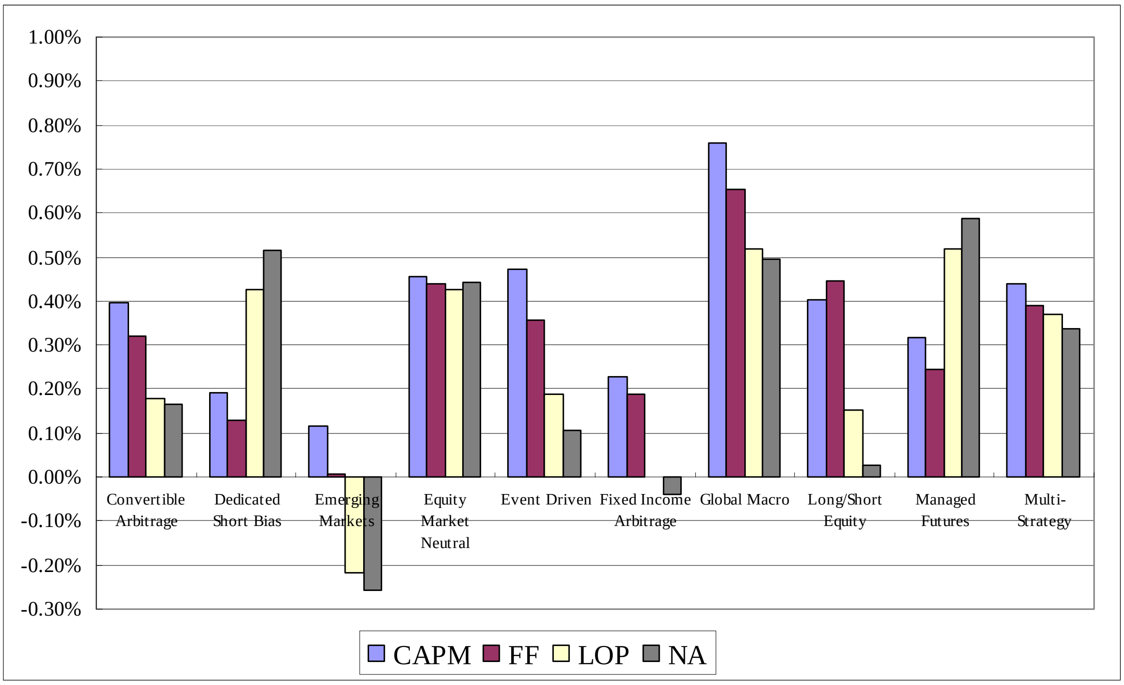

Figure 2. Unconditional LOP and NA implied Pricing Kernels

Time series of the (implied) unconditional pricing kernels whose basis assets are the 6 size and book/market portfolios and one month T-bill. The LOP pricing kernel is an empirical random variable which prices exactly basis assets by construction. The NA pricing kernel is an empirical random variable which is non-negative and also prices exactly basis assets. Data are monthly from April 1994 to December 2006, a total of 153 observations.

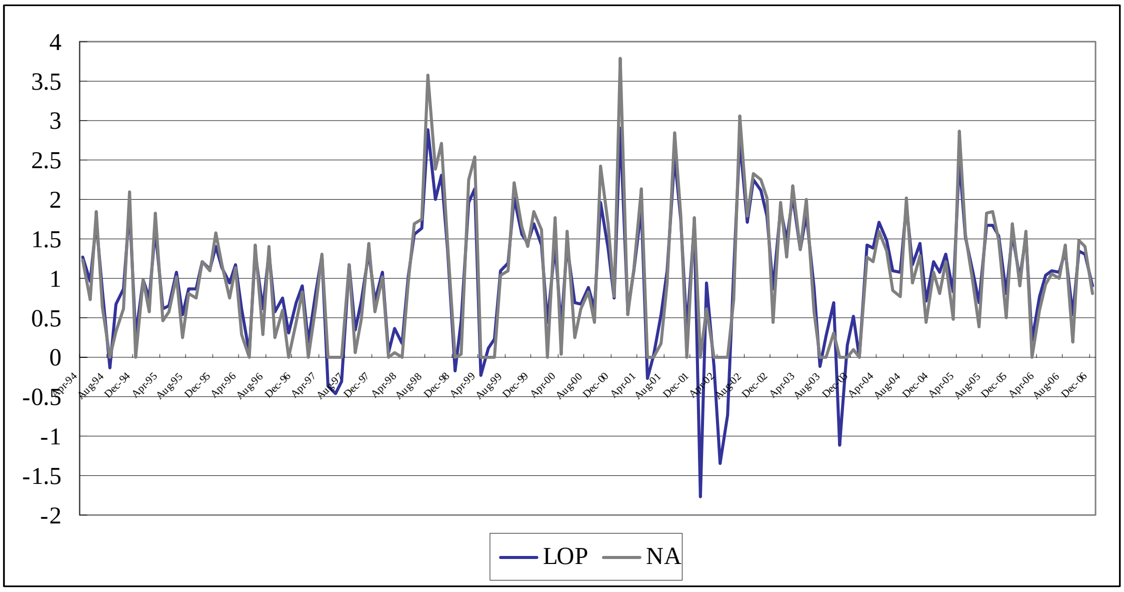

Figure 3. Conditional Performance Measures

Conditional performance measures for the hedge funds as reported in Table 4. For each hedge funds, the figure shows the abnormal performance estimate from the CAPM measure, the Fama and French (1993) measure, the LOP (law of one price) measure, and the NA (no arbitrage) measure. The measures are expressed in percentage per month. Data are monthly from April 1994 to December 2006, a total of 153 observations.

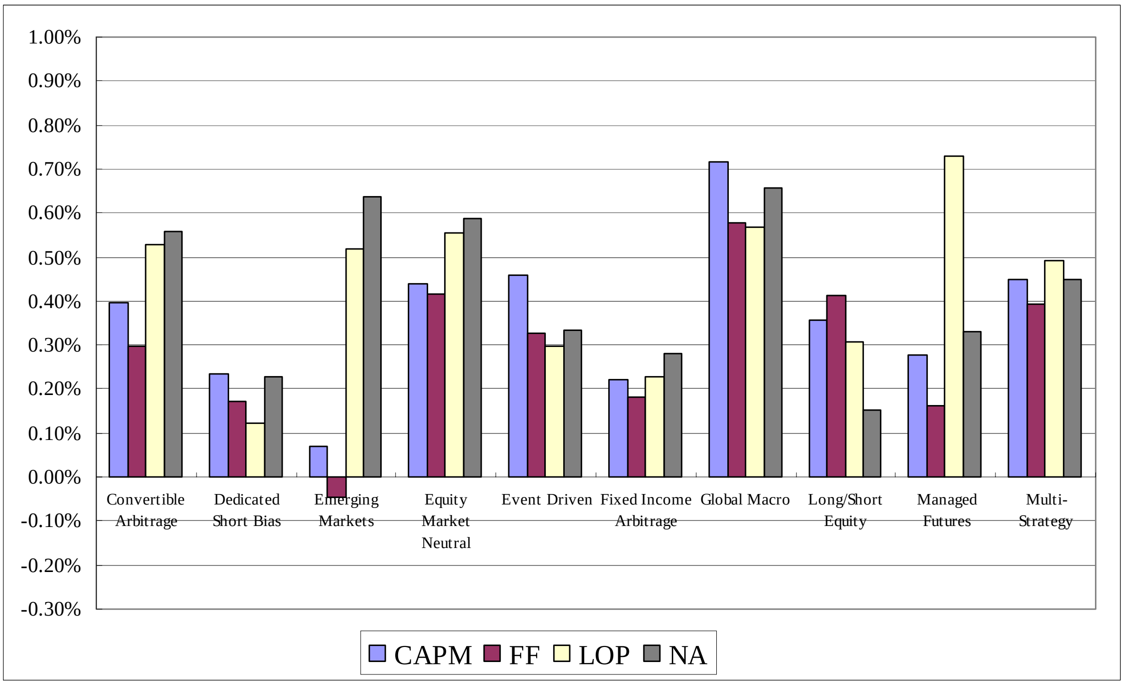

Figure 4. Conditional LOP and NA implied Pricing Kernels

Time series of the (implied) conditional pricing kernels extracted from which managed portfolios. We construct managed portfolios by scaling the conditioning variable, default spread, to the basis assets (6 size and book/market portfolios and one month T-bill). The LOP pricing kernel is an empirical random variable which prices exactly managed portfolios by construction. The NA pricing kernel is an empirical random variable which is non-negative and also prices exactly managed portfolios. Data are monthly from April 1994 to December 2006, a total of 153 observations.

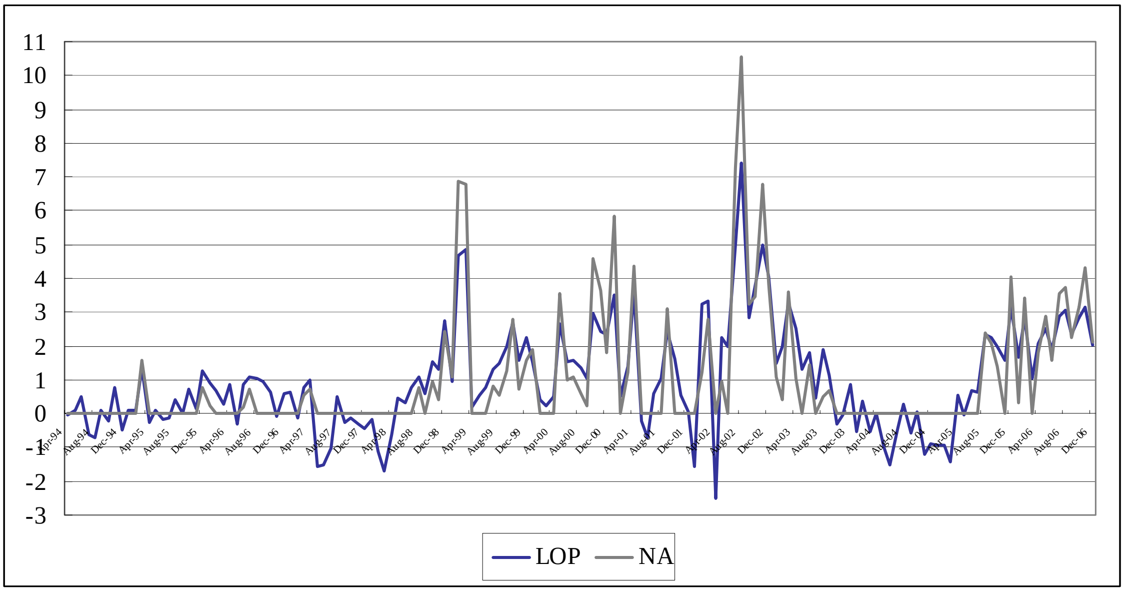

Figure 5. Default Spread

Time series of the default spread. The default spread is defined as the difference between Moody's BAA rated corporate bond yield and the AAA rated corporate bond. Data are monthly from March 1994 to November 2006, a total of 153 observations.