Detecting Switching Strategies In Equity Hedge Funds Returns

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The development of a parsimonious model that adequately explains hedge fund returns is a great challenge for alternative investment research. Such a model would allow one to measure risk adjusted performance, identify the style mix employed by funds, and eventually devise optimal hedge funds portfolios. It would also allow measurement of manager's skill: assuming that investors are only willing to reward managers for superior performance that cannot be easily replicated, the fund returns may be decomposed into the part explained by the model, which may be replicated by standard assets baskets and common trading strategies, and model residuals, attributed to the fund manager's skill.

The factor models that are commonly used to model traditional assets appear have limited success in explaining hedge fund returns. The highly dynamic derivatives strategies that are often levered in hedge fund portfolios do not have standard relationships with asset or index returns.[1] Consequently many authors have considered non-linear models, either employing factors that themselves have non-linear relationships with traditional asset classes,[2] or using non-linear multi-factor models where the pricing model is non-linear in market returns.[3] These approaches have also been subject to criticism due to the arbitrary nature of their specification.

The belief that most financial assets returns are driven by regime switching processes is now widely accepted.[4] The existence of different market regimes, with deterministic or stochastic switching processes, has important implications for portfolio managers who, ideally, should be adopting regime dependent strategies. Regime switching hedge fund strategies can be defined by regime dependent returns distributions, and/or regime dependent exposures to underlying risk factors, and/or regime dependent alphas. The simplest case of a regime switching strategy is a long-or-short equity strategy (e.g., a strategy which is long equity during bull markets and short equity during bear markets). Another simple example is style switching, where the strategy has regime conditional exposures to different investment style benchmarks.[5]

Hedge funds, being the least constrained players in the investments arena, are perhaps most likely to implement dynamic switching strategies. At least, their increased demand for signal processing and advanced filtering techniques indicates a significant effort of the industry to extract time-varying signals that can be exploited by switching strategies. However, regime switching strategies cannot be detected using standard linear models,[6] and this can be a reason why traditional models fail to explain hedge fund returns.

Given the likelihood that many hedge funds do apply switching strategies, a natural technique for modeling their returns is as Markov switching processes of their underlying benchmarks. Markov switching models can provide a systematic approach to modeling multiple breaks and regime shifts in the data generating process. In Markov switching models, the regime shifts are considered to be stochastic, rather than deterministic events. This fits our problem well, as we have no knowledge of the exact strategies and signals used by individual funds to switch their positions.

The aim of this study is to infer, just from the pattern of historical returns, the type of strategies followed by equity hedge funds as well as their switching times by using Markov switching models. Such models are only appropriate if the switching benchmark is the one assumed in the model. Clearly, a more thorough investigation of the benefits of using Markov switching models to explain hedge fund returns is a fruitful area for further research. But for the purpose of this study we simply assume that our selection of benchmarks is appropriate and then attempt to answer the following questions: What proportion of equity funds have switching strategies in place? Which are the most popular instruments for switching strategies? And what is the relationship between the switching times of different funds?

A MARKOV SWITCHING MODEL FOR HEDGE FUNDS RETURNS

Regime switching models belong to a very general class of time series models. They encompass both nonlinear and time-varying parameter models. The importance of these models has long been accepted, and the pioneering work of Hamilton has given rise to a huge research literature.[7] Hamilton [1989] provided the first formal statistical representation of the idea that economic recessions and expansions influence the behavior of economic variables. He demonstrated that real output growth might follow one of two different autoregressions, depending on whether the economy is expanding or contracting, with the shift between the two states generated by the outcome of an unobserved Markov chain.

In finance, the applications of Markov switching techniques have been many and very diverse: from modeling state dependent returns (Perez-Quiros and Timmermann [2000]) and volatility regimes (Hamilton and Lin [1996]), to option pricing (Aingworth, Das, and Motwani [2002]), to detecting bull and bear markets (Maheu and McCurdy [2000]) and periodically collapsing bubbles (Hall, Psaradakis, and Sola [1999]), or to measuring mutual fund performance (Kosowski [2001]). Despite their limited forecasting abilities (Dacco and Satchell [1999]), Markov switching models have been successfully applied to constructing trading rules in equity markets (Hwang and Satchell [2000]), equity and bond markets (Brooks and Persand [2001]), and foreign exchange markets (Dueker and Neely [2004]).

In order to test the existence of switching relationships, for each individual fund and with respect to several benchmarks we specify a simple Markov switching model with two states. First we examine single factor models, with only one benchmark, avoiding the assumption that switching times for different benchmarks are the same, or that there are more than two regimes. Thereafter we test explicit benchmark switching (between cash and equities, and between value and growth) by adding a second factor to the switching model.

In the general form of the estimated model the regression coefficients and the variance of the error term are all assumed to be state dependent. Following Hamilton [1994], we let S_t denote the latent state variable, which can take one of k possible values at time t. Then the model can be written:

$$y_t = \mathbf{Z}_t \gamma_{S,t} + \varepsilon_{S,t} \tag{1}$$

where $\boldsymbol{y} = (y_1, \ldots, y_T)$ is the vector of the hedge fund returns; $\mathbf{Z} = (\mathbf{1}\ \mathbf{X})$ is matrix of explanatory variables including several benchmark returns; $\gamma_S = (\alpha_S, \beta_S)$ is the vector of state dependent regression coefficients; and ε_S is the vector of disturbances, assumed to be normally distributed with state dependent variance σ_S^2. The transition probabilities between states are assumed to follow a first-order Markov chain and to be constant over time:

$$P\{S_t = j \mid S_{t-1} = i, S_{t-2} = l, \ldots\} = P\{S_t = j \mid S_{t-1} = i\} = p_{ij}$$

A maximum likelihood estimation approach as in Hamilton [1994] now allows the estimation of two sets of coefficients for the regression and variance of the residual terms, together with a set of transition probabilities, and the time series of regime probabilities.[8] We shall assume there are just two possible states for the market, (i.e., k = 1 or 2). Thus we have only two transition probabilities to estimate: p_{11}, the probability of remaining in state 1 at time t given the market is already in state 1 at time $t-1$; and p_{22}, the probability of remaining in state 2 at time t given the market is already in state 2 at time $t-1$. Clearly p_{12}, which is the probability of being in state 2 at time t given the market is in state 1 at time $t-1$,

E X H I B I T 1

Percentage of Funds Operating Switching Strategies: Single Factor Equity Models

Strategy	SP500	SP500v	SP500g	SC600	SC600v	SC600g	**Overall**
Switch sign on equity exposure	11%	9%	7%	4%	5%	4%	**21**%
Equity exposure in only one regime	28%	34%	28%	29%	38%	39%	**70**%
Switch sign on alpha	43%	37%	42%	19%	35%	31%	**65**%
Significant alpha in only one regime	37%	39%	35%	44%	36%	45%	**72**%

is given by $1 - p_{11}$ and similarly $p_{21} = 1 - p_{22}$. For further details on the specification of this model, see Alexander and Dimitriu [2005].

DATA

The hedge fund returns data were extracted from the Hedge Funds Research (HFR) dead and alive funds databases, for the period January 1990 to December 2002. We selected a total of 100 equity funds reporting net of all fees in U.S. dollars, with funds under management above US$10 million and not using leverage. Additionally, since we will be estimating switching models on the returns of individual funds, we require that they have at least 60 months of reporting available. Out of the 100 funds in our selected database, 25 had ceased reporting before December 2002, the end of our data sample. For each fund in our selected database, we used the entire set of returns available during the period January 1990 to December 2002. In Markov switching models it is essential to ensure a sufficiently long data sample for correctly identifying the time-variability of parameters. From this perspective, the scarcity of monthly hedge fund data is a serious limitation and the coefficients' level of significance is likely to be understated. Also, despite the considerable efforts of data providers, hedge fund data are well known to be subject to selection bias, survivorship bias, instant history bias, and multi-period sampling bias (see Fung and Hsieh [2000]). These biases are likely to obscure any underlying switching relationships in the data generating process, so we should expect evidence of switching to be much stronger on "cleaner" data.

As benchmarks for U.S. equity funds we use several S&P indexes: SP500 as a broad equity benchmark, SP500v and SP500g as proxies for value and growth equity investment styles, and SC600, SC600v, and SC600g as proxies for several small-cap investment styles. Additionally we use the three-month U.S. T-bill rates as a proxy for cash investments.

RESULTS

For each fund we estimated several single factor switching models using, in turn, each of the benchmarks described in the previous section. Although exactly 100 switching models were estimated for each benchmark, in a few isolated cases the models did not converge. The non-convergence cases were too few to make any noticeable difference when translating results from the number, out of 100 funds, to a percentage, and consequently the results in this section will be phrased in terms of percentages. We find evidence of switching strategies if there are:[9]

1. different signs of the benchmark exposure in the two regimes, revealing a strategy that is either long or short that benchmark depending on market circumstances; or
2. a significant benchmark exposure in only one of the states, revealing a strategy which trades on that benchmark (or a similar one) only at certain times.

Another aspect of interest is the behavior of the intercept in the two regimes identified by the switching model, the issue here being the persistence of risk adjusted returns in different market circumstances. The single factor risk adjustment, even in a non-linear framework, is not meant to produce an accurate measure of manager "skill," and we will not interpret it as such.

Exhibit 1 summarizes the results of estimating single factor switching models for all the funds in our database. We report, for each index, the number of funds for which we have found evidence of switching either in their exposure to the benchmark or in their intercept. The last column

EXHIBIT 2

Percentage of Funds Operating Switching Strategies: Cash-Equity Models

Strategy	SP500	SP500v	SP500g	SC600	SC600v	SC600g	**Overall**
Switch sign on equity exposure	7%	10%	5%	6%	5%	6%	**23**%
Equity exposure in only one regime	27%	33%	34%	31%	42%	28%	**77**%
Switch sign on cash exposure	3%	5%	5%	4%	7%	4%	**16**%
Cash exposure in only one regime	43%	41%	42%	42%	45%	41%	**85**%
Switch between cash and equities	4%	3%	2%	3%	6%	2%	**16**%
Switch on alpha	10%	9%	10%	15%	12%	11%	**33**%
Significant alpha in only one regime	49%	46%	52%	40%	41%	37%	**84**%

presents "aggregated results," i.e., the number of funds that evidence switching on at least one of the benchmarks.

Overall, estimating the model (1) with a single factor reveals 21% of funds that had long-or-short strategies on one of the equity benchmarks in place. Also, an impressive 70% of funds appear to be timing their exposures to benchmarks such that in one regime their exposure is not statistically significant. Note that the largest number of funds chose value benchmarks for switching in and out: 34% of funds switched in and out of the SP500v and 38% switched in and out of the SC600v. Regime dependent alphas are also quite interesting, as 65% of funds showed different signs of intercept in the two states and 72% of funds had significant intercepts in only one of the regimes. However, the alpha switching effect detected here may simply be capturing a switching exposure to an omitted risk factor: in fact we will now show that it is indeed the case.

Switching *out* of one instrument/benchmark is most often combined with a switch *into* another instrument. The most obvious example is the switch between equity and cash. In order to detect this type of combined switching, we estimated a two-factor Markov switching model for each fund, having both cash and an equity benchmark as factors. The results are summarized in Exhibit 2.

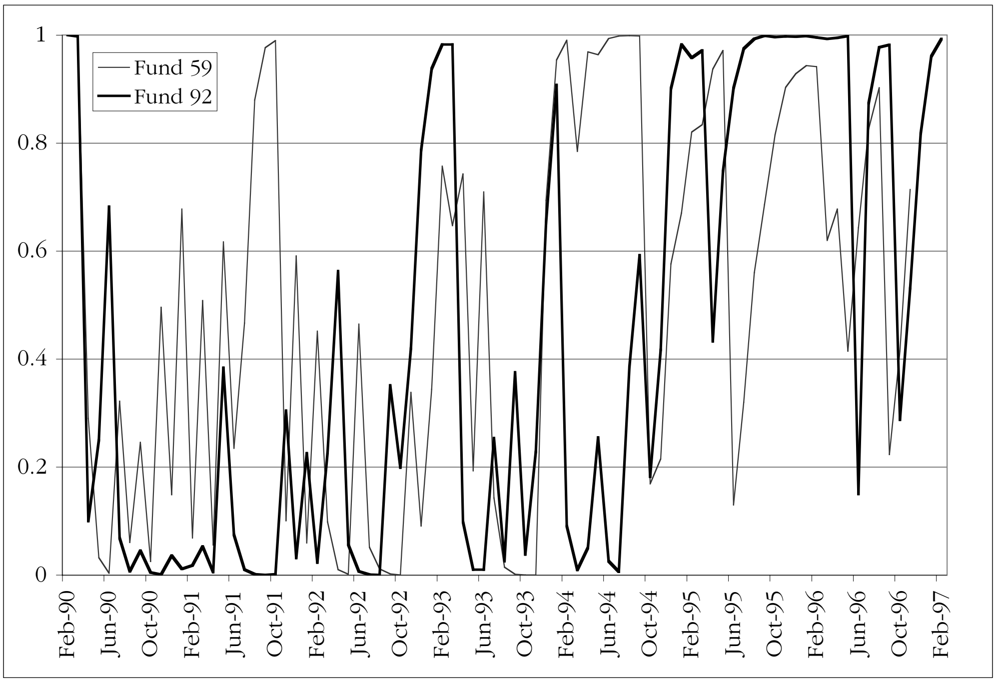
Adding the cash factor to the switching model does not change results dramatically. We found that overall, 23% of funds were switching from long to short exposures on at least one equity benchmark. Also 77% of funds (as opposed to 70% of funds in the single factor switching models) had significant exposure to equities in only one market regime and, again, the value stocks were most targeted for the switching. In fact, the only notable difference when the extra cash factor is added is that the number of funds that have different signs for alpha in the two states decreases dramatically: from 65%, when there is a single factor, to only 33% of funds. Thus in the single factor model, the change in sign of alpha captured a switch in the cash position/exposure of many funds. It is notable that 85% of the funds in our sample have a significant exposure to cash in only one of the market regimes.

To complete the picture, we also tested the hypothesis of combined switching between value and growth exposures, this being one very common style pair for individual investors (see for instance Kumar [2002]). However, we actually found that very few funds appear to be operating a value-growth switch. Only five funds demonstrated an explicit switch between the two styles. Some funds do switch the sign of their long and short exposures to value or growth stocks, but their number is relatively small. Most of the funds appear to adopt significant exposures to specific styles in only one market regime.

The third and final question we ask is whether there is any evidence of dependency between the switching times of different funds. This is a natural question to ask because, while regimes in broad market indices are known to be related to macroeconomic cycles (e.g., the business cycle and/or the credit cycle),[10] on the other hand there is some evidence that it is pure sentiment that drives investors' choice of style.[11] If demand is driven by investors'

EXHIBIT 3

Estimated Probability of Stock Investment Regime for Two Different Funds Switching Between Small Cap Value Stocks and Cash



sentiment rather than general market circumstances, there may be no relation at all between the switching times of different funds unless, for instance, both funds have informed traders with identical information. To investigate this issue we examined the estimate regime probabilities for a subset of funds that evidenced switching between cash and value stocks as these funds are, possibly, more likely than others to display evidence of correlation between switching times. Exhibit 3 shows the estimated switching probability for two funds that switched between small-cap value and cash. For these two funds there does appear to be some relationship between switching times, but we found that this was the exception rather than the rule.

CONCLUSIONS

The inability of traditional models to capture and explain the dynamic and complex nature of hedge fund strategies lies at the heart of the mystery surrounding the new world of alternative investments. Consequently many non-linear multi-factor models have been proposed in recent literature. While some of these models might provide a better fit than standard models to historical hedge fund returns there is, nevertheless, a degree of arbitrariness in their specification.

This study has made a first, tentative step towards the development of regime switching models for hedge fund returns. We have examined the evidence in the HFR database for equity hedge funds that switch investment styles and exposures depending on their perception of the prevailing market circumstances. We found much evidence of regime dependent exposures to broad market indices and, in particular, of switching between value stocks and cash. On the other hand, we only detected value-growth switching in very few (i.e., 5%) of the funds. This, however, can be the result of our benchmark selection; using a broader universe of benchmarks may show more evidence of value-growth style switching. We also found very little evidence of relationships between the switching times of funds that operated similar switching strategies. We conclude that, measured against our (relatively small) set of benchmarks, the fund managers appear to base their switching decisions on subjective assessments of the prevailing market regime.

The methodology developed in this study could be useful to investors that wish to determine whether and when a fund has been timing the market. We have demonstrated how this can be detected from modeling a historical series of funds' reported returns. However, for any general conclusions drawn from our empirical switching analysis a final word of caution is necessary. We have employed a small subset of a commercial hedge fund database for these results and therefore, despite the fact that there is nothing in our selection criteria to obviously bias our switching analysis results, we should not conclude that they carry over to the general population of hedge funds.

ENDNOTES

[1]See Fung and Hsieh [1997], Amin and Kat [2001], Agarwal and Naik [2004], and many others.

[2]See Fung and Hsieh [2001], Lhabitant [2001], Mitchell and Pulvino [2001], Schneeweis and Spurgin [2001], and Agarwal and Naik [2004].

[3]See Bansal, Hsieh, and Viswanathan [1993], Harvey and Siddique [2000], and Dittmar [2002].

[4]A time series is subject to shifts in regime when the parameters of the statistical model are only time invariant within a particular state. Put another way, the model parameters become conditional on a latent state variable that indicates the regime prevailing at the time. See Hamilton [1994].

[5]See for instance Kumar [2002] and Guidolin and Timmerman [2003], among others.

[6]For a simple illustration of why this is so, consider a market timer that has perfect forecasting abilities in a regime switching market. The *un*conditional market correlation can be zero even though the strategy is perfectly positively correlated with up-markets and perfectly negatively correlated with down-markets.

[7]See Hansen [1992, 1996]; Diebold, Lee, and Weinbach [1994]; Kim [1994]; Psaradakis and Sola [1998]; Clarida, Sarno, Taylor, and Valente [2003], and many other papers.

[8]Considering the relatively high number of parameters to be estimated, the selection of starting values is critical for the convergence of the estimation. To reduce the risk of data mining, we have not used any state dependent priors as starting values. Instead, we have used the unconditional estimates of regression coefficients and the standard error of the residual term. The starting values for the transition probabilities were set at 0.5. A number of restrictions needed to be imposed on the coefficient values, in order to ensure their consistency with model assumptions. The transition probabilities, as well as the conditional state probabilities were restricted to be between 0 and 1, while a non-negativity constraint was imposed on the standard deviation of residuals in both states.

[9]Note that this is a very strong version of the switching definition, which would occur also when a fund changes significantly its exposure to a benchmark from one regime to another, without necessarily changing the sign of its exposure.

[10]See Hamilton [1989], Hamilton and Lin [1996], Perez-Quiros and Timmermann [2000], Kosowski [2001], and Alexander and Dimitriu [2005].

[11]Fisher and Statman [2000].

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