Do Peso Problems Explain Positive Alpha in Hedge Funds?

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Abstract

Hedge funds are known to produce significantly positive OLS-regression alphas. I test whether the positive OLS alpha could be consistent with a rational outcome from a peso problem. To test this, I construct a two-state regime-switching model which can capture a potential future crash state with a small probability. By applying the time-series version of testing a peso problem based on Ang, Gu, and Hochberg (2007), I provide evidence that an *ex-ante* rational expectation of zero alpha can frequently produce an *ex-post* positive OLS alpha. My results suggest that the positive OLS alpha in hedge funds can be a rational outcome.

Keywords: Hedge Funds; Alpha; Peso Problem; Regime-Switching; Crash Risk

JEL Classification Codes: G11; G12; G14; G23

1. Introduction

This paper investigates whether apparently positive hedge fund alphas can be explained by a peso problem. The main motivation follows from the insight in Stulz (2007). He views that hedge funds engage in trading strategies that provide payoffs similar to those of an insurance company that sells earthquake insurance. Thus, the insurance company enjoys positive profits during normal times, but once a disaster hits the company, it would lose all the cumulative profits from good times. Therefore, as long as a hedge fund faces a non-zero probability of a crash event, but the crash event occurred less frequently in the sample period than was rationally expected *ex-ante*, we should see positive hedge fund alphas from *ex-post* historical data.

To test a peso problem hypothesis, I take the following steps. First, in order to confirm the existence of positive alphas from *ex-post* historical data, I run a traditional OLS regression with the Capital Asset Pricing Model (CAPM) for thirteen hedge fund index returns, and find that eight out of thirteen indexes have significantly positive OLS alphas. Second, I estimate parameter values of a two-state regime-switching model from historical data under the *ex-ante* rational expectations null of a zero expected value of alpha. Third, based on these parameter estimates, I simulate new time-series returns data 5,000 times for each index, and construct the small sample distribution of the OLS alpha. Finally, I provide evidence that the new data based on *ex-ante* rational expectation generate positive OLS alpha frequently, making the originally significant alpha in the first step become mostly insignificant (seven out of eight significant alphas become insignificant with p-values greater than 5%). Therefore, the significantly positive OLS alpha of hedge funds can be a rational outcome under the presence of a peso problem, which is consistent with the insight of Stulz (2007).

My approach to test for a peso problem is based on the following prior literature. The peso problem has been raised as a potential answer to solve seemingly irrational market behavior such as the equity premium puzzle (Rietz (1988), Cecchetti, Lam, and Mark (1993), Jorion and Goetzmann (1999), and Barro (2006)), the foreign exchange risk premium puzzle (Evans and Lewis (1995)), the term structure anomaly (Bekaert, Hodrick, and Marshall (2001)), and IPO long-run underperformance (Ang, Gu, and Hochberg (2007)). Interestingly, most of the papers rely on a regime-switching model. In addition, Evans (1996), in the survey paper on "peso problem", documents that a regime-switching model provides a formal framework to test a peso problem because the problem can be created by the potential for discrete shifts in the distribution of future shocks. Thus, a regime-switching model is a reasonable choice to test the peso problem for the positive hedge fund alpha.

This paper is also related to the non-normal and non-linear behavior of hedge fund returns. These non-normal and non-linear behaviors are expected because hedge funds typically engage in dynamic trading strategies that can generate non-normal and non-linear payoffs based on derivatives, short-sales, and high leverages. Thus, the traditional performance measures such as the Sharpe ratio and Jensen's alpha may prematurely conclude that hedge funds produce superior returns. In particular, both the Sharpe ratio and the Jensen's alpha underestimate the possibility of a future crash state. The Sharpe ratio relies on volatility based on historical return data that do not contain enough crash events and the Jensen's alpha assumes the normal distribution of errors that assigns a smaller probability to a future crash event than what is rationally expected. Therefore, the results in this paper are also consistent with the efforts to find a new metric for hedge fund performance (e.g. Goetzmann, Ingersoll, Spiegel, and Welch (2007)).

The rest of the paper is organized as follows. Section 2 discusses the data and provides summary statistics. Section 3 reports the results from a traditional OLS regression for the CAPM model. Section 4 explains the main methodology for testing a peso problem using a two-market and two-fund state regime-switching model, reports the results from the model, and provides the results from a robustness check. Section 5 concludes.

2. Data and Summary Statistics

For the hedge fund's style-based index level analysis, I use Credit Suisse/Tremont hedge fund index monthly return data[1] from January 1994 to October 2014.[2] According to the data provider, each index is an asset-weighted index of funds that report timely and accurate net asset value (NAV) of fund every month, have audited financial statements, manage at least $50 million assets, and maintain at least one-year track record. In addition, index represents at least 85% of assets under management in selection universe for each sector. I also use the monthly return of S&P 500 index to proxy for the market return. The one-month Treasury bill rate from Ibbotson Associates is used to proxy for the monthly risk-free rate.[3]

Table 1 reports the summary statistics for monthly time-series returns of thirteen hedge fund indexes (twelve style-based indexes and one composite hedge fund index) and the market. Panel A presents distributional characteristics such as four moments (mean, standard deviation, skewness, and kurtosis) of time-series returns, Sharpe ratios based on annualized average excess

[1] The data can be freely downloaded from http://www.hedgeindex.com.
[2] I exclude multi-strategy index because the return data is available from April 1994.
[3] Kenneth French's website provides the data.

returns and annualized standard deviations of excess returns, and normality test statistics based on the Jarque-Bera (1987) test. Traditional portfolio theory tells us that the market is mean-variance efficient. However, eight out of thirteen indexes have higher Sharpe ratios than the market. Since the Sharpe ratio is based on only two moments of time-series returns, it can be a proper measure only when other moments do not matter much, which is not the case in here. Several hedge fund index returns have negative skewness and positive excess kurtosis. As a formal normality test statistics, the Jarque-Bera test shows that twelve out of thirteen indexes reject the normality of their time-series returns, and their Jarque-Bera statistics are greater than that of the market. Hence, the time-series return behaviors of hedge fund indexes are clearly different not only from the normal distribution but also from the market return behavior.

Panel B reports the *p*-values of the Durbin-Watson statistics to test the positive autocorrelation of time-series returns for each hedge fund index and the market. I consider the autocorrelations of current month returns with up to six-month previous returns. Contrary to the statistically insignificant autocorrelations of the market returns, nine out of thirteen hedge fund indexes show significantly positive autocorrelations with past month returns, having less-than-5% *p*-values. Furthermore, six hedge fund indexes have significantly positive autocorrelations with longer-than-one-month previous returns. Combining with the results from panel A, it is clear that most of hedge fund index returns violate the typical assumptions on errors that are independently and identically distributed (*IID*) in an OLS regression.

3. OLS Regressions

In this section, I report the OLS time-series regression results which are conventionally used to measure the performance of each hedge fund index. The capital asset pricing model (CAPM) is used as a benchmark risk model. Table 2 shows the OLS regression results. The patterns of alphas are generally consistent with the patterns of Sharpe ratios reported in table 1. Eight out of thirteen indexes earn significantly positive alphas.

Hedge funds are typically designed to have relatively low correlations with the stock market. The OLS regression results show that most of hedge funds generally have low correlations with the market. Eleven out of thirteen indexes have betas that are less than 0.5 in an absolute term. Moreover, twelve indexes have the adjusted R^2 values that are less than 50%.

4. Regime-Switching Model and Test of a Peso Problem

4.1. Bayesian Estimation using Gibbs Sampling and Test of Zero Alpha in the CAPM

The CAPM regression model can be viewed as a regime-switching model with one market state and one fund state. Hence, I first apply the main methodologies, both Gibbs sampling and test based on simulated data, to the CAPM regression model. First, I estimate the parameters of the following CAPM regression model using Gibbs sampling method under the null hypothesis of $\alpha_i = 0$:

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \varepsilon_{i,t}, \;\; where\ \varepsilon_{i,t} \sim IID\ N\left(0, \sigma_i^2\right), \tag{1}$$

$r_{i,t}$ is the excess return of hedge fund index i in month t and $r_{m,t}$ is the excess return of the S&P 500 index in month t. A general procedure of estimating the model is given in the Appendix. By iterating the Gibbs sampling procedure 5000 more times after initial 2000 burn-in periods, the posterior distribution of each parameter is obtained.

Table 3 reports the mean and standard deviation of the posterior distribution for each parameter value. The parameter estimates are similar to the results in previous tables. The estimated betas are very close to the beta estimates in table 2. The patterns of estimated idiosyncratic volatilities across hedge fund indexes are also similar to the patterns of annualized standard deviations in table 1. In addition, the adjusted R^2 values are almost identical to those reported in table 2.

Second, I test whether the originally reported (in table 2) OLS alpha of each hedge fund index is indeed significantly positive under the null hypothesis of the model. For each hedge fund index, I generate a new time-series return data from the model based on the parameter estimates. Given the new return data, I run the same OLS CAPM regression as in section 3, and obtain a new OLS alpha. By repeating the procedure 5000 times, I can construct the distribution of newly obtained OLS alphas, and check where the originally reported OLS alpha is located in the distribution. As a test statistic, I report p-value representing the probability that a randomly chosen new OLS alpha under the null hypothesis is greater than the originally reported OLS alpha. Table 3 reports the original OLS alpha and corresponding p-value for each hedge fund index in the right-end column. Interestingly, the results are consistent with the conventional judgments based on t-statistics in table 2. As reported in table 2, eight out of thirteen hedge fund indexes show p-values that are less than 5%, so that their OLS alphas are still abnormally positive from the perspective of the equation (1) with zero alpha value.

4.2. *Regime-Switching Model*

The traditional OLS regression is based on the normality assumption with independently and identically distributed errors (or returns). The results reported in table 1, however, show that most of hedge fund index returns are far from the normality assumption because their returns show negative skewness and positive excess kurtosis. In addition, most of hedge fund index returns have significantly positive autocorrelations. Furthermore, the OLS regression requires the parameter coefficients to be constant over time, which may lead to a poor fit to explain the time-series variation of hedge fund index returns.

A regime-switching model is an alternative to overcome the weaknesses of the OLS regression. A regime-switching model is particularly suitable for generating non-normal characteristics such as negative skewness and positive kurtosis because the model allows multiple states, and the errors are assumed to be drawn from a different normal distribution across states. In other words, one aspect of a regime-switching model can be viewed as a mixture of normal distributions, which has a good property of capturing the above mentioned non-normal characteristics. Another advantage of using a regime-switching model comes from a transition probability matrix. For example, a two-state regime-switching model has a 2×2 transition matrix. As long as each diagonal probability is greater than 50%, there will be a higher-than-50% chance to face the same state in the next period, which can cause a positive autocorrelation. Therefore, a regime-switching model is better than the traditional OLS model for describing hedge fund index returns.

A regime-switching model is also useful for testing a peso problem. A peso problem is often associated with a rare event that has not been sufficiently reflected in the sample. Agarwal and Naik (2004) show that a large number of hedge fund strategies exhibit payoffs from writing a put option. Lo (2001) and Fung, Xu, and Yau (2002) also show that the down-market betas for hedge funds are higher than the up-market betas. These results suggest that hedge funds tend to make a severe loss in a crash period, which happens with a small probability. Thus, if hedge funds have not sufficiently experienced the rare event, the historical average return of hedge funds would be higher than the true expected return reflecting both a normal time and a small probability of crash, which can cause a peso problem. For the purpose of testing the peso problem, a regime-switching model is useful because the parameter values of the model can be estimated under the null hypothesis that the expected alpha is zero, which is different from the null hypothesis that the alpha is constantly zero in the OLS regression.

4.3. Regime-Switching Model and Test of a Peso Problem

In specifying a regime-switching model, we need to consider a variable that might experience a significant change in structure. In addition, it is also important to determine the number of regimes for the variable of interest. Furthermore, the specified regime-switching model should be useful for testing a peso problem.

In here, I specify a regime-switching model as follows:

$$\begin{aligned} r_{i,t} &= \alpha_i(s_{i,t}) + \beta_i(s_{m,t})r_{m,t} + \sigma_i(s_{i,t})\varepsilon_{i,t} \\ r_{m,t} &= \mu_m(s_{m,t}) + \sigma_m(s_{m,t})u_{m,t} \end{aligned}, \qquad (2)$$

where $r_{i,t}$ is the excess return of hedge fund index *i* in month *t* and $r_{m,t}$ is the excess return of the S&P 500 index in month *t*. In addition, $\varepsilon_{i,t}$ and $u_{m,t}$ are *IID N*(0,1). For the excess market return, I assume that the market state $s_{m,t}$ follows a Markov chain that can take a value in {1, 2} at time *t*. I also impose $\mu_m(1)>\mu_m(2)$ and $\sigma_m(1)<\sigma_m(2)$ to classify two market states in a meaningful way. Market state 1 can be viewed as high market return and low market volatility state, and market state 2 as low market return and high market volatility state. Once market states are determined, the coefficient $\beta_i(s_{m,t})$ represents the sensitivity of each hedge fund index return to the excess market return conditioning on the market state. Although the beta of each hedge fund index depends on the market state ($s_{m,t}$), the other parameters of each hedge fund index, alpha and idiosyncratic volatility, depend on its own state ($s_{i,t}$). Similar to the market state, I assume that each hedge fund state $s_{i,t}$ follows a Markov chain that can take a value in {1, 2} at time *t*. I also impose the restriction, $\sigma_i(1)<\sigma_i(2)$, to classify two states so that the first state can be viewed as a lower idiosyncratic volatility state and the second state as higher. In addition, a transition probability matrix P^i in the Markov chain for each hedge fund index state takes the following form:

$$P^i = \left(P^i_{jk}\right)_{2\times 2} = \begin{bmatrix} P^i_{11} & 1-P^i_{11} \\ 1-P^i_{22} & P^i_{22} \end{bmatrix}, \tag{3}$$

where $P^i_{jk} = \Pr(s_{i,t} = k \mid s_{i,t-1} = j)$ and *j* and *k* can take a value in {1, 2}. Furthermore, the stable probability of each hedge fund state, $\Pi^i = (\pi^i_1 \ \pi^i_2)'$, can be computed as follows:

$$\Pi^i = P^i \Pi^i \ \Rightarrow \ \pi^i_1 = \frac{1-P^i_{22}}{2-P^i_{11}-P^i_{22}} \ \mathit{and} \ \pi^i_2 = 1-\pi^i_1 . \tag{4}$$

The main focus in this paper is to test for a peso problem. Ang, Gu, and Hochberg (2007) uses a regime-switching model for testing whether the long-run underperformance of an IPO can be explained by a peso problem. They assume that an IPO firm's stock return is drawn from one of the three possible states, outperforming, benchmark, or underperforming states. Under the null hypothesis of an *ex-ante* average benchmark performance, they construct a small sample distribution of *ex-post* CARs (cumulative abnormal returns) and test for a peso problem by reporting the *p*-value of historical CARs under the small sample distribution. Their methodology can be viewed as a cross-sectional version of testing a peso problem. Building on their methodology, this paper uses a regime-switching model for a time-series version of testing a peso problem.

In the previous specification of a two-state regime-switching model, a hedge fund's alpha can be drawn from one of the two possible states, low or high idiosyncratic volatility states. To test for a peso problem, the model is estimated under the null hypothesis that the expected value of alpha is zero:

$$H_0 : E(\alpha_i) = \pi_1^i \alpha_i(1) + \pi_2^i \alpha_i(2) = 0 \;\; \Leftrightarrow \;\; \alpha_i(2) = -\frac{\pi_1^i \alpha_i(1)}{\pi_2^i}. \tag{5}$$

In the regime-switching model, the first state is interpreted as a quiet and normal state and the second state is interpreted as a volatile and crash risk state. In other words, a rational investor, who has a view on ex-ante zero average alpha of a hedge fund, expects the fund to face one of the two states: state 1 with a small positive alpha, a low idiosyncratic volatility, and a high probability of occurrence, or state 2 with a large negative alpha, a high idiosyncratic volatility, and a low probability of occurrence.

Under the null hypothesis of rational expectation assumption, I estimate parameters in the two-state regime-switching model by using a Bayesian Gibbs sampling procedure. Given that each parameter value of the regime-switching model is based on the conditioning state, and the final likelihood function is highly nonlinear and complex, the Gibbs sampling method can be more attractive than a traditional maximum likelihood estimation method in terms of efficiency and computational speed.

As in section 4.1, I construct the posterior distribution of parameters by iterating the Gibbs sampling procedure 5000 times after 2000 times burn-in period, and report the mean and standard deviation of the posterior distribution for each parameter value. In addition, based on the mean parameter estimates, I simulate new hedge fund return data under the rational expectation assumption, and obtain an OLS alpha from the new return series. By repeating the procedure 5000 times, I can construct the small sample distribution of OLS alphas for each hedge fund index under the null of ex-ante zero average alpha. Finally, I provide a peso problem test statistics, the *p*-value of the original OLS alpha based on historical data under the small sample distribution.

4.4. Results

Table 4 reports the mean and standard deviation of the posterior distribution for each parameter value. Due to the way of defining each hedge fund state, there are a large differential between two idiosyncratic volatilities across two states. For example, the "Long/Short Equity" index has a volatility of 1.49% per month in the first state, but the index has a volatility of 7.52% per month in the second state. Interestingly, the two states are associated with clearly different level of unconditional stable probabilities (π_1 and π_2). The stable probabilities of the first state are in the range of 77.60~93.30%, while those of the second state are in the range of 6.70~22.40%. Therefore, the estimation results of the regime-switching model suggest that the first state can be viewed as the normal state with a low volatility and a high chance of occurrence, and the second state can be viewed as the crash state with a high volatility and a low chance of occurrence.

The null hypothesis in equation (5) makes it possible that the regime-switching model estimates each hedge fund's alpha values across states under the rational expectation assumption. For examples, the "Long/Short Equity" index has a monthly alpha of 0.21% per month in the normal state, while the index has a monthly alpha of -2.33% per month in the crash state.

Finally, I report p-values to test for a peso problem. Following Ang, Gu, and Hochberg (2007), I generate new time-series return data for each hedge fund index based on the parameter estimates under the rational expectation assumption. For each newly generated time-series return data, I run the OLS regression and obtain an OLS alpha value. By repeating the procedure 5000 times, I construct the small sample distribution of OLS alpha value, and test whether the historical OLS alpha is statistically significant under the distribution. As a test statistic, p-value represents the probability that a rational investor expects higher value than the historical OLS alpha under the null hypothesis. If the historical OLS alpha is abnormally high under the rational expectation assumption, the p-value should be less than 5%. On the other hand, if the peso problem can explain the significantly positive OLS alpha, the p-value should be greater than 5%. Interestingly, table 4 reports that twelve out of thirteen hedge fund indexes have p-values greater than 5%. These results suggest that most of hedge fund index returns are consistent with a rational outcome under the assumption that the expected value of alpha is zero.

4.5. *When Both Alphas are Zero across Two States*

The regime-switching model used in Section 4.4 has many different features from the OLS regression. For example, Ang and Chen (2007) document that time-varying betas can frequently produce the significantly positive OLS alpha. To examine whether time-varying betas alone in the regime-switching model can frequently produce the significantly positive OLS alpha, the two-state regime-switching model is estimated under the following null hypothesis, $H_0 : \alpha_i(1) = \alpha_i(2) = 0$. If the *p*-value of the historical OLS alpha for each hedge fund index is greater than 5% under the null hypothesis, then the result would suggest that the significantly positive OLS alpha is mostly driven by time-varying betas, not by the peso problem.

Table 5 reports the p-values in the last column of the table, suggesting that time-varying betas alone cannot explain the significantly positive OLS alpha. The *p*-values for eight out of thirteen indexes are less than 5%, which is similar to the result of the OLS regression. Therefore, the results in table 5 imply that the peso problem is the most likely source for explaining the significantly positive OLS alpha.

5. Conclusion

This paper takes a step to explain the significantly positive OLS alphas in hedge funds from the perspective of a peso problem. The main motivation comes from the insight of Stulz (2007) that the payoffs of hedge funds are similar to those of an insurance company that sells earthquake insurance. Thus, within our sample period that does not include enough crash event, the positive OLS alphas of hedge funds can be consistent with a rational expectation.

I construct a time-series version of testing a peso problem which builds on the cross-sectional version of testing a peso problem in Ang, Gu, and Hochberg (2007). To capture hedge funds' crash state with a small probability, a two-state regime-switching model is used. Under the null hypothesis that the expected value of alpha is zero, the model's parameter values are estimated by a Bayesian Gibbs sampling method. Interestingly, simulated hedge fund returns based on the null hypothesis often lead to positive OLS alphas, suggesting that the significantly positive OLS alphas in hedge funds can be a rational outcome. In addition, a robustness check suggests that the result is not driven by time-varying betas.

Appendix

The procedure of estimating the regime-switching model using Gibbs sampling is adapted from the Appendix in Ang, Gu, and Hochberg (2007), whose methodology builds on Kim and Nelson (1999).

For hedge fund index i, the parameter set to be estimated is

$$\Theta \equiv \left(\tilde{\alpha}_i, \tilde{\beta}_i, \tilde{\sigma}_i, \tilde{P}^i;\ \tilde{\mu}_m, \tilde{\sigma}_m, \tilde{P}^m\right).$$

The Bayesian Gibbs sampling procedure generates random numbers from the following conditional distribution under a certain restriction. In the following algorithm, one loop simulates a drawing from the joint posterior distribution of all the state variables and the parameters of the model, given the data:

A1) Generate $\tilde{s}_m$, conditional on $\tilde{\mu}_m$, $\tilde{\sigma}_m$, $\tilde{P}^m$, and $\tilde{r}_m$.

A2) Generate $\tilde{\mu}_m$, conditional on $\tilde{s}_m$, $\tilde{\sigma}_m$, and $\tilde{r}_m$.

A3) Generate $\tilde{\sigma}_m$, conditional on $\tilde{s}_m$, $\tilde{\mu}_m$, and $\tilde{r}_m$.

A4) Generate $\tilde{P}^m$, conditional on $\tilde{s}_m$.

A5) Generate $\tilde{s}_i$, conditional on $\tilde{\alpha}_i$, $\tilde{\beta}_i$, $\tilde{\sigma}_i$, $\tilde{P}^i$, $\tilde{r}_i$, and $\tilde{r}_m$.

A6) Generate $\tilde{\alpha}_i$ and $\tilde{\beta}_i$, conditional on $\tilde{s}_i$, $\tilde{s}_m$, $\tilde{\sigma}_i$, $\tilde{P}^i$, $\tilde{r}_i$, and $\tilde{r}_m$.

A7) Generate $\tilde{\sigma}_i$, conditional on $\tilde{s}_i$, $\tilde{s}_m$, $\tilde{\alpha}_i$, $\tilde{\beta}_i$, $\tilde{r}_i$, and $\tilde{r}_m$.

A8) Generate $\tilde{P}^i$, conditional on $\tilde{s}_i$.

References

Agarwal, Vikas, and Narayan Y. Naik. "Risks and portfolio decisions involving hedge funds." *The Review of Financial Studies* 17.1 (2004): 63-98.

Ang, Andrew, and Joseph Chen. "CAPM over the long run: 1926–2001." *Journal of Empirical Finance* 14.1 (2007): 1-40.

Ang, Andrew, Li Gu, and Yael V. Hochberg. "Is IPO underperformance a peso problem?." *Journal of Financial and Quantitative Analysis* 42.3 (2007): 565-594.

Barro, Robert J. "Rare disasters and asset markets in the twentieth century." *The Quarterly Journal of Economics* 121.3 (2006): 823-866.

Bekaert, Geert, Robert J. Hodrick, and David A. Marshall. "Peso problem explanations for term structure anomalies." *Journal of Monetary Economics* 48.2 (2001): 241-270.

Cecchetti, Stephen G., Pok-sang Lam, and Nelson C. Mark. "The equity premium and the risk-free rate: Matching the moments." *Journal of Monetary Economics* 31.1 (1993): 21-45.

Evans, Martin D.D. "21 Peso problems: Their theoretical and empirical implications." *Handbook of Statistics* 14 (1996): 613-646.

Evans, Martin D.D, and Karen K. Lewis. "Do long-term swings in the dollar affect estimates of the risk premia?." *The Review of Financial Studies* 8.3 (1995): 709-742.

Fung, Hung-Gay, Xiaoqing Eleanor Xu, and Jot Yau. "Global hedge funds: risk, return, and market timing." *Financial Analysts Journal* 58.6 (2002): 19-30.

Goetzmann, William, Jonathan Ingersoll, Metthew Spiegel, and Ivo Welch. "Portfolio performance manipulation and manipulation-proof performance measures." *The Review of Financial Studies* 20.5 (2007): 1503-1546.

Jarque, Carlos M., and Anil K. Bera. "A test for normality of observations and regression residuals." *International Statistical Review* (1987): 163-172.

Jorion, Philippe, and William N. Goetzmann. "Global stock markets in the twentieth century." *The Journal of Finance* 54.3 (1999): 953-980.

Kim, Chang-Jin, and Charles R. Nelson. "State-space models with regime switching: classical and Gibbs-sampling approaches with applications." *MIT Press Books* 1 (1999).

Lo, Andrew W. "Risk management for hedge funds: Introduction and overview." *Financial Analysts Journal* 57.6 (2001): 16-33.

Rietz, Thomas A. "The equity risk premium a solution." *Journal of monetary Economics* 22.1 (1988): 117-131.

Stulz, René M. "Hedge funds: Past, present, and future." *The Journal of Economic Perspectives* 21.2 (2007): 175-194.

Table 1
Summary Statistics of Monthly Hedge Fund Index Returns

Panel A reports distributional characteristics such as four moments (mean, standard deviation, skewness and kurtosis) of monthly hedge fund index returns, the Sharpe ratios, Jarque-Bera (1987) normality test statistics and corresponding *p*-values. Both mean and standard deviation are reported in annualized percentage forms. Panel B reports *p*-values of Durbin-Watson statistics to test for the presence of positive auto-correlation up to six months for each hedge fund index returns. The sample period is from January 1994 to October 2014.

Panel A: Distributional Characteristics

Style	mean	std	Sharpe	skew	kurt	JB-stat	*p*-value
Hedge Fund Index	8.43	7.19	0.80	-0.17	2.91	84.54	0.00
Convertible Arbitrage	7.10	6.59	0.67	-2.71	17.43	3,334.65	0.00
Dedicated Short Bias	-4.48	16.40	-0.44	0.74	1.64	48.46	0.00
Emerging Markets	8.00	14.09	0.38	-0.78	5.88	367.60	0.00
Equity Market Neutral	5.32	9.78	0.27	-12.31	177.95	323,012.40	0.00
Event Driven	9.08	6.12	1.05	-2.21	10.90	1,384.89	0.00
Distressed	10.05	6.36	1.16	-2.18	11.44	1,498.77	0.00
Multi-Strategy	8.64	6.62	0.90	-1.73	7.73	717.62	0.00
Risk Arbitrage	6.00	4.07	0.83	-0.94	4.50	236.49	0.00
Fixed Income Arbitrage	5.45	5.41	0.51	-4.66	34.70	12,922.53	0.00
Global Macro	10.85	9.22	0.89	0.08	4.48	198.74	0.00
Long/Short Equity	9.39	9.50	0.71	-0.02	3.63	129.94	0.00
Managed Futures	5.81	11.46	0.27	0.01	0.00	0.01	0.99
S&P 500 Index	10.30	14.97	0.51	-0.70	1.14	32.52	0.00

Panel B: P-values of Durbin-Watson Statistics for Positive Auto-correlation Test

Style	Lag1	Lag2	Lag3	Lag4	Lag5	Lag6
Hedge Fund Index	0.00	0.04	0.14	0.54	0.30	0.48
Convertible Arbitrage	0.00	0.00	0.01	0.11	0.34	0.24
Dedicated Short Bias	0.09	0.77	0.56	0.85	0.91	0.65
Emerging Markets	0.00	0.18	0.26	0.63	0.87	0.92
Equity Market Neutral	0.13	0.28	0.01	0.46	0.70	0.87
Event Driven	0.00	0.00	0.01	0.14	0.52	0.56
Distressed	0.00	0.00	0.00	0.06	0.28	0.56
Multi-Strategy	0.00	0.00	0.01	0.28	0.66	0.63
Risk Arbitrage	0.00	0.33	0.67	0.57	0.00	0.07
Fixed Income Arbitrage	0.00	0.00	0.03	0.13	0.80	0.79
Global Macro	0.08	0.20	0.07	0.74	0.00	0.81
Long/Short Equity	0.00	0.10	0.46	0.82	0.99	0.08
Managed Futures	0.31	0.98	0.97	0.40	0.77	0.94
S&P 500 Index	0.10	0.65	0.07	0.21	0.37	0.83

Table 2
OLS Regression Results for the CAPM

This table reports the results of OLS regressions for the Capital Asset Pricing Model (CAPM) using monthly hedge fund index returns. For each parameter value, the first row reports the estimated value and the second row reports its corresponding *t*-statistic. The alpha estimate is reported in a percentage form. The adjusted R^2 value from the regression is also reported. S&P 500 index is used as a proxy for the market portfolio. The sample period is from January 1994 to October 2014.

Capital Asset Pricing Model (CAPM)			
Style	alpha	sp500rf	adj.-R2
Hedge Fund Index	0.30	0.27	0.3248
	(2.81)	(10.99)	
Convertible Arbitrage	0.27	0.16	0.1260
	(2.36)	(6.07)	
Dedicated Short Bias	-0.06	-0.84	0.5959
	(-0.33)	(-19.19)	
Emerging Markets	0.12	0.51	0.2887
	(0.54)	(10.10)	
Equity Market Neutral	0.10	0.19	0.0862
	(0.56)	(4.95)	
Event Driven	0.37	0.26	0.3960
	(4.22)	(12.82)	
Distressed	0.45	0.26	0.3744
	(4.85)	(12.25)	
Multi-Strategy	0.33	0.26	0.3373
	(3.36)	(11.30)	
Risk Arbitrage	0.19	0.13	0.2456
	(2.99)	(9.06)	
Fixed Income Arbitrage	0.15	0.12	0.1056
	(1.62)	(5.51)	
Global Macro	0.59	0.14	0.0516
	(3.58)	(3.81)	
Long/Short Equity	0.29	0.42	0.4483
	(2.23)	(14.26)	
Managed Futures	0.30	-0.06	0.0018
	(1.40)	(-1.21)	

Table 3
Bayesian Gibbs Sampling Estimation of OLS Regression and Test of Zero Alpha

This table reports the results from a Bayesian Gibbs sampling method of the OLS regression for thirteen hedge fund index monthly returns under the null of zero alpha value. For each parameter, first and second rows report the mean and standard deviation of the posterior distribution of each parameter, respectively. The adjusted R^2 value from the regression is also reported. By generating new time-series return data 5000 times based on the mean parameter estimates for each hedge fund index, the small sample distribution of the OLS alpha for each index is constructed. Finally, I report the *p*-value, the probability that an OLS alpha in the small sample distribution exceeds the historical OLS alpha (the first row in "OLS_alpha" column, which is alpha in table 2), for each index. The sample period is from January 1994 to October 2014.

Capital Asset Pricing Model (CAPM)

	Under H0: alpha = 0			OLS_alpha
Style	β	σ	adj.-R2	**(p-value)**
Hedge Fund Index	0.2835	0.0172	0.3270	0.0030
	(0.0249)	(0.0008)		**(0.0024)**
Convertible Arbitrage	0.1671	0.0179	0.1290	0.0027
	(0.0260)	(0.0008)		**(0.0102)**
Dedicated Short Bias	-0.8463	0.0300	0.5975	-0.0006
	(0.0442)	(0.0013)		**(0.6376)**
Emerging Markets	0.5127	0.0344	0.2916	0.0012
	(0.0497)	(0.0016)		**(0.2994)**
Equity Market Neutral	0.1972	0.0268	0.0898	0.0010
	(0.0389)	(0.0012)		**(0.2908)**
Event Driven	0.2690	0.0142	0.3975	0.0037
	(0.0204)	(0.0007)		**(0.0000)**
Distressed	0.2743	0.0151	0.3757	0.0045
	(0.0224)	(0.0007)		**(0.0000)**
Multi-Strategy	0.2678	0.0158	0.3394	0.0033
	(0.0228)	(0.0007)		**(0.0008)**
Risk Arbitrage	0.1390	0.0102	0.2480	0.0019
	(0.0146)	(0.0005)		**(0.0024)**
Fixed Income Arbitrage	0.1251	0.0149	0.1090	0.0015
	(0.0217)	(0.0007)		**(0.0522)**
Global Macro	0.1635	0.0264	0.0544	0.0059
	(0.0382)	(0.0012)		**(0.0002)**
Long/Short Equity	0.4333	0.0205	0.4503	0.0029
	(0.0296)	(0.0009)		**(0.0122)**
Managed Futures	-0.0493	0.0333	0.0057	0.0030
	(0.0490)	(0.0015)		**(0.0790)**

Table 4
Bayesian Gibbs Sampling Estimation of a Regime-Switching Model and Test of a Peso Problem

This table reports the results from a Bayesian Gibbs sampling method of the regime-switching model with two market states and two fund states for thirteen hedge fund index monthly returns under the null of zero expected value of alpha. Alpha and idiosyncratic volatility (sigma) depend on each fund state, but beta depends on the market state. P_{11} and P_{22} denote diagonal components (state 1 to state 1, and state 2 to state 2, respectively) of transition probability matrix. For each parameter, first and second rows report the mean and standard deviation of the posterior distribution of each parameter, respectively. Π_1 and Π_2 are the stable probability of state 1 and 2, respectively. The adjusted R^2 value from the regression is also reported. By generating new time-series return data 5000 times based on the mean parameter estimates for each hedge fund index, the small sample distribution of the OLS alpha for each index is constructed. Finally, I report the *p*-value, the probability that an OLS alpha in the small sample distribution exceeds the historical OLS alpha (the first row in "OLS_alpha" column, which is alpha in table 2), for each index. The sample period is from January 1994 to October 2014.

A Two-State Regime-Switching CAPM (where alpha and sig are fund-state dependent, and beta is market-state dependent)

	Estimates under (H0: Expected value of alpha = 0) and (sig(1) < sig(2))										OLS_alpha
Style	alpha(1)	alpha(2)	beta(1)	beta(2)	sig(1)	sig(2)	P11	P22	π1 / π2	adj.-R2	**(p-value)**
Hedge Fund Index	0.0040	-0.0294	0.2881	0.2184	0.0110	0.0475	0.9449	0.6423	0.8665	0.3000	0.0030
	(0.0009)	(0.0159)	(0.0503)	(0.0304)	(0.0011)	(0.0134)	(0.0240)	(0.1250)	0.1335		**(0.0600)**
Convertible Arbitrage	0.0045	-0.0429	0.0699	0.0797	0.0106	0.0628	0.9651	0.6996	0.8959	0.0835	0.0027
	(0.0008)	(0.0199)	(0.0431)	(0.0215)	(0.0007)	(0.0169)	(0.0157)	(0.1268)	0.1041		**(0.1222)**
Dedicated Short Bias	0.0005	-0.0064	-1.0013	-0.8159	0.0256	0.0587	0.8851	0.3886	0.8419	0.6205	-0.0006
	(0.0029)	(0.0229)	(0.1125)	(0.0573)	(0.0021)	(0.0265)	(0.1195)	(0.2736)	0.1581		**(0.4810)**
Emerging Markets	0.0062	-0.0258	0.3745	0.4123	0.0189	0.0641	0.9605	0.8632	0.7760	0.3272	0.0012
	(0.0016)	(0.0180)	(0.0849)	(0.0439)	(0.0018)	(0.0108)	(0.0205)	(0.0697)	0.2240		**(0.2532)**
Equity Market Neutral	0.0033	-0.0443	0.1022	0.1173	0.0088	0.2546	0.9772	0.6817	0.9330	0.2628	0.0010
	(0.0006)	(0.0166)	(0.0377)	(0.0166)	(0.0004)	(0.1473)	(0.0124)	(0.2148)	0.0670		**(0.7918)**
Event Driven	0.0051	-0.0655	0.2638	0.1909	0.0110	0.0456	0.9723	0.6588	0.9250	0.6577	0.0037
	(0.0008)	(0.0227)	(0.0432)	(0.0241)	(0.0008)	(0.0222)	(0.0102)	(0.1426)	0.0750		**(0.3066)**
Distressed	0.0059	-0.0744	0.2749	0.1806	0.0121	0.0575	0.9753	0.6972	0.9246	0.5910	0.0045
	(0.0009)	(0.0263)	(0.0482)	(0.0281)	(0.0009)	(0.0353)	(0.0105)	(0.1385)	0.0754		**(0.2660)**
Multi-Strategy	0.0050	-0.0646	0.2444	0.2089	0.0128	0.0435	0.9727	0.6547	0.9268	0.6211	0.0033
	(0.0009)	(0.0231)	(0.0516)	(0.0259)	(0.0009)	(0.0221)	(0.0106)	(0.1541)	0.0732		**(0.3476)**
Risk Arbitrage	0.0025	-0.0331	0.1359	0.1122	0.0091	0.0301	0.9680	0.5823	0.9288	0.4585	0.0019
	(0.0007)	(0.0135)	(0.0368)	(0.0177)	(0.0006)	(0.0288)	(0.0147)	(0.2136)	0.0712		**(0.3162)**
Fixed Income Arbitrage	0.0040	-0.0424	0.0418	0.0513	0.0069	0.0505	0.9577	0.5802	0.9084	0.3234	0.0015
	(0.0006)	(0.0157)	(0.0296)	(0.0147)	(0.0005)	(0.0120)	(0.0139)	(0.1261)	0.0916		**(0.2160)**
Global Macro	0.0070	-0.0280	0.1122	0.0187	0.0127	0.0585	0.9713	0.8916	0.7909	-0.1400	0.0059
	(0.0012)	(0.0238)	(0.0625)	(0.0360)	(0.0025)	(0.0231)	(0.0203)	(0.1370)	0.2091		**(0.0230)**
Long/Short Equity	0.0021	-0.0233	0.5122	0.3757	0.0149	0.0752	0.9766	0.7549	0.9129	0.4114	0.0029
	(0.0011)	(0.0161)	(0.0575)	(0.0353)	(0.0009)	(0.0226)	(0.0112)	(0.1260)	0.0871		**(0.1830)**
Managed Futures	0.0026	-0.0120	0.3186	-0.1372	0.0299	0.0499	0.8523	0.4420	0.7907	0.1780	0.0030
	(0.0064)	(0.0278)	(0.1452)	(0.0617)	(0.0028)	(0.0348)	(0.1669)	(0.2584)	0.2093		**(0.4074)**

Table 5
Bayesian Gibbs Sampling Estimation of a Regime-Switching Model and Test of Zero Alpha

This table reports the results from a Bayesian Gibbs sampling method of the regime-switching model with two market states and two fund states for thirteen hedge fund index monthly returns under the null of zero alpha value. Idiosyncratic volatility (sigma) depends on each fund state, but beta depends on the market state. P_{11} and P_{22} denote diagonal components (state 1 to state 1, and state 2 to state 2, respectively) of transition probability matrix. For each parameter, first and second rows report the mean and standard deviation of the posterior distribution of each parameter, respectively. Π_1 and Π_2 are the stable probability of state 1 and 2, respectively. The adjusted R^2 value from the regression is also reported. By generating new time-series return data 5000 times based on the mean parameter estimates for each hedge fund index, the small sample distribution of the OLS alpha for each index is constructed. Finally, I report the *p*-value, the probability that an OLS alpha in the small sample distribution exceeds the historical OLS alpha (the first row in "OLS_alpha" column, which is alpha in table 2), for each index. The sample period is from January 1994 to October 2014.

A Two-State Regime-Switching CAPM (where alpha and sig are fund-state dependent, and beta is market-state dependent)

	Estimates under (H0: alpha(1) = alpha (2) = 0) and (sig(1) < sig(2))								OLS_alpha
Style	beta(1)	beta(2)	sig(1)	sig(2)	P11	P22	π1 / π2	adj.-R2	**(p-value)**
Hedge Fund Index	0.3464	0.2212	0.0092	0.0254	0.9678	0.9376	0.6598	0.3318	0.0030
	(0.0402)	(0.0345)	(0.0007)	(0.0024)	(0.0211)	(0.0413)	0.3402		**(0.0104)**
Convertible Arbitrage	0.1444	0.0946	0.0108	0.0458	0.9667	0.7653	0.8756	0.1086	0.0027
	(0.0405)	(0.0253)	(0.0007)	(0.0081)	(0.0186)	(0.1085)	0.1244		**(0.0212)**
Dedicated Short Bias	-0.9915	-0.8136	0.0241	0.0496	0.8251	0.4742	0.7504	0.6037	-0.0006
	(0.1029)	(0.0532)	(0.0027)	(0.0224)	(0.1836)	(0.3263)	0.2496		**(0.4622)**
Emerging Markets	0.4621	0.4160	0.0189	0.0553	0.9742	0.9307	0.7287	0.2821	0.0012
	(0.0778)	(0.0446)	(0.0014)	(0.0055)	(0.0216)	(0.0513)	0.2713		**(0.3208)**
Equity Market Neutral	0.1546	0.1213	0.0094	0.3379	0.9872	0.3425	0.9810	0.0777	0.0010
	(0.0366)	(0.0180)	(0.0005)	(0.1869)	(0.0075)	(0.2541)	0.0190		**(0.3660)**
Event Driven	0.3463	0.2140	0.0120	0.0549	0.9738	0.4716	0.9527	0.3949	0.0037
	(0.0454)	(0.0259)	(0.0007)	(0.0471)	(0.0199)	(0.1987)	0.0473		**(0.0008)**
Distressed	0.3691	0.2293	0.0127	0.0616	0.9589	0.5509	0.9161	0.3770	0.0045
	(0.0485)	(0.0325)	(0.0013)	(0.0847)	(0.0514)	(0.2670)	0.0839		**(0.0000)**
Multi-Strategy	0.3235	0.2194	0.0132	0.0468	0.9633	0.4945	0.9322	0.3364	0.0033
	(0.0518)	(0.0284)	(0.0008)	(0.0220)	(0.0303)	(0.1919)	0.0678		**(0.0020)**
Risk Arbitrage	0.1782	0.1371	0.0064	0.0137	0.9238	0.8971	0.5747	0.2469	0.0019
	(0.0279)	(0.0194)	(0.0007)	(0.0015)	(0.0541)	(0.0995)	0.4253		**(0.0028)**
Fixed Income Arbitrage	0.1192	0.0481	0.0079	0.0487	0.9747	0.7248	0.9157	0.0754	0.0015
	(0.0297)	(0.0193)	(0.0004)	(0.0107)	(0.0129)	(0.1326)	0.0843		**(0.1042)**
Global Macro	0.2272	0.0349	0.0121	0.0391	0.9826	0.9655	0.6648	0.0528	0.0059
	(0.0543)	(0.0346)	(0.0008)	(0.0030)	(0.0122)	(0.0204)	0.3352		**(0.0014)**
Long/Short Equity	0.5431	0.3793	0.0143	0.0568	0.9777	0.7822	0.9073	0.4571	0.0029
	(0.0521)	(0.0422)	(0.0013)	(0.0214)	(0.0156)	(0.1413)	0.0927		**(0.0480)**
Managed Futures	0.3371	-0.1344	0.0257	0.0360	0.5559	0.6939	0.4080	0.0754	0.0030
	(0.1276)	(0.0613)	(0.0062)	(0.0144)	(0.2564)	(0.2698)	0.5920		**(0.3642)**