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Pricing strategy: hedge funds

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Abstract

Hedge funds are privately organized investment pools, the strategies of which include long and short positions, arbitrage, and buying and selling undervalued securities. Hedge fund strategies are used to reduce risk, preserve capital and deliver positive returns to their investors. The aim of this study is to propose a suitable pricing model within the CAPM model of different form, through reducing hedge funds, which consist of many strategies, in consideration with their time series features by the help of time series factor analysis. In the application, it is proposed that with this new approach, the CAPM model of quadratic form for 2 lags is obtained as the suitable model with the minimum AIC result; and that as the relationships between the strategies and lag structure are considered, more objective pricing models can be obtained.

Keywords: Hedge Funds ·Tests of Asset Pricing Models ·Time-Series Techniques

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1. Introduction

The public perception of hedge funds has been shaped by press coverage on the large losses incurred by Long-Term Capital Management (LTCM) and the large returns generated by George Soros and his Quantum Fund in betting on the British pound. As a result, hedge funds are generally associated with excessive volatility. Such “speculative” funds have been categorized under the guise of hedge funds, yet are quite distinct in the sense that they make more concentrated and highly leveraged. Yet the classic purpose and definition of a “hedge” is in fact to reduce risk (Varadi 2001, p.4).

The hedge fund investment profiles have always been different than other traditional investment products, especially in the private, illiquid, and over-the-counter (OTC) asset classes. Due to their complex strategies and risky investment universe, hedge funds still have problems in standardizing their asset pricing. By their very nature, pricing models will still differ from any of the hedge fund strategies and as the same model can be interpreted in various ways.

Actually, in the literature, Capital Asset Pricing Model (CAPM) is commonly used model, which is based on Markowtiz’s theory introduced in 1952. This theory has been developed to the point that, these concepts today form the basis of most asset pricing models. This theory mainly focused on risk and return trade off. The exclusive focus on only two dimensions of the return distribution assumes that return follows a normal distribution, where the first two moments have sufficient statistics to represent the whole distribution (Amenc et al. 2005, p.7). Therefore the CAPM model has serious difficulties to explain the past superior performance of hedge funds (Ranaldo and Favre 2005, p.2). The empirical evidence shows that the normality hypothesis had to be rejected for many hedge fund returns (Ranaldo and Favre 2005, p.1). From this point of view, Ronaldo and Favre (2005) conducted a research to analyze how to price hedge funds from two-to four-moment CAPM. They compared traditional CAPM based on the mean-variance criterion with extensions of the CAPM that account for coskewness and cokurtosis. The key result is that the risk-return characteristics of hedge funds can differ widely. The use of a unique pricing model may be misleading. Hedge funds have not to be treated as an asset class per se but it is more appropriate to specify different pricing models for different hedge fund management strategies (Ranaldo and Favre 2005, p.16).

However, the fact that hedge funds include many different strategies complicates pricing and results in loss of time. Forming CAPM for each of these strategies can be regarded as an effortful and time-consuming approach. Reducing these strategies with an appropriate statistical model, calculating their meaningful factors and evaluating them within the CAPM model would yield reflective results. Drawing on this approach, Time Series Factor Analysis (TSFA) will be used in order to reduce dimension for the time series data and differing factors of the strategies will be determined for different lags. And these factors will be analyzed within CAPM in quadratic and cubic form. So in the study we answer these questions as follows;

1) How can we adopt and use time series factor analysis in hedge funds?
2) What are the advantages of using time series factor analysis when hedge funds are priced?
3) Which model or models are suitable in hedge fund pricing?

The rest of the paper is structured as follows: Section 2 describes certain features of hedge funds. Section 3 presents empirical analysis. Section 4 is devoted to the conclusion.

2. Literature Review And Hypotheses

2.1. Certain Features of Hedge Funds

Hedge funds were little known before the late 1980s. The first funds were started by traders with significant experience in trading for mutual funds, currency desks, or proprietary trading firms (Black 2004, p. 3). It is generally believed that Alfred W. Jones, who was a writer for Forbes and had a PhD in sociology, started the first hedge fund in 1949, which he ran into the early 1970s. He raised $60,000 and invested $40,000 of his own money to pursue a strategy of investing in common stocks and hedging the positions with short sales (Stulz 2007, p. 176).

Hedge fund is typically defined as a pooled investment vehicle that is privately organized, administered by professional investment managers, and not widely available to public (Gaurav and Kat 2003, p. 251). Legal status of the hedge funds places few restrictions on their portfolios and transactions, leaving their managers free to use short sales, derivative securities, and leverage to raise returns and cushion risk (Barry Eichengreen et al. 1998, p. 2). Likewise, hedge funds do not represent a single asset class, but are a type of investment vehicle that provides exposure to a wide range of investment strategies. Hedge funds come in different sizes and have different management strategies and styles. They follow different administrative, valuation, and disclosure practices. Therefore, management of a hedge fund portfolio must be appropriate for its particular investments. However, because hedge funds all have in common a low level of regulatory protection for their investors, there are minimum levels of diligence required for all hedge fund investors. Beyond this minimum, hedge funds pursuing higher risk strategies - for example, funds making significant use of leverage, or funds investing in illiquid assets - will require more extensive investor sophistication and oversight (Report of the Investors' Committee 2008, p. 3). The main features of hedge funds and traditional products are summarized in Table 1.

Table 1 Defining features of hedge funds

Hedge funds typically…	Traditional products typically…
• Invest both long and short	• Invest long only
• Are leveraged	• Not leveraged
• Have a high, performance-based fee structure	• Have a lower, ad valorem fee structure
• Normally require co-investment by fund manager	• Do-not encourage co-investment
• Are able to use futures and other derivatives	• Are restricted in using derivatives
• Have a broad investment universe	• Often have a limited investment universe
• Can have large cash allocations	• Are required to stay fully invested
• Have an absolute return objective	• Have a relative return objective
• Investor access regulated, but the product itself is lightly regulated	• Are frequently heavily regulated

Source: (Wyman 2005, p. 5)

The unique structure and status of hedge funds suggest that they have the potential to fill some of the gaps left by pension funds and mutual funds. Hedge funds are not subject to the same costly regulation as other institutions. Whereas mutual funds must have an independent board and permit shareholders to approve certain actions, hedge funds can, if they prefer, separate ownership and control in a more exact way. The typical hedge fund is a partnership managed by a general partner; the investors are limited partners who are passive and have little or no say in the hedge fund's business. So they are permitted to trade on margin and engage in short sales and strategies that are not available to other institutions, such as mutual and pension funds (Brav et al. 2006, pp. 7-8).

2.2. Emprical Analyses

Hedge funds, which behave as investment funds and differ significantly in terms of arrangement and risk profile, have become widespread in recent years because they provide the investors and fund managers with high degrees of return. Hedge funds have become widespread recently especially due to the use of derivative products. Hedge funds pursue absolute return irrespective of the sector indicators or index performance. In order to ensure absolute return, hedge funds apply aggressive strategies. They take positions such as short sale, buying and selling of derivative products and leverage (borrowing) to increase risk/return profile.

Hedge funds have a big concept and within this scope exists a high number of different working methods and strategies for managers. Hedge fund investment strategies are developed with an expectation to benefit from the possible return differences of the portfolios consisting of instruments such as bonds, equities, credit derivative instruments, which generally belong to similar risk categories.

Hedge funds disperse risk and improve pricing in accordance with these. They perform various and necessary functions in the financial markets. They contribute to the dispersing of market risk and credit risk among the market participants. They behave very fast and have a flexible structure. They attempt to eliminate the weaknesses of the market. They help to determine the prices of different products. Hedge funds are specialized in finding out mispriced entities. They take actions related to these entities and help to ensure that the price reflects the risk regarding the entity. If the entities are priced correctly, resources can be distributed more efficiently and risk might be managed better. In new and complex markets, hedge funds are significant factors with respect to taking opportunities and undertaking risks. They contribute to the increase of liquidity by undertaking the risk. All these factors are reflected in the development of financial stability. In other words, according to their advocates, hedge funds help to ensure the stability of the financial system.

For this function to be performed, correct pricing is the basic operation. There are studies on the pricing of different strategies. In these studies, a CAPM model is developed for each strategy and strategies are compared with each other. 17 Barclay hedge fund sub indices which are hedge fund strategies appearing in Table 2 were examined within the scope of this study. The data is analyzed for the period 1995.01-2009.12. Drawing on this approach, in the first phase of the application Time Series Factor Analysis (TSFA) will be used in order to reduce dimension for the time series data and differing factors of the strategies will be determined for different lags. In the second phase, these factors will be analyzed within CAPM in quadratic and cubic form. The aim is to illustrate how these strategies of time series feature can be reduced with a suitable method; then, to analyze CAPM model in the square and cubic form (on the basis of Ranaldo and Favre, 2003 study) through these reduced factors and to propose a new approach for pricing.

Table 2: Barclay hedge fund strategies

Type of Hedge Fund Strategies	Explanation
1)Convertible Arbitrage Index	This strategies identified by hedge fund investing in the convertible securities of a company.
2)Distressed Securities Index	Fund managers in this non-traditional strategy invest in the debt,

	equity or trade claims of financial in financial distress or already in default.
3)Emerging Markets Index	This strategy involves in equity or fixed income investing in emerging markets around the world.
4)Equity Long Bias Index	Equity Long/Short managers are typically considered long-biased when the average net long exposure of their portfolio is greater than 30%.
5)Equity Long/Short Index	This directional strategy involves equity-oriented investing on both long and short sides of the market.
6)Equity Market Neutral Index	This investment strategy is designed to exploit equity market inefficiencies and usually involves being simultaneously long and short matched equity portfolios of the same size within a country.
7)Equity Short Bias Index	Short biased managers take short positions in mostly equities and derivatives.
8)European Equities Index	This directional strategy involves equity-oriented investing on both the long and short sides of the market.
9)Event Driven Index	This strategy defined as ‘‘special situations’’ investing designed to capture price movement generated by a significant pending corporate event such as a merger, corporate restructuring, liquidation, bankruptcy or reorganization.
10)Fixed Income Arbitrage Index	The fixed income arbitrageur aims to profit from price anomalies between related interest rate securities.
11)Fund of Funds Index	Fund of funds is a fund that invests in a portfolio in different funds to provide broad exposure to the hedge fund industry and to diversify the risks associated with a single fund.
12)Global Macro Index	Global Macro managers carry long and short positions in any world’s major capital or derivative markets.
13) Healthcare & Biotechnology Index	This directional strategy involves equity-oriented investing on both the long and short sides of the market.
14)Merger Arbitrage Index	Merger arbitrage funds typically invest simultaneously long and short in the companies involves in a merger and acquisition.
15)Multi Strategy Index	Multi-Strategy funds are characterized by their ability to dynamically allocate capital among strategies falling within several traditional hedge fund disciplines.
16)Pacific Rim Equities Index	This directional strategy involves equity-oriented investing on both the long and short sides of the market.
17) Technology Index	This directional strategy involves equity –oriented investing on both the long and short sides of the market.

Source: Barclayhedge.com [homepage on the Internet]. BarclayHedge, Barclay Hedge Fund Indices, [cited 1 Jul 2010]. Available from:http://www.barclayhedge.com/research/hedge-funds-indices.html

3. Methodology

3.1. Time Series Factor Analysis

Factor Analysis (FA) is one of the multivariate analysis techniques used frequently in many fields, especially in social sciences. The aim of FA is to find few new unrelated variables by bringing together the interrelated variables. Thus, it is a method of reducing dimension and eliminating dependence structure. However, it is not so successful in terms of time series that examine economic variables. FA is not suitable because it does not provide assumptions such as independent observation and similar distribution of data, which are required by the data structure of time series. In the time-dependent economic data there is often an upward trend and dependency in the series. Time Series Factor Analysis (TSFA) is developed in order to analyze hidden factors in time series with the minimum possible number of assumptions and to reduce dimension in this kind of data, providing solution to a significant problem.

The large number of series means that asymptotics can be used in which both dimensions of the data matrix are diverging to infinity. Model assumptions such as the uncorrelatedness of error terms can then be relaxed and both the parameters and the underlying factors can be consistently estimated. See, e.g., Chamberlain and Rothchild (1983), Forni et al. (2000), Bai and Ng (2002), Bai (2003), and Stock and Watson (2005) for these models. In contrast, TSFA is suitable for a fixed (relatively small) number of series and therefore relies on somewhat stronger model assumptions.

TSFA should be useful when the researcher does both measurement and modeling, because specific assumptions about factor dynamics are usually much more fragile than the assumption that factors exist. With TSFA the factors can be measured before modeling their dynamics. However, TSFA may be especially important where one group (e.g., a statistics agency or central bank) measures data for many researchers to use.

Geweke (1977) also defined a factor analysis model for a multivariate time series without explicitly specifying the dynamic model for the factors, but he assumed covariance stationarity. This allowed estimation of parameters in the frequency domain. In contrast, TSFA does not assume covariance stationarity and estimation is in the time domain.

TSFA is also closely related to the "*P*-technique", proposed by Cattell (1943) and Cattell et al. (1947), which applied standard FA to multivariate time series. In the development of *P*-technique no explicit assumptions were stated and practices were used for which the methodological basis is questionable. First, the data were not de-trended. Estimators are shown below to have desirable statistical properties such as consistency after de-trending, which may not be the case otherwise. Second, a substantive model was estimated in an attempt to accommodate the dynamic process. This was done by including exogenous variables and deterministic functions of time that were treated as additional indicators, and by using a matrix of the largest cross-correlations rather than an ordinary correlation matrix. That is, if x and y are two observed variables, Corr(xt; yt) was replaced by Corr(xt; ys), where s is such that the absolute value of this correlation is maximized. The *P*-technique, and especially this implementation, has been heavily criticized by Anderson (1963) and Holtzman (1962). TSFA does not include exogenous variables and deterministic functions of time, and only uses a proper covariance matrix (or correlation matrix).

Furthermore, data is de-trended by differencing and weak assumptions under which TSFA gives consistent estimates are explicitly stated below.

Finally, this paper is related to Spanos (1984), both in terms of methodology and application. He first estimated a FA model from first differences of a multivariate time series, and then predicted the factor scores, which he used in a subsequent analysis of an economic model. Explicit assumptions are missing, but i.i.d. appears to be assumed. After model specification, he re-estimated the complete model in a state-space form without a dynamic factor relationship. In the application to measuring money, he used only one factor and presumed that this would represent liquidity, as he thought that this was the most common aspect of the various indicators. In contrast, below weak assumptions are stated explicitly and subsequent economic models are not discussed, the properties of the estimators and factor score predictors are studied through simulation, and in the application a number of different choices (number of factors, construction of the indicators) are made.

Gilbert and Pichette (2002, 2003), and in many of the references cited in those papers. While these traditional measures are now largely unused, we hope that a better understanding of the financial side of the economy would be useful, and ultimately lead to models which are better for policy and prediction. Better measurement is a necessary first step in this process.

TSFA is advantageous with respect to application because it works with fewer assumptions. Normality, absence of autocorrelation in series, independent and similar distribution, and validity of stability of covariance assumptions are not required. Moreover, TFSA can yield effective results in the case of few observations and thus contributes significantly to the multivariate analysis techniques. As the hedge fund strategies have time series features, FA will not be the suitable reduction method. TFSA methodology is as follows:

The k unobserved processes of interest (the *factors*) for a sample of T time periods will be indicated by ξ_t, $t = 1,...,T$, $i = 1,...k$. The M observed processes will be denoted by y_{it}, $t = 1,...,T$, $i = 1,...,M$. The factors and indicators for period t are collected in the (column) vectors ξ_t and y_t, respectively. It is assumed there is a measurement model relating the indicators to the factors given by (Gilbert and Meijer 2005, p. 5):

$$y_t = \alpha + B\xi_t + \varepsilon_t$$

(1)

where α is an M- vector of intercept parameters, B is an M x k matrix parameter of *factor loadings* or simply *loadings*, and ε_t is a random M- vector of measurement errors, disturbances, and unique or idiosyncratic factors. In the example application it is assumed that $\alpha = 0$, but the theory is developed for the general case. Equation (1) is a standard FA model except that indicators are indexed by time and intercepts are explicitly included, whereas in FA means are usually subtracted. The fact that data are time series is important mainly because economic data are typically growing and thus not covariance stationary. Other than this, the sequential order of the data is irrelevant in TSFA as opposed to DFA (Gilbert and Meijer 2005, p. 6).

FA is usually applied to cross-sectional data where it is reasonable to assume i.i.d. observations. Then the mean and covariance are the same for every observation, which is convenient for parameter estimation. With time series, the i.i.d. assumption is problematic, and it is unnecessary. If the series ξ_t and ε_t are serially dependent, but ξ_t and ε_t are uncorrelated (at t) with zero means and constant covariances Γ and Ψ, then the mean and covariance of y_t are $\mu_y = \alpha$ and $\Sigma_y = B\,\Gamma B' + \Psi$ respectively. Under some regularity conditions the sample mean and covariance of y will be consistent estimators of μ_y and Σ_y, and therefore the usual estimators of the parameters (such as ML) are consistent. This principle is now demonstrated under considerably weaker assumptions (Gilbert and Meijer 2005, p. 6).

A slightly more general variant of (1) is used (Gilbert and Meijer 2005, p. 6):

$$y_t = \alpha_t + B\xi_t + \varepsilon_t$$

(2)

where α_t is a possibly time-varying intercept vector, but loadings are assumed time-invariant. Many time series integrate order 1 so the variances of the indicators increase in time. This violates assumptions for standard estimators where parameters are constant and moments converge in probability to finite limits (Wansbeek and Meijer 2000, p. 234).

Often y_t integrates but has a stationary first difference. Thus differencing is a common practice in time series analysis and the consequences of differencing (2) are examined. Below it is shown that assuming a stationary differenced series is stronger than necessary and a weaker form of boundedness suffices. Defining D as the difference operator (2) becomes (Gilbert and Meijer 2005, p. 6):

$$Dy_t \equiv y_t - y_{t-1} = (\alpha_t - \alpha_{t-1}) + B(\xi_t - \xi_{t-1}) + (\varepsilon_t - \varepsilon_{t-1}) \text{ or}$$

(3)

$$Dy_t = \tau_t + BD\xi_t + D\varepsilon_t$$

(4)

The latter is again an equation with a factor structure, and with the same loadings B. Thus a standard FA model can be estimated with the differenced data. Following are sufficient conditions (assumptions) such that this leads to consistent estimators of relevant parameters. First, measurement model (2) and hence (3) is assumed. Second, it is assumed that $\tau_t = \tau$ is a constant vector in (3). In the application $\alpha_t = 0$ and therefore $\tau_t = 0$ for all *t*, but the theory is developed with the more general specification of non-zero but time-constant τ. Third, the following conditions are assumed (Gilbert and Meijer 2005, p. 7):

1. $\kappa \equiv \text{p}\lim_{T\to\infty} \sum_{t=1}^{T} D\xi_t / T$ exists and is finite.

2. $\text{p}\lim_{T\to\infty} \sum_{t=1}^{T} D\varepsilon_t / T = 0$

3. $\Phi \equiv \text{p}\lim_{T\to\infty} \sum_{t=1}^{T} (D\xi_t - \kappa)(D\xi_t - \kappa)' / T$ exists and is finite and positive definite.

4. $\Omega \equiv \text{p}\lim_{T\to\infty} \sum_{t=1}^{T} D\varepsilon_t D\varepsilon_t' / T$ exists and is finite and positive definite.

5. $\text{p}\lim_{T\to\infty} \sum_{t=1}^{T} (D\xi_t - \kappa) D\varepsilon_t' / T = 0$

Although unit roots in $D\xi_t$ and/or $D\varepsilon_t$ violate the assumptions, no other explicit assumptions are made about the possible autocorrelation of the differenced data, and these assumptions allow considerable serial dependence in the variables. Furthermore, it is not assumed that means and variances are constant over time, but only that they are bounded in such a way that the required probability limits exist. This allows, for example, GARCH processes (Bollerslev 1986, pp.311-312).

The conditions 2 and 5 are implied by the alternative condition E($D\varepsilon_t / D\xi_t$) = 0 combined with the finiteness of Φ and Ω. This is a substantively more meaningful assumption than 2 and 5 and therefore is assumed to be satisfied as well. The sample mean and covariance of the differenced series D_{yt} will be denoted by $\overline{D_y}$ and S_{Dy}, respectively. That is (Gilbert and Meijer 2005, p. 7):

$$\overline{Dy} \equiv \frac{1}{T} \sum_{t=1}^{T} Dy_t$$

(5)

and,

$$S_{Dy} \equiv \frac{1}{T} \sum_{t=1}^{T} (Dy_t - \overline{Dy})(Dy_t - \overline{Dy})'$$

(6)

From the stated assumptions, it follows that

$$\operatorname*{plim}_{T\to\infty} \overline{D_y} = \mu \equiv \tau + B\kappa \text{ and}$$

(7)

$$\operatorname*{plim}_{T\to\infty} S_{Dy} = \Sigma \equiv B\Phi B' + \Omega$$

(8)

Conventional FA estimators (such as ML) use the sample covariance to estimate the loadings B, the factor covariance Φ, and the error covariance Ω. From (5) it follows that these estimators must also be consistent when S_{Dy} is used as the sample covariance. Neither normality nor serial independence is required for this result. However, just as in standard FA, consistency is only obtained if B, Φ and Ω are identified from this equation. Therefore it is assumed that this is the case. Most of the applications are assumed to be diagonal. Then, if the Ledermann bound;

$$(M-k)^2 \geq M+k$$

(9)

is satisfied, Ω is generally identified (Wansbeek and Meijer 2000, pp. 169-170). As in standard FA, the parameter matrices B and Φ are uniquely defined either by imposing restrictions on their elements or by choosing a rotation method.

Given estimators $\hat{B}$, $\hat{\Phi}$ and $\hat{\Omega}$ estimators for τ and/or k can be obtained from (4). The number of sample means in this equation is smaller than the number of parameters and therefore some restrictions must be imposed. In a typical FA model, the intercepts are free parameters, so that the means of the factors can be arbitrarily but conveniently restricted to zero, giving the restriction k = 0 and estimator $\hat{\tau}$ = D_y. This illustrates why the means are usually neglected in FA applications. When τ = 0 and k is not zero, a natural and consistent estimator of k is the GLS estimator:

$$\hat{\kappa} = (\hat{B}'\hat{\Omega}^{-1}\hat{B})^{-1}\hat{B}'\hat{\Omega}^{-1}\overline{Dy}$$

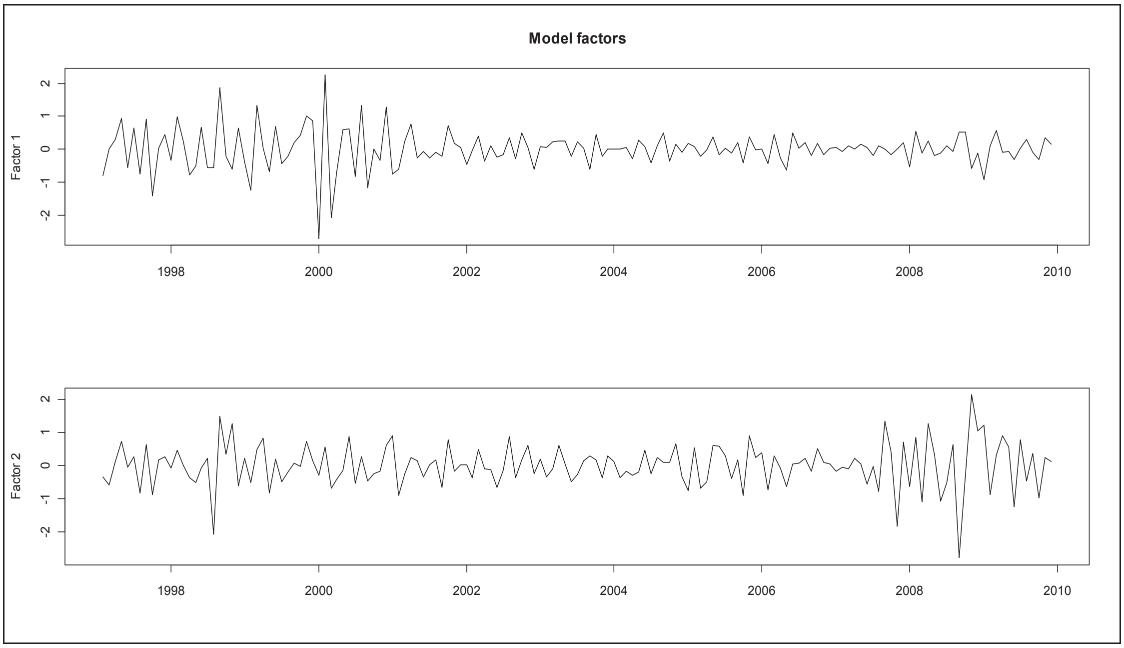
(10)

It is also possible to estimate all parameters jointly from the mean and covariance structure, i.e. use (7) and (8) jointly (Gilbert and Meijer 2005, p. 8).

4. Analyses and Results

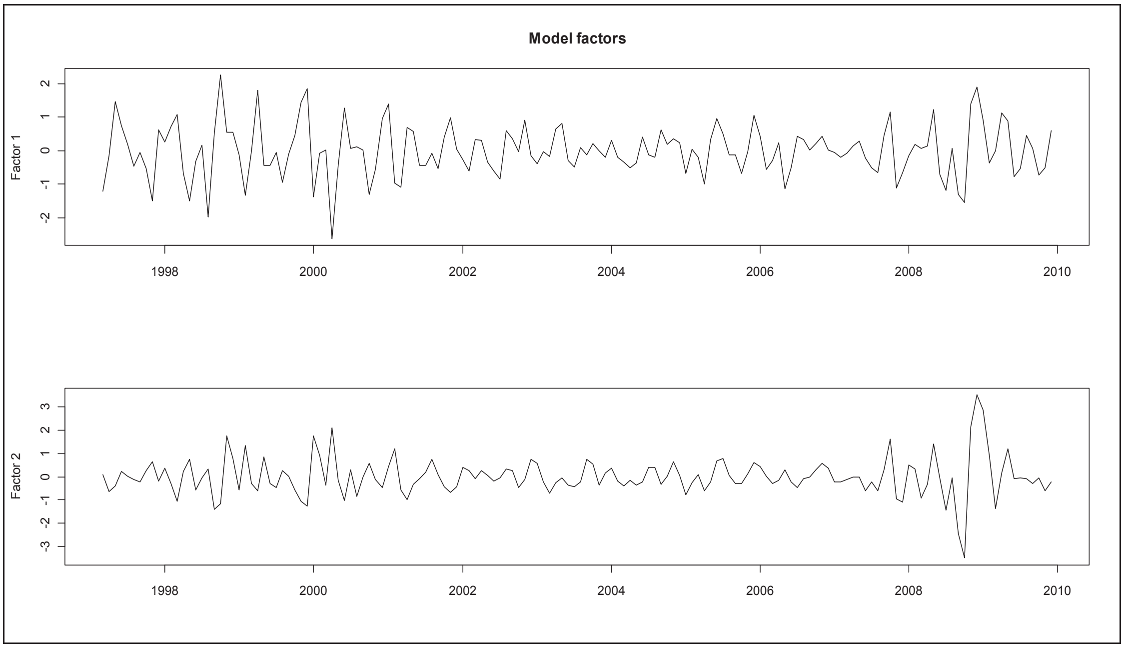
Results are obtained from R package program. Tests are conducted for oblimin rotation[a] in different lag levels. As the results obtained for more than two lag levels are similar to each other, the factor results for lag 1 (See Figure 1) and the factor results for lag 2 (See Figure 2).

Figure 1: Factor results for lag 1



[a] Oblimin rotation is preferred in this study because it is the most widely used method in applications.

Figure 2: Factor results for lag 2



In Table 3, Table 4 and Table 5, 17 strategies for both lag 1 and lag 2 are reduced to 2 explanatory factors. CAPM results, analyzed on the basis of these factor series, are presented in Table 3, Table 4 and Table 5. For the calculation of the market, quadratic and cubic model the formulas are used as below:

The Market Model: $\mathrm{R}_{\mathrm{i,t}} - \mathrm{R}_{\mathrm{f,t}} = \alpha_1 + \alpha_{2,i}(\mathrm{R}_{\mathrm{m,t}} - \mathrm{R}_{\mathrm{f,t}}) + \varepsilon_{\mathrm{t}}$ (11)

Table 3 The market model estimate results

	Factors	α_1	α_2	R^2	AIC
lag 1	Factor 1	0,010	0,234	0,782	-4,945
	Factor 2	0,081	0,518	0,810	-4,983
lag 2	Factor 1	0,003	0,159	0,791	-5,321
	Factor 2	0,063	0,206	0,822	-5,446

The Quadratic Model:

$$\mathrm{R}_{\mathrm{i,t}} - \mathrm{R}_{\mathrm{f,t}} = \alpha_1 + \alpha_{2,i}(\mathrm{R}_{\mathrm{m,t}} - \mathrm{R}_{\mathrm{f,t}}) + \alpha_{3,i}\left(\mathrm{R}_{\mathrm{m,t}} - E(\mathrm{R}_{\mathrm{m}})\right)^2 + \varepsilon_{\mathrm{t}} \tag{12}$$

Table 4 The quadratic model estimate results

	Factors	α_1	α_2	α_3	R^2	AIC
lag 1	Factor 1	0,015	0,366	- 1,840	0,800	-5,468
	Factor 2	0,007	0,208	- 3,611	0,834	-5,601
lag 2	Factor 1	0,003	0,170	- 2,607	0,816	-5,503
	Factor 2	0,004	0,224	- 1,993	0,854	-5,990

The Cubic Model:

$$R_{i,t} - R_{f,t} = \alpha_1 + \alpha_{2,i}(R_{m,t} - R_{f,t}) + \alpha_{3,i}\left(R_{m,t} - E(R_m)\right)^2 + \alpha_{4,i}\left(R_{m,t} - E(R_m)\right)^3 + \varepsilon_t \; ($$

Table 5 The cubic model estimate results

	Factors	α_1	α_2	α_3	α_4	R^2	AIC
lag 1	Factor 1	0,002	0,351	- 1,345	- 15,411	0,751	-5,808
	Factor 2	0,041	0,214	- 1,288	- 22,890	0,792	-5,903
lag 2	Factor 1	0,003	0,205	- 0,990	- 9,875	0,785	-5,899
	Factor 2	0,009	0,196	- 1,941	- 11,040	0,801	-5,398

As the results illustrate, the Quadratic Model results are more suitable compared to the market and cubic models. The AIC value is low and R^2 values are high. Thus, it is determined that in pricing quadratic model is statistically more suitable. It is also determined that in lag 2 level, the meaningfulness of the model increases. In the results of all models, it is observed that model conformity of 2 lags is better. After making a reduction with an appropriate analysis for the strategies comprising the fund of a time serious feature, working with correct factor in terms of statistics and determining the direction of the pricing is of critical importance for analysts. According to the analysis conducted for each strategy, models with high statistical conformity were obtained. Time series factor analysis method is a suitable reduction method and is also appropriate for studies on this issue as it considers the effects of lags. Eventually, CAPM models in lag 2 level yielded better results.

5. Conclusion

Correct pricing of entities could ensure effective distribution of the resources and a better risk management. Thus, correct pricing models is of key importance. Hedge funds are raised with different strategies. The high number of these strategies and the possibly strong interrelations between them necessitated the reduction of the variables to a basic dimension and obtaining re-formed and fewer variables (factors) out of this set of variables. Due to the time series feature of the hedge fund strategies, Time Series Factor Analysis (TSFA) was chosen as the appropriate technique to be applied in this reduction. Thus, fewer factors obtained ensure the development of simpler models and strengthens the interpretative process. As the suitable pricing model, CAPM was applied in quadratic and cubic form. An effective model is described through the evaluation of the outputs of these different models.

In the first phase of the study, TFSA was reduced to 2 factors through oblimin rotation for 2 lags. As there will be a loss of data due to the increase in lag level and a single factor is obtained in the higher levels, 2 lags were preferred in order to ensure objectivity. The 2 factors obtained from this application were analyzed within the CAPM model as the representative of 17 strategies in question. The suitable model was determined for 2 lags and as quadratic according to the AIC results. A 2-period lagged relationship was observed between the strategies, and it was concluded that market and cubic models are not suitable for CAPM. The CAPM in quadratic form was determined to be the suitable pricing model. Thus, it is obvious that performing the reduction of the variables dealt with in pricing models via a correct technique will consider the interrelations between the variables and will reflect data in a more effective way than the models developed separately for each strategy. It is proposed as a new application approach for the practitioners, which would enable them to consider also the lagged relationships. In the further phases of this study, different techniques such as Dynamic Factor Analysis are planned to be applied for the reduction of hedge fund strategies.

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