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AN EMPIRICAL EVALUATION OF HEDGE FUND MANAGERIAL SKILLS USING BAYESIAN TECHNIQUES

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ABSTRACT

This paper makes use of the Bayesian method to evaluate hedge fund managers' selectivity, market timing and outperformance skills separately, and investigates their persistence from January 1995 to June 2010[1]. We divide this sample period into four overlapping sub-sample periods that contain different economic cycles. We define a skilled manager as a manager who can outperform the market in two consecutive sub-sample periods. We employ Bayesian linear CAPM and Bayesian quadratic CAPM to generate skill coefficients during each sub-sample period. We found that fund managers who possess selectivity skills can outperform the market at 7.5% significant level if and only if the economic conditions that governed the financial market during the period between sub-sample period2 and sub-sample period3 remain the same.

Keywords: selectivity, outperformance and market timing skills, Bayesian quadratic CAPM, priors, posteriors, beliefs

INTRODUCTION

In this paper, we investigate the persistence of fund managers' selectivity, market timing and outperformance skills during different economic cycles. This persistence analysis constitutes in itself a due diligence requirements that investors need to consider before including hedge funds in their portfolios for diversification

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purposes. We implement a Bayesian regression in order to overcome what is termed as estimation risk in traditional frequentist regression based performance analysis. We consider a set of returns on monthly hedge fund indices from January 1995 to June 2010 provided by Hedge Fund Research Inc. (HFRI). Appendix A exhibits the labels of 26 investment styles used in this paper. Following Capocci and Hübner (2004) hedge fund data starting after 1994 are more reliable and do not contain any survivorship bias. We divide our sample period into four overlapping sub-sample periods that include different economic cycles such as the 1998 Japanese crisis, the Dotcom bubble, the 2001 South African currency crisis, and the 2008–2009 sub-prime crisis. Our aim is not to identify crisis dates that are already known by average informed investors, but instead to assess the effectiveness of these investment styles during different economic cycles.

The subdivision of our entire sample into four sub-sample periods follows Capocci and Hübner (2004) who use the Russell 3000 as the benchmark index to represent the market portfolio, and consider March 2000 as a separation date between sub-sample period1 (before March 2000) and sub-sample period2 (after March 2000). We extend their idea to include two more sub-sample periods in our study; sub-sample period3; spanning January 2003 and January 2007, and sub-sample period4; spanning February 2007 and June 2010. The subdivision of the sub-sample periods is intended to include different economic cycles in our study in such a way that the results are not affected by generally upward market trend as discussed by Ennis and Sebastian (2003).

The analysis of the persistence of posterior performance measures reveals that at very low significance level (1% or lower) fund managers do not exhibit any skill persistence. Outperformance skill as measured by the Jensen alpha is found at 2.5% or higher during sub-sample period1 to sub-sample period2, and between sub-sample period2 and sub-sample period3 (at 7.5% or higher). However at 5% or lower we found evidence of neither selectivity skills nor market timing skills (at 7.5% or lower) among all fund managers. The lack of market timing at lower significance level can be explained by the difficulties that many fund managers have to forecast future direction of markets and thereby invest heavily in assets that would outperform the benchmark.

In general our results show a relatively low evidence of market outperformance due to both selectivity and market timing skills (at 10% or higher) among hedge fund managers before the sub-prime crisis. We use simultaneously three different techniques: the contingence table, the chi-square test and the cross-sectional regression. The results obtained with all three techniques reinforce previous findings by Agarwal and Naik (2000) and Hwang and Salmon (2002) who found relatively small evidence for market outperformance.

Many studies on hedge fund performance carried out exclusively during upward (downward) market trends only, have led to contradictory conclusions. Considering only one period framework for their study, Brown, Goetzman and Ibbotson (1999), and Kosowski, Naik and Teo (2007) find hardly any evidence of the existence of differential managers' skills; whereas, Agarwal and Naik (2000) and Hwang and Salmon (2002) in a two-period framework analysis find evidence of managers' skills in hedge fund performance. Furthermore, using two periods as well as multi-periods framework analyses, Capocci and Hübner (2004) argue that managers' skills can be found among average performers.

Moreover, most hedge funds' performance analysis assumes that the historical return distribution is normal and that risk is represented by the historical standard deviation (Sharpe, 1966, Treynor, 1965). Since the distribution of future expected returns is unknown, at least precisely, we argue that using historical parameters of the returns distribution such as the mean and the standard deviation generates some estimation risk that needs to be taken into account. Contrarily to the work done by Ackerman, McEnally and Ravenscraft (1999), and Brown et al. (1999) (who use frequentist single-factor model); and Liang (1999); and Agarwal and Naik (2000) (who employ a frequentist multi-factor model); this paper overcomes the problem of estimation risk by making use of the Bayesian linear as well as non-linear CAPM to generate the estimates of the selectivity, market timing and outperformance skill coefficients.

METHODOLOGY

Outperformance Skill

The Jensen's alpha (Jensen, 1968) is the simplest and one of the most widely used measure of outperformance skill in practice. Jensen's alpha, α_i^J calculates the performance of a portfolio by measuring the deviation of a portfolio's returns from the securities market line as follows:

$$r_{it} - r_f = \alpha_{it}^J + \beta_i (r_{mt} - r_f) + \varepsilon_{it} \tag{1}$$

where $r_{it}, r_f, r_{mt}, \beta_i, r_{it} - r_f$, and $r_{mt} - r_f$ represent the returns of the main investment style *i*, the risk free rate, the market returns at time *t* , the systematic risk of the main investment style, the excess returns on investment style *i* , and the risk premium respectively. This model is based on the assumption that markets are efficient in the famous Fama (1984) efficient market hypothesis context. In this context, all market participants have the same beliefs about asset prices, which presumably suggest no mispricing in the market; that is, the Jensen's alpha and beta in (1) are statistically equal to zero and one respectively.

A fund manager with outperformance skills attempts to exploit any mispricing that occurs in the market, thereby generating a certain value of alpha statistically different from zero. Where the value of alpha is positive (negative) it is a signal that the investment style whose rate of returns is r_{it} ; is underpriced (overpriced) and the fund manager would gain from the strategy if s/he takes a long (short) position.

Selectivity and Market Skills

The Treynor and Mazuy (1966) measure is a performance measure for hedge fund managers' selectivity and market timing skills. If a fund manager is able to time the market and forecast correctly future market trends, then the returns on his managed portfolio will not be linearly related to the market return. This is because the manager will have to gain more than the market does when the market return is forecast to rise and he will lose less than the market does when the market is forecast to fall. Hence, his portfolio returns will be a concave function of the market returns. Of the form:

$$r_{it} - r_f = \alpha_i + \beta_{1i}(r_{mt} - r_f) + \beta_{2i}(r_{mt} - r_f)^2 + \varepsilon_{it} \tag{2}$$

Admati, Bhattacharya, Pfleiderer and Ross (1986) suggest that α_i in Equation (2) can be interpreted as the selectivity skill and the $E[\beta_{2i}(r_{mt} - r_f)^2]$ as the market timing skill.

Estimation of Outperformance, selectivity and market timing (Equations 1 and 2) is done using Bayesian regression. The benefit of using the Bayesian regression over frequentist regression is straight forward; Bayesian regression overcomes estimation risk induced by using the parameters of historical return distribution as such the standard deviation to represent risk.

Bayesian Estimation

Equations (1) and (2) can be rewritten in a closed form as follows:

$$y_i = \alpha + \sum_{k=1}^{n} \beta_k x_{ki} + e_i \tag{3}$$

where $k = 1$ or 2, $x_1 = (r_{mt} - r_f)$ for $k = 1$ or $x_2 = (r_{mt} - r_f)^2$ for $k = 2$, $y_i = r_{it} - r_f$ and $x_{ki}, \alpha, \beta_k, e_i$ represent the alpha, sensitivity of x_{ki} to changes in y_i and the disturbance term respectively. This Equation (3) nests a linear and quadratic CAPM model for $k = 1$ and $k = 2$ respectively.

The vector of parameters to be estimated is either $\mathrm{B} = (\alpha, \beta_1)$ for a linear CAPM or $\mathrm{B} = (\alpha, \beta_1, \beta_2)$ for a quadratic CAPM and the error variance σ^2 respectively.

We set up a Bayesian regression model with diffuse improper priors as follows: firstly we construct a multivariate prior distribution $\prod(\mathrm{B}, \sigma^2)$ of the parameter vectors to be estimated. Secondly; based on the observed investment style returns we derive the likehood function $L(\mathrm{B}, \sigma^2/\mathrm{Y}, \mathrm{X})$ where Y, X are the excess returns on investment style i , and the vector of risk premiums respectively. Thirdly the posterior distribution of the parameter vectors is obtained by multiplying the prior and the likelihood function i.e. $\mathrm{p}(\mathrm{B}, \sigma^2/\mathrm{Y}, \mathrm{X}) \propto \mathrm{L}(\mathrm{B}, \sigma^2/\mathrm{Y}, \mathrm{X}) \prod(\mathrm{B}, \sigma^2)$.

Lastly numerical values of estimated parameters are obtained by simulating from the posterior distribution using a Monte Carlo simulation method known as the Gibbs sampler.

The joint diffuse improper prior distribution of B and σ^2 that we use is given by

$$\prod(\mathrm{B}, \sigma^2) \propto \frac{1}{\sigma^2} \tag{4}$$

Following Muteba Mwamba (2012) the likelihood function is a multivariate normal distribution of the form:

$$L(\mathrm{B}, \sigma/\mathrm{Y}, \mathrm{X}) = (2\pi\sigma^2)^{-n/2} \exp\left\{-\frac{1}{2\sigma^2}(\mathrm{Y} - \mathrm{XB})'(\mathrm{Y} - \mathrm{XB})\right\} \tag{5}$$

Posterior distributions are obtained by multiplying Equations (4) and (5). The posterior distribution of B condition on σ^2 is a multivariate normal distribution;

$$p(\mathrm{B}/\mathrm{Y}, \mathrm{X}, \sigma^2) = \mathrm{N}(\hat{\mathrm{B}}, (\mathrm{X'X})^{-1}\sigma^2) \tag{6}$$

where $\hat{\mathrm{B}}$ is the OLS estimator of B and $(\mathrm{X'X})^{-1}\sigma^2$ is the covariance matrix of $\hat{\mathrm{B}}$. The unconditional posterior distribution of σ^2 is an inverted χ^2:

$$p(\sigma^2/\mathrm{Y}, \mathrm{X}) = \mathrm{Inv} - \chi^2(N - K, \hat{\sigma}^2) \tag{7}$$

where $\hat{\sigma}^2$ is the OLS estimator of σ^2. The unconditional posterior distribution of B is known to be a multivariate Student's t-distribution:

$$p(\mathrm{B/Y,X}) \propto ((\mathrm{n}-k)+(\mathrm{B}-\hat{\mathrm{B}})'\frac{\mathrm{X'X}}{\hat{\sigma}^2}(\mathrm{B}-\hat{\mathrm{B}})^{-n/2} \tag{8}$$

We simulate the posterior distributions in Equations (7) and (8) to obtain σ^2 and B respectively using the Gibbs Sampler[2].

Performance Analysis

Once the outperformance, selectivity and market timing coefficients (Equations 1 and 2) are estimated with the Bayesian regression model; we proceed with the performance analysis of these posterior coefficients in a two-period framework. Three techniques are used for this purpose: contingency table, Chi-square test and cross sectional auto-regression.

Two-Period Tests of Performance Persistence

We basically use two-period persistence in performance methodologies. Our aim is to find out whether the fund manager can outperform the market in two consecutive sub-sample periods. i.e. from sub-sample period1 to sub-sample period2; from sub-sample period2 to sub-sample period3; or from sub-sample period3 to sub-sample period4. In fact, we want to find out whether fund managers have skills to beat the market during consecutive different economic cycles.

Three different measures of skills are used; the outperformance, the selectivity skills and the market timing skills. We refer to selectivity skills as the ability to select investments that will outperform the benchmark, and market timing skills as the ability to forecast the future direction of security markets. The existence of persistence in skills over a long period will be evidence that the manager can outperform the market continuously. We therefore define a fund manager as a winner if the investment style that he uses generates a performance measure (i.e. Jensen's alpha or selectivity or market timing) that is higher than the median of all the managers' performance measure that use the same strategy; and a loser otherwise.

Contingency Table

For two-period tests of persistence performance, we use a contingency table of winners and losers. Persistence in this context relates to fund managers that are winners in two consecutive periods (from sub-sample period1 to sub-sample period2 or from sub-sample period2 to sub-sample period3 or from sub-sample period3 to sub-sample period4) denoted by WW, or losers in two consecutive periods, denoted LL. Similarly, winners in the first period and losers in the second period are denoted by WL, and LW denoted the reverse. We use both the cross product ratio (CPR) proposed Christensen (1990) and the Chi-square test statistics to detect the persistence in performance of fund managers. The CPR is given by:

$$CPR = \frac{(WW * LL)}{(WL * LW)} \tag{9}$$

The CPR captures the ratio of the funds which show persistence in performance to the ones which do not. Under the null hypothesis of no persistence in performance, the CPR is equal to one. This implies that each of the four categories denoted by WW, WL, LW, LL represent 25% of all funds. To make a decision about the rejection of the null hypothesis, we make use of the Z-statistic given by:

$$\text{Z - statistic} = \frac{\mathrm{Ln}(\mathrm{CPR})}{\sigma_{\mathrm{Ln(CPR)}}} \tag{10}$$

$$\text{where } \sigma_{Ln(CPR)} = \sqrt{\frac{1}{WW} + \frac{1}{WL} + \frac{1}{LW} + \frac{1}{LL}} \tag{11}$$

For example, a Z-statistic greater than 1.96 indicates evidence of the presence of significant persistence in performance at a 5% confidence level[3].

Chi-Square Test Statistics

The Chi-square test statistic is used to compare the distribution of observed frequencies for the four categories WW, WL, LW, and LL, for each fund manager with the expected frequency distribution. Studies carried out in persistence performance using chi-square test statistics (Carpenter & Lynch, 1999; Park & Staum, 1998) reveal that the chi-square test based on the numbers of winners and losers is well specified, powerful and more robust compared to other test methodologies, as it deals carefully with the presence of survivorship bias. Following Agarwal and Naik (2000) the chi-square test statistic is given by:

$$\chi^2_{Cal} = \frac{(WW - D_1)^2}{D_1} + \frac{(WL - D_2)^2}{D_2} + \frac{(LW - D_3)^2}{D_3} + \frac{(LL = D_4)^2}{D_4} \tag{12}$$

$$\text{where}\left\{\begin{aligned} D_1 &= \frac{(WW+WL)*(WW+LW)}{N} \\ D_2 &= \frac{(WW+WL)*(WL+LL)}{N} \\ D_3 &= \frac{(LW+LL)*(WW+LW)}{N} \\ D_4 &= \frac{(LW+LL)*(WL+LL)}{N} \end{aligned}\right\}$$

We compare this statistic to the critical value of chi-square at 1%, 2.5%, 5%, 7.5% and 10% with degree of freedom equal to one.

Cross-sectional Auto-Regression

We double check our persistence analysis by making use of a cross-sectional autoregressive regression of the form:

$$\mathrm{Perf}_t = \mathrm{a} + \mathrm{bPerft}_{-1} + \mathrm{u}_t \tag{14}$$

where Equation (14) represents the relationship between performance parameter (i.e. outperformance or selectivity or market timing) during sub-sample period *t* and that of previous sub-sample period *t*–1. If the coefficient of a parameter in previous sub-sample periods is positive and statistically significant, it is an indication of persistence in two consecutive sub-sample periods.

EMPIRICAL RESULTS

We use all 26 investment styles and run 26 Bayesian linear CAPM models using Equation (1) to obtain the outperformance skill. The Russell 3000 index is used as proxy for the market portfolio while the three-month US Treasury Bill is used as a proxy for the risk-free asset. We also run 26 other Bayesian quadratic CAPM models using Equation (2) to obtain selectivity and market timing posterior coefficients. Once these skill coefficients are estimated, three techniques are used to investigate the persistence in performance. The skill posterior coefficients as well as the winners/losers results for each sub-sample period are shown in Tables 7, 8, 9, 10, 11 and 12 in Appendix B.

To investigate the persistence of each manager's skill we use three different techniques namely the contingence table, the Chi-square test and the cross-section regression analysis. Using the contingence table we first compute the Z-statistic for each manager's skill during the same sub-sample period. The Z-statistic values for each skill are exhibited in Table 1.

Table 1
Posterior Z-statistic

	P1–P2	P2–P3	P3–P4
Outperform	2.5306	1.8342	1.0722
Selectivity	0.2780	0.2780	1.8342
Timing	1.7723	-0.1000	0.1604

These statistic values are compared with their critical value drawn from a standard normal distribution at a different level of significance. Whenever the Z-statistic value is greater than its critical value it is an indication of the presence of a given skill. Table 2 summarises the persistence analysis at different significance levels.

Table 2
Posterior performance persistence with contingence table

α	1%	2.50%	5%	7.50%	10%
Z(1–α/2)	2.5758	2.2414	1.9600	1.7805	1.6449
Outperform	no skill	skill 1–2	skill 1–2	skill 1–2 & 2–3	skill 1–2 & 2–3
Selectivity	no skill	no skill	no skill	skill 2–3	skill 2–3
Timing	no skill	no skill	no skill	no skill	skill 1–2

Table 2 shows that there is no evidence of any fund managers' skill at 1% significance level. However, at 2.5% and 5% significance level we found great evidence of outperformance skill during sub-sample period1 and sub-sample period2. Notice that this market outperformance is not due to selectivity or market timing skills; therefore it would be due to luck only. At 7.5% or higher significance level we find enough evidence of market outperformance in hedge fund managers between sub-sample period1 and sub-sample period3. This market outperformance is due to luck between sub-sample period1 and sub-sample period2; and to selectivity skill during sub-sample period2 to sub-sample period3. Market timing skill explains this market outperformance only at 10% significance level during sub-sample period1 and sub-sample period2. These results emphasise major difficulties that have fund managers to accurately time the market.

We secondly use the chi-square technique and compute the chi-square statistic value for each manager's skill.

Table 3
Posterior chi-square statistic

	P1–P2	P2–P3	P3–P4
Outperform	7.2284	3.5536	1.1699
Selectivity	0.0774	0.0774	3.5536
Timing	3.3462	0.010	0.0258

These statistic values are thereafter compared with their critical values drawn from the chi-square distribution at different significance level. The null hypothesis tested here is that there is "no skill" in fund managers. Table 4 summarises the persistence of each manager's skill.

Table 4
Posterior persistence performance with chi-square technique

α	1%	2.50%	5%	7.50%	10%
CHI α	6.6349	5.0239	3.8415	3.1701	2.7055
Outperform	skill 1–2	skill 1–2	skill 1–2	skill 1–2 & 2–3	skill 1–2 & 2–3
Selectivity	no skill	no skill	no skill	skill 2–3	skill 2–3
Timing	no skill	no skill	no skill	skill 1–2	skill 1–2

Table 4 reports the same results as Table 2 with the only difference that market timing explains the overall market outperformance at 7.5% or higher (instead of 10% as reported in Table 2) during sub-sample period1 and sub-sample period2.

Lastly, the cross-section regression technique is used to investigate the robustness of these managers' skill persistence. We regress current period performance parameters on previous parameters. Whenever the coefficient of the previous parameter is positive and statistically significant we conclude that there is persistence in performance between the two consecutive periods. Table 5 highlights the regression results.

Table 5
Posterior cross-section regression coefficients

Period	1–2	2–3	3–4
Outperform	–0.155 (0.305)	0.573(0.0003)	0.138(0.4065)
Selectivity	–0.292 (0.148)	0.520(0.0001)	0.958(0.3437)
Timing	0.108 (0.141)	0.272(0.0526)	0.205(0.061)

Again Table 5 reinforces previous results; market outperformance is due to selectivity rather than market timing skill during sub-sample period2 and sub-sample period3. No evidence of market outperformance due to timing skill is found among these fund managers (regression results at 5% only).

CONCLUSION

This paper aimed at investigating the persistence of hedge fund managerial skills. The main objective was to determine whether fund managers can outperform the market during different economic market trends. In other words, the paper attempted to answer the question of whether fund managers can outperform the market consistently in both bear and bull markets. For this purpose, monthly returns (net of fees) on hedge fund indices were collected from HFR for the period between January 1995 and June 2010. We divided our entire sample into four overlapping sub-samples to see whether skilled fund manager would consistently outperform the market in these different sub-sample periods. Based on the efficient market hypothesis as a prediction model we assume that the market is efficient and that fund managers cannot outperform it.

Using the Gibbs sampler with 21 thousand simulations; our results exhibited in Table 6, show that fund managers have skills to outperform the market during sub-sample period1 through sub-sample period3. This market outperformance is due to market timing skill during sub-sample period1 and sub-sample period2, and to selectivity skill during sub-sample period2 through sub-sample period3.

Table 6
Persistency per sample period

		Sub-sample
Contingence	Outperform	P1–P2; P2–P3
	Selectivity	P2–P3
	Timing	P1–P2
Chi-square	Outperform	P1–P2; P2–P3
	Selectivity	P2–P3
	Timing	P1–P2
Regression	Outperform	P2–P3
	Selectivity	P2–P3
	Timing	None

These results contradict the EMH paradox and show that fund managers who possess selectivity skills can outperform the market at 7.5% significant level if and only if the economic conditions that governed the financial market during the period between sub-sample period2 and sub-sample period3 remain constant i.e. fast domestic growth coupled with low interest rates.

NOTES

1. Due to data availability, we were able to get data only up to 2010.
2. See Geman and Geman (1984) for more details.
3. See Kat and Menexe (2003) and De Souza and Gokcan (2004).

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APPENDIX A

List of Labels

The labels of investment styles used throughout the paper.

1. **ED:** HFRI Event-Driven (Total) Index
    - HFRI ED: Distressed/Restructuring Index: **ED_RES**
    - HFRI ED: Merger Arbitrage Index: **ED_MA**
    - HFRI ED: Private Issue/Regulation D Index: **ED_PVT**
2. **EH:** HFRI Equity Hedge (Total) Index:
    - HFRI EH: Equity Market Neutral Index: **EH_EMN**
    - HFRI EH: Quantitative Directional: **EH_QUANT**
    - HFRI EH: Sector - Energy/Basic Materials Index: **EH_ENERG**
    - HFRI EH: Sector - Technology/Healthcare Index: **EH_TECH**
    - HFRI EH: Short Bias Index: **EH_SBIAS**
3. **EM:** HFRI Emerging Markets (Total) Index:
    - HFRI Emerging Markets: Asia ex-Japan Index: **EM_ASIA-JP**
    - HFRI Emerging Markets: Global Index: **EM_GLOBAL**
    - HFRI Emerging Markets: Latin America Index: **EM_LAT_AM**
    - HFRI Emerging Markets: Russia/Eastern Europe Index: **EM_EAST-EU**
4. **FoF:** HFRI Fund of Funds Composite Index:
    - HFRI FOF: Conservative Index: **FoF_CONSV**
    - HFRI FOF: Diversified Index: **FoF_DIVERS**
    - HFRI FOF: Market Defensive Index: **FoF_MKT-DFENS**
    - HFRI FOF: Strategic Index: **FoF_STRATG**
5. **FWC:** HFRI Fund Weighted Composite Index:
    - HFRI Fund Weighted Composite Index CHF: **FWC_CHF**
    - HFRI Fund Weighted Composite Index EUR: **FWC_EUR**
    - HFRI Fund Weighted Composite Index GBP: **FWC_GBP**
    - HFRI Fund Weighted Composite Index JPY: **FWC_JPY**

6. **MCRO:** HFRI Macro (Total) Index:
    - HFRI Macro: Systematic Diversified Index: **MCRO_SYST-DIV**
7. **RV:** HFRI Relative Value (Total) Index:
    - HFRI RV: Fixed Income-Asset Backed: **RV_FIAB**
    - HFRI RV: Fixed Income-Convertible Arbitrage Index: **RV_FICA**
    - HFRI RV: Fixed Income-Corporate Index: **RV_FICORP**
    - HFRI RV: Multi-Strategy Index: **RV_MSTRAT**
    - HFRI RV: Yield Alternatives Index: **RV_YEILDA**

APPENDIX B

The Bayesian Estimation

The Jensen alpha, the Treynor and Mazuy selectivity and timing skills:

Table 7
Posterior outperformance skill

	Period 1	Period 2	Period 3	Period 4
ED_RES	1.248	4.0178	–2.5425	1.0417
ED_MA	1.4147	3.935	–3.214	1.0736
ED_PVT	3.16	3.3281	–2.9835	0.06922
EH_EMN	1.322	3.92	–3.3072	0.6969
EH_QUANT	1.2228	3.9854	–3.244	0.9912
EH_ENERG	2.2134	4.5321	–2.4139	1.2346
EH_TECH	2.2239	3.0759	–3.546	1.444
EH_SBIAS	1.517	4.347	–3.207	0.3229
EM_ASIA_JP	0.3156	3.3237	–2.575	1.6126
EM_GLOBAL	0.1285	3.752	–2.6925	1.4088
EM_LAT_AM	0.5334	3.8591	–2.7503	1.5566
EM_EAST_EU	0.3702	5.7529	–1.3025	1.0322
FoF_CONSV	1.2838	3.7451	–3.198	0.688
FoF_DIVERS	0.9787	3.5669	–3.2023	0.7436
FoF_MKT_DFENS	1.1297	4.0162	–3.3682	1.1143
FoF_STRATG	1.085	3.5086	–3.159	0.7746
FWC_CHF	1.004	3.7648	–3.264	0.9605

(*continued on next page*)

Table 7: (*continued*)

	Period 1	Period 2	Period 3	Period 4
FWC_EUR	2.6339	3.905	–3.1198	1.0539
FWC_GBP	1.3807	3.9846	–2.9473	1.1132
FWC_JPY	0.8741	3.5563	–3.3251	0.9313
MCRO_SYST_DIV	1.5046	3.9258	–3.2543	1.2655
RV_FIAB	1.2995	4.4361	–2.9079	1.3871
RV_FICA	1.4947	4.3177	–3.278	1.4658
RV_FICORP	0.9012	3.7697	–2.8449	1.0499
RV_MSTRAT	1.1197	4.1141	–3.0372	1.0243
RV_YEILDAT	0.7561	4.3275	–3.0203	0.7972

Table 8
Posterior selectivity skill

	Period 1	Period 2	Period 3	Period 4
ED_RES	0.4295	1.4314	–0.3176	0.9008
ED_MA	0.3744	1.0415	–0.7369	0.9047
ED_PVT	2.0792	0.3669	–0.2644	0.8204
EH_EMN	0.2352	0.7802	–0.9527	0.5187
EH_QUANT	0.5581	1.0809	–0.9245	0.8189
EH_ENERG	1.1334	0.2148	–0.5451	0.8407
EH_TECH	2.0245	0.0508	–1.0376	1.085
EH_SBIAS	–0.0396	1.6598	–0.978	0.5382
EM_ASIA_JP	–0.5133	0.8136	–0.0945	1.1605
EM_GLOBAL	–0.3389	1.1158	–0.4861	1.2368
EM_LAT_AM	0.1711	0.7678	–0.5528	1.1189
EM_EAST_EU	0.4485	3.5233	1.4334	0.9165
FoF_CONSV	0.3244	0.796	–0.8203	0.6002
FoF_DIVERS	0.1707	0.6352	–0.8166	0.555
FoF_MKT_DFENS	0.1826	0.6081	–0.738	1.082
FoF_STRATG	0.3181	0.5884	–0.7957	0.6208
FWC_CHF	0.195	0.7706	–0.9247	0.7684
FWC_EUR	1.8849	0.9096	–0.7815	0.8714
FWC_GBP	0.5664	0.9856	–0.616	0.9546
FWC_JPY	0.0541	0.5584	–0.9867	0.6909

(*continued on next page*)

Table 8: (*continued*)

	Period 1	Period 2	Period 3	Period 4
MCRO_SYST_DIV	0.6073	0.4472	–0.7961	1.38
RV_FIAB	0.2462	1.6528	–0.6331	1.2336
RV_FICA	0.4347	1.4624	–0.8276	0.9565
RV_FICORP	–0.0583	0.9674	–0.5946	1.026
RV_MSTRAT	0.133	1.1201	–0.7192	0.7642
RV_YEILDAT	–0.1645	1.1605	–0.4647	0.6

Table 9
Posterior market timing skill

	Period 1	Period 2	Period 3	Period 4
ED_RES	0.043	0.0422	–0.0549	0.0018
ED_MA	0.0547	0.0472	–0.0611	0.0022
ED_PVT	0.0568	0.0484	–0.067	–0.0024
EH_EMN	0.0571	0.0513	–0.0581	0.0024
EH_QUANT	0.0348	0.0474	–0.0572	0.0023
EH_ENERG	0.0565	0.0705	–0.0463	0.0057
EH_TECH	0.0101	0.0493	–0.0619	0.0052
EH_SBIAS	0.0817	0.0437	–0.055	0.0038
EM_ASIA_JP	0.0435	0.0409	–0.0612	0.0066
EM_GLOBAL	0.0244	0.043	–0.0545	0.0022
EM_LAT_AM	0.0187	0.0504	–0.0543	0.0064
EM_EAST_EU	–0.0048	0.0362	–0.0675	0.0012
FoF_CONSV	0.0504	0.0482	–0.0587	0.0009
FoF_DIVERS	0.0424	0.0479	–0.0588	0.0025
FoF_MKT_DFENS	0.0498	0.0557	–0.0649	0.0001
FoF_STRATG	0.0402	0.0477	–0.0583	0.002
FWC_CHF	0.0425	0.0489	–0.0577	0.0026
FWC_EUR	0.0393	0.0489	–0.0577	0.0024
FWC_GBP	0.0428	0.049	–0.0575	0.002
FWC_JPY	0.0431	0.0489	–0.0577	0.0033
MCRO_SYST_DIV	0.0471	0.0568	–0.0606	–0.0023
RV_FIAB	0.0553	0.0454	–0.0561	0.002
RV_FICA	0.0557	0.0466	–0.0605	0.0075

(*continued on next page*)

Table 9: (*continued*)

	Period 1	Period 2	Period 3	Period 4
RV_FICORP	0.0504	0.0457	–0.0555	–0.0001
RV_MSTRAT	0.0519	0.0489	–0.0572	0.0036
RV_YEILDAT	0.0484	0.0517	–0.063	0.0026

The series of winners and losers for each skill are shown below.

Table 10
Posterior winners/losers for outperformance skill

	Period 1	Period 2	Period 3	Period 4
ED_RES	L	W	W	W
ED_MA	W	W	L	W
ED_PVT	W	L	W	L
EH_EMN	L	L	L	L
EH_QUANT	L	W	W	W
EH_ENERG	W	W	W	W
EH_TECH	W	L	L	W
EH_SBIAS	W	W	W	L
EM_ASIA_JP	L	L	W	W
EM_GLOBAL	L	L	L	L
EM_LAT_AM	W	W	L	W
EM_EAST_EU	W	W	W	L
FoF_CONSV	W	W	W	L
FoF_DIVERS	L	L	L	L
FoF_MKT_DFENS	W	W	L	W
FoF_STRATG	L	L	W	W
FWC_CHF	L	L	L	L
FWC_EUR	W	W	W	W
FWC_GBP	W	W	W	W
FWC_JPY	L	L	L	L
MCRO_SYST_DIV	W	W	W	W
RV_FIAB	W	W	W	W
RV_FICA	W	W	L	W
RV_FICORP	L	L	W	W
RV_MSTRAT	W	L	L	L
RV_YEILDAT	L	W	W	L

Table 11
Posterior winners/losers for selectivity skill

	Period 1	Period 2	Period 3	Period 4
ED_RES	W	W	W	W
ED_MA	L	W	L	W
ED_PVT	W	L	W	L
EH_EMN	L	W	W	L
EH_QUANT	W	W	W	W
EH_ENERG	W	L	W	W
EH_TECH	W	L	L	W
EH_SBIAS	L	W	L	L
EM_ASIA_JP	L	L	W	W
EM_GLOBAL	L	W	L	W
EM_LAT_AM	W	L	L	L
EM_EAST_EU	W	W	W	L
FoF_CONSV	W	W	L	L
FoF_DIVERS	L	W	L	L
FoF_MKT_DFENS	L	L	W	W
FoF_STRATG	W	L	W	W
FWC_CHF	L	L	L	L
FWC_EUR	W	W	W	W
FWC_GBP	W	W	W	W
FWC_JPY	L	L	L	L
MCRO_SYST_DIV	W	W	W	W
RV_FIAB	W	W	W	W
RV_FICA	W	W	L	W
RV_FICORP	L	L	W	W
RV_MSTRAT	W	L	L	L
RV_YEILDAT	L	W	W	L

Table 12
Posterior winners/losers for market timing skill

	Period 1	Period 2	Period 3	Period 4
ED_RES	L	L	W	W
ED_MA	W	W	W	W
ED_PVT	W	W	L	L
EH_EMN	W	W	L	L
EH_QUANT	L	L	W	L
EH_ENERG	W	W	W	W
EH_TECH	L	W	L	W
EH_SBIAS	W	L	W	W
EM_ASIA_JP	W	L	L	W
EM_GLOBAL	W	W	W	L
EM_LAT_AM	L	W	W	W
EM_EAST_EU	L	L	L	L
FoF_CONSV	W	W	W	L
FoF_DIVERS	L	L	L	W
FoF_MKT_DFENS	W	W	L	L
FoF_STRATG	L	L	W	W
FWC_CHF	L	W	W	W
FWC_EUR	L	W	W	L
FWC_GBP	W	W	W	L
FWC_JPY	W	W	W	W
MCRO_SYST_DIV	W	W	W	W
RV_FIAB	W	L	W	L
RV_FICA	W	W	L	W
RV_FICORP	L	L	W	L
RV_MSTRAT	W	W	W	W
RV_YEILDAT	L	W	L	W