

# Measuring Hedge Fund Timing Ability Across Factors

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In recent years there has been an extensive examination of the ability of mutual funds to provide alpha. Most of the studies have focused on some sort of asset pricing model as the basis for determining excess performance or use the characteristic-based approach.<sup>1</sup> These studies have used a variation of the CAPM, the Fama–French factors, and the Fama–French factors plus additional factors for momentum and liquidity. Generally, the studies have found that after adjusting for various factors in the economy, the excess performance or alpha of most mutual funds vanishes. In fact, some have shown that after fees and trading costs, these mutual funds might slightly underperform. There have also been quite a few studies on mutual fund timing ability.<sup>2</sup> Most of these studies find that mutual fund managers do not exhibit timing ability, and some studies find negative timing ability.<sup>3</sup>

Fewer studies have focused on the selection ability or persistence of performance for hedge funds (Ackermann, McEnally, and Ravenscraft [1999], Liang [1999], Agarwal and Naik [2004], Edwards and Caglayan [2001]) and even fewer studies have focused on the market timing ability of hedge funds (Fung, Xu, and Yau [2002], Chen and Liang [2007], Chen [2007]). The studies on excess performance of hedge funds find that hedge funds have abnormal performance and outperform mutual funds in terms of higher

returns and lower volatilities. The substantially fewer studies on hedge fund market timing might be because of the large amount of studies showing no market timing ability for mutual funds or for some of the problems associated with tests of market timing (Goetzmann et al. [2000], Jagannathan and Korajczyk [1986], and Fung and Hsieh [1997, 2001]). The conclusion of the studies on hedge fund market timing is that there seems to be some degree of market timing depending on the fund's focus.

In particular, Chen [2007], following the suggestion of Ferson and Schadt [1996], measures market timing of hedge funds using a conditional multi-factor approach and examines the timing ability of hedge funds not just to the market but to the market in which they focus. He finds that many individual hedge funds in certain hedge fund categories have timing ability. He finds timing ability in the convertible arb, funds, global macro funds, and managed futures categories. He finds little evidence of timing ability for equity market neutral funds and long–short equity hedge funds. Chen and Liang [2007] study a subset of hedge funds more likely to engage in market timing and find that there is significant market timing ability at the individual fund and aggregate levels.

In this article, we extend the market timing literature in two ways. First, we examine whether adjusting for the daily

timing variable of Goetzmann, Ingersoll, and Ivkovic [2000] (GII henceforth) alters the conclusions about market timing for hedge funds. Second, we specifically alter the specification of the market timing tests. To our knowledge, all of the market timing tests are based upon *timing the general equity market*.<sup>4</sup> Hedge funds are usually sophisticated players that may build portfolios to isolate particular factors (Chincarini and Kim [2006]) and thus even if they are engaged in market timing are more likely than mutual funds to time specific factors, rather than just the broad market.<sup>5</sup> To the extent that there is correlation between *market-factor timing* and other-factor timing, we should pick this up even in the general market timing tests. However, by altering the specification of the timing regressions, we will be able to attribute timing in a more accurate way and also avoid erroneously measuring alpha when it is actually factor timing.

Using a sample of 3,348 equity hedge funds from the Hedge Fund Research (HFR) database from January 1994 to June 2009, we measure the multi-factor timing ability of equity hedge funds.

The article is organized as follows: the first section presents the asset-pricing models used to measure hedge fund selection and timing ability, the next section describes and documents the potential misspecification bias that occurs from ignoring factor timing variables with the use of simulations, the third section describes the hedge fund database used in this study, the fourth section presents and discusses the selection and timing ability results over the sample period and various sub-sample periods, the fifth section discusses issues related to hedge fund performance persistence, and the last section concludes.

## MODELS OF PERFORMANCE MEASUREMENT

To understand both the market timing ability of hedge funds and the unexplained or excess performance, we employ several standard models of performance measurement on equity-style hedge funds. The models are the standard CAPM (Jensen [1968], Fama and MacBeth [1973], and Jegadeesh and Titman [1993]), the Fama–French three-factor model (Fama and French [1993]), and the Fama–French model with an additional factor for momentum (Carhart [1997]).<sup>6</sup> In addition to these standard models, we employ a market-timing factor and

a timing factor for each of the Fama–French factors. Thus, the models estimated are the following:

$$\tilde{r}_i = \alpha_{i,T} + \beta_{i,T} \text{RMRF}_i + \varepsilon_{i,t} \quad t = 1, 2, \dots, T \quad (1)$$

$$\tilde{r}_i = \alpha_{i,T} + \beta_{i,T} \text{RMRF}_i + \beta_{2i,T} \text{SMB}_i + \beta_{3i,T} \text{HML}_i + \varepsilon_{i,t} \quad t = 1, 2, \dots, T \quad (2)$$

$$\tilde{r}_i = \alpha_{i,T} + \beta_{i,T} \text{RMRF}_i + \beta_{2i,T} \text{SMB}_i + \beta_{3i,T} \text{HML}_i + \beta_{4i,T} \text{MOM}_i + \varepsilon_{i,t} \quad t = 1, 2, \dots, T \quad (3)$$

where  $\tilde{r}_i (= r_{i,t} - r_{f,t})$  is the return on a hedge fund portfolio in excess of the risk-free rate;  $\text{RMRF}_i$  is the excess return on a value-weighted aggregate market proxy;  $\text{SMB}_i$ ,  $\text{HML}_i$ , and  $\text{MOM}_i$  are the returns on value-weighted, zero-investment, factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns as computed by Fama and French.<sup>7</sup> These models are typically employed to extract the stock picking skill of the portfolio manager or, as Henriksson and Merton [1981] like to call it, security analysis or the microforecasting ability of the portfolio manager.

For the tests of market timing, these models have been modified to include a term that captures the market timing ability (or macroforecasting skills) of the portfolio manager.

$$\tilde{r}_i = \alpha_{i,T} + \beta_{i,T} \text{RMRF}_i + \gamma_{i,T} \text{TIMING}_i + \varepsilon_{i,t} \quad t = 1, 2, \dots, T \quad (4)$$

$$\tilde{r}_i = \alpha_{i,T} + \beta_{i,T} \text{RMRF}_i + \beta_{2i,T} \text{SMB}_i + \beta_{3i,T} \text{HML}_i + \gamma_{i,T} \text{TIMING}_i + \varepsilon_{i,t} \quad t = 1, 2, \dots, T \quad (5)$$

$$\tilde{r}_i = \alpha_{i,T} + \beta_{i,T} \text{RMRF}_i + \beta_{2i,T} \text{SMB}_i + \beta_{3i,T} \text{HML}_i + \beta_{4i,T} \text{MOM}_i + \gamma_{i,T} \text{TIMING}_i + \varepsilon_{i,t} \quad t = 1, 2, \dots, T \quad (6)$$

where  $\text{TIMING}_i$  is one of the standard measures of market timing, either  $\max(0, -[r_{M,t} - r_{f,t}])$  (Henriksson and Merton [1981]), or  $[(\prod_{d \in t} \max(1 + r_{M,d}, 1 + r_{f,d})) - 1] - r_{M,t}$  (Goetzmann et al. [2000]).<sup>8</sup> Focusing on the first equation, which is a standard CAPM test with a timing variable, a perfect market timer should have a  $\beta = 1$  and a  $\gamma = 1$ . This would imply an equity portfolio manager that is 100% invested in equities; however, in any month where the return of the market is less than the risk-free rate, the manager will sell the entire portfolio and put the securities in cash.<sup>9</sup> In reality, it will be rare for hedge fund managers to engage in such an extreme market timing

procedure, however Merton [1981] shows that as long as the timer has greater than random accuracy in predicting up and down markets and that he or she alters beta accordingly in up and down markets, then  $\gamma$  will be positive and significant. Thus, a test for a positive and significant  $\gamma$  is sufficient to find market timing ability. The GII market timing measure should equal 1 for a perfect daily market timer, but for a market timer that times at a less frequent interval, a precise value cannot be given without more information about the distribution of returns.<sup>10</sup>

With the exception of one paper on mutual funds (Chan et al. [2002]), every study of the market timing of mutual funds and hedge funds focuses on some form of the timing ability of the general stock market. One might think, however, that the above equations are somewhat misspecified for hedge funds. Hedge funds are generally more sophisticated traders and engage in significant short-selling, leverage, and quantitative models of the market. Thus, one might believe that hedge funds may indeed engage in the timing of various components of equity returns. Although these components might be very complicated, as in the case of commodity trading advisors, they might be captured by creating timing measures for each of the Fama–French factors, rather than just the market factor. In particular, one might measure performance measurement as follows:

$$\begin{aligned} \tilde{r}_{it} = & \alpha_{it} + \beta_{1it} \text{RMRF}_t + \beta_{2it} \text{SMB}_t + \beta_{3it} \text{HML}_t \\ & + \gamma_{1it} \text{TRMRF}_t + \gamma_{2it} \text{TSMB}_t + \gamma_{3it} \text{THML}_t \\ & + \varepsilon_{it} \quad i = 1, 2, \dots, T \end{aligned} \quad (7)$$

where  $\text{TRMRF}_t = \max(0, -[r_{M,t} - r_{f,t}])$ ,  $\text{TSMB}_t = \max(0, -\text{SMB}_t)$ , and  $\text{THML}_t = \max(0, -\text{HML}_t)$ .<sup>11</sup> In theory, if a portfolio manager does exhibit market timing ability across factors and the regression equation is misspecified, it might show up as either a larger  $\alpha$  and/or a larger coefficient on the market-timing factor, but this need not always be the case. In all cases, it will not reveal the true timing and investment process of the hedge fund manager.

## SIMULATIONS

To provide additional insights into the basic premise of specification of the port-

folio measurement equations, we conduct simulations to examine the efficacy of various measurement methods in explaining the performance of hedge fund managers.

## Simulation Methodology

For each simulation, we generate 120 months of returns for each of the three Fama–French factors. We create these returns by taking the estimated mean and variance–covariance matrix of the factors from January 1970 to June 2009 and simulate them as a random draw from a multi-variate normal distribution. Once these factor returns are generated, we create various types of simulated hedge fund timers that have a range of forecasting ability for the factors from no forecasting ability to perfect forecasting ability. The portfolio manager is assumed to have forecasting ability in timing any of the three Fama–French factors. The factor returns were generated with means of 0.50, 0.17, and 0.43 percent per month for  $\text{RMRF}_t$ ,  $\text{SMB}_t$ , and  $\text{HML}_t$  and a correlation matrix shown in Exhibit 1, which are just the sample estimates from historical data for the period January 1970 to June 2009. Skill level for each factor ranges from 0 (absolutely no ability) to 1 (perfect foresight). At a level of 0.5, the forecaster’s ability is equivalent to an unbiased coin flip. Thus, a value of 0.6 indicates that the forecaster has a 60% chance of correctly calling the return of that factor for the next month.

## EXHIBIT 1 Factor Returns Summary Statistics

Factor Portfolio	Cross-Correlations						
	Monthly Mean Return	S.D.	t-stat for Mean = 0	RMRF	SMB	HML	MOM
RMRF	0.50	4.55	2.19	1.00	0.23	-0.35	-0.09
SMB	0.17	3.15	1.07	0.23	1.00	-0.30	-0.04
HML	0.43	3.06	2.84	-0.35	-0.30	1.00	-0.09
MOM	0.76	4.62	3.30	-0.09	-0.04	-0.09	1.00

*Note:* This exhibit reports the time-series averages and correlations of the four Fama–French factors from January 1970–June 2009.  $\text{RMRF}_t$ ,  $\text{SMB}_t$ , and  $\text{HML}_t$  are the Fama–French factors for the market return over the risk-free rate, size, and book-to-market as computed by Fama–French.  $\text{MOM}_t$  is a factor-mimicking portfolio for one-year return as computed by Fama–French.

One thousand simulations are performed for many of the combinations of skill levels, but not all.<sup>12</sup> To do all skill level combinations in increments of 0.1 would require 1,331 various combinations ( $11^3$ ), which would be too cumbersome to report. Thus, a subset of these was chosen to represent the skill levels of 1, 0.8, 0.5, and 0.2 or a total of 64 combinations. There are many potential ways of creating the behavior of a hedge fund manager with market timing ability. The manager could go long or short factors or simply go in and out of the market. To keep in line with previous research, we construct the behavior of the hedge fund market timer as follows: If the following month's market forecast is positive, the manager chooses to invest 100% in the market; otherwise, he chooses to invest in the risk-free asset. If the forecast is  $SMB_t > 0$ , the manager places 100% in  $SMB_t$  and otherwise chooses to remain out of the market. If the forecast is  $HML_t > 0$ , the manager places 100% in  $HML_t$  and otherwise chooses to be out of this market. Technically, this may require situations for the manager to be three-times levered. We could have chosen to restrict each investment to 33%, but this would have made the interpretation of the results less consistent with prior literature. With our formulation, a perfect market timer invested in all three asset classes should have  $\beta_{iit} = 1$  and  $\gamma_{iit} = 1$ .

For every simulation of the combination of simulated timers, we create a portfolio of returns over the 120 months. For our particular combination of timing ability, this creates 64 portfolios. We then run a regres-

sion to examine selection and timing ability using the standard Henriksson–Merton test and the multi-factor timing test. We adjust standard errors for cases where serial correlation or heteroscedasticity is detected using Newey–West [1987]. The estimated parameters for each regression are stored and a new simulation is conducted. Once all 1,000 simulations are complete, we average parameter estimates for each forecasting combination and report them in the exhibits in the next section.

## Simulation Results

The results from the market timing regressions on the simulated market timers are contained in Exhibit 2. The column entitled Forecasting Skill indicates the forecasting ability for the particular simulated timer. The numbers are listed in the following order: the first number is the timing ability for the market factor, the second number is the timing ability for the size factor, and the third number is the timing ability for the value factor. For each set of the simulated timers, we estimate the standard market timing test and the multi-factor timing test. For example, the row of 1–1–1, represents a hedge fund manager that can perfectly market time all three factors. The standard test finds a positive timing coefficient but a very high  $\hat{\alpha}$ , even though the manager has no selection ability whatsoever. Thus, the standard timing test incorrectly concludes that the manager has significant selection ability. The reason for this is primarily because the performance model

## EXHIBIT 2

### Simulated Mean Values of Selection and Timing Coefficients from Different Measuring Models

Forecasting Skill	Market Timing						Factor Timing							
	$\alpha$	$\beta_{RMRF}$	$\beta_{SMB}$	$\beta_{HML}$	$\gamma$	$\bar{R}^2$	$\alpha$	$\beta_{RMRF}$	$\beta_{SMB}$	$\beta_{HML}$	$\gamma_{RMRF}$	$\gamma_{SMB}$	$\gamma_{HML}$	$\bar{R}^2$
1–1–1	73.19	1.09	0.50	0.50	1.16	0.77	-0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1–1–0.8	58.57	1.07	0.51	0.50	1.13	0.69	-0.23	1.00	1.01	0.79	1.01	1.01	0.59	0.83
1–1–0.5	37.15	1.03	0.50	0.50	1.07	0.65	-0.43	1.00	1.00	0.50	1.01	1.00	0.00	0.75
1–1–0.2	16.34	0.99	0.50	0.50	0.99	0.69	0.46	1.00	1.00	0.19	1.00	1.00	-0.61	0.83
1–0.8–1	58.03	1.07	0.50	0.50	1.14	0.69	-0.10	1.00	0.80	1.00	1.00	0.60	1.01	0.83
1–0.8–0.8	43.40	1.05	0.50	0.50	1.10	0.63	-0.33	1.00	0.80	0.80	1.00	0.60	0.60	0.70
1–0.8–0.5	21.99	1.02	0.50	0.50	1.04	0.59	-0.54	1.00	0.80	0.50	1.00	0.60	0.01	0.63
1–0.8–0.2	1.17	0.98	0.50	0.50	0.96	0.62	0.36	1.00	0.79	0.19	1.00	0.59	-0.61	0.69
1–0.5–1	35.17	1.06	0.51	0.50	1.12	0.66	-0.57	1.00	0.51	1.00	1.01	0.01	1.00	0.75
1–0.5–0.8	20.55	1.04	0.51	0.50	1.08	0.60	-0.80	1.00	0.52	0.79	1.01	0.01	0.59	0.64
1–0.5–0.5	-0.87	1.01	0.50	0.50	1.02	0.56	-1.00	1.00	0.51	0.50	1.01	0.01	0.00	0.57
1–0.5–0.2	-21.68	0.97	0.50	0.50	0.94	0.58	-0.11	1.00	0.51	0.19	1.01	0.01	-0.61	0.62
1–0.2–1	13.15	1.03	0.50	0.50	1.08	0.70	0.33	1.00	0.21	0.99	1.00	-0.59	0.99	0.83
1–0.2–0.8	-1.47	1.01	0.50	0.50	1.04	0.63	0.10	1.00	0.21	0.79	1.00	-0.58	0.58	0.69

## EXHIBIT 2 (continued)

Forecasting Skill	Market Timing						Factor Timing							
	$\alpha$	$\beta_{\text{RMRF}}$	$\beta_{\text{SMB}}$	$\beta_{\text{HML}}$	$\gamma$	$R^2$	$\alpha$	$\beta_{\text{RMRF}}$	$\beta_{\text{SMB}}$	$\beta_{\text{HML}}$	$\gamma_{\text{RMRF}}$	$\gamma_{\text{SMB}}$	$\gamma_{\text{HML}}$	$R^2$
1-0.2-0.5	-22.89	0.98	0.50	0.50	0.98	0.59	-0.11	1.00	0.21	0.49	1.01	-0.59	-0.01	0.62
1-0.2-0.2	-43.70	0.94	0.49	0.50	0.90	0.61	0.79	0.99	0.20	0.19	1.00	-0.59	-0.62	0.69
0.8-1-1	73.31	0.88	0.50	0.50	0.76	0.63	-0.41	0.79	1.00	1.01	0.59	1.00	1.02	0.84
0.8-1-0.8	58.68	0.86	0.51	0.50	0.72	0.57	-0.64	0.80	1.01	0.80	0.60	1.00	0.61	0.70
0.8-1-0.5	37.27	0.83	0.50	0.50	0.66	0.54	-0.84	0.79	1.00	0.51	0.60	1.00	0.02	0.63
0.8-1-0.2	16.45	0.79	0.50	0.50	0.58	0.57	0.06	0.79	1.00	0.20	0.59	1.00	-0.60	0.69
0.8-0.8-1	58.14	0.87	0.50	0.50	0.73	0.57	-0.51	0.79	0.80	1.01	0.59	0.59	1.02	0.70
0.8-0.8-0.8	43.52	0.85	0.51	0.50	0.70	0.52	-0.74	0.80	0.80	0.80	0.60	0.60	0.61	0.59
0.8-0.8-0.5	22.10	0.81	0.50	0.50	0.64	0.49	-0.95	0.79	0.80	0.51	0.60	0.59	0.02	0.53
0.8-0.8-0.2	1.29	0.77	0.50	0.50	0.56	0.52	-0.05	0.79	0.79	0.20	0.59	0.59	-0.59	0.58
0.8-0.5-1	35.29	0.85	0.51	0.50	0.71	0.54	-0.97	0.80	0.51	1.01	0.60	0.01	1.02	0.63
0.8-0.5-0.8	20.67	0.83	0.51	0.50	0.68	0.50	-1.20	0.80	0.52	0.80	0.61	0.01	0.61	0.53
0.8-0.5-0.5	-0.75	0.80	0.51	0.50	0.62	0.47	-1.41	0.79	0.51	0.51	0.61	0.01	0.02	0.48
0.8-0.5-0.2	-21.56	0.76	0.50	0.49	0.54	0.49	-0.51	0.79	0.51	0.20	0.60	0.00	-0.59	0.52
0.8-0.2-1	13.27	0.83	0.50	0.50	0.67	0.57	-0.08	0.79	0.21	1.00	0.59	-0.59	1.01	0.69
0.8-0.2-0.8	-1.36	0.81	0.50	0.50	0.64	0.52	-0.31	0.79	0.21	0.80	0.60	-0.58	0.60	0.58
0.8-0.2-0.5	-22.77	0.78	0.50	0.50	0.57	0.49	-0.51	0.79	0.21	0.50	0.60	-0.59	0.01	0.52
0.8-0.2-0.2	-43.58	0.74	0.50	0.50	0.49	0.50	0.38	0.79	0.20	0.19	0.59	-0.59	-0.61	0.57
0.5-1-1	73.36	0.58	0.50	0.50	0.16	0.56	0.19	0.50	1.00	1.00	-0.00	0.99	1.01	0.76
0.5-1-0.8	58.74	0.56	0.51	0.50	0.12	0.51	-0.04	0.50	1.00	0.80	0.00	1.00	0.60	0.63
0.5-1-0.5	37.32	0.53	0.50	0.50	0.06	0.49	-0.24	0.50	1.00	0.50	0.00	0.99	0.01	0.57
0.5-1-0.2	16.51	0.49	0.50	0.50	-0.02	0.51	0.66	0.49	0.99	0.20	-0.00	0.99	-0.60	0.62
0.5-0.8-1	58.20	0.57	0.50	0.50	0.13	0.51	0.09	0.50	0.79	1.01	-0.01	0.59	1.01	0.63
0.5-0.8-0.8	43.57	0.55	0.50	0.50	0.10	0.47	-0.14	0.50	0.80	0.80	-0.00	0.59	0.60	0.53
0.5-0.8-0.5	22.16	0.52	0.50	0.50	0.04	0.45	-0.35	0.50	0.79	0.51	-0.00	0.59	0.01	0.48
0.5-0.8-0.2	1.35	0.48	0.50	0.50	-0.04	0.47	0.55	0.49	0.79	0.20	-0.01	0.58	-0.60	0.52
0.5-0.5-1	35.35	0.56	0.51	0.50	0.11	0.49	-0.37	0.50	0.51	1.00	0.00	-0.00	1.01	0.57
0.5-0.5-0.8	20.72	0.54	0.51	0.50	0.08	0.45	-0.60	0.50	0.51	0.80	0.01	0.01	0.60	0.48
0.5-0.5-0.5	-0.69	0.50	0.50	0.50	0.02	0.43	-0.81	0.50	0.51	0.50	0.01	0.00	0.01	0.43
0.5-0.5-0.2	-21.51	0.46	0.50	0.50	-0.06	0.45	0.09	0.49	0.50	0.19	0.00	-0.00	-0.60	0.48
0.5-0.2-1	13.33	0.53	0.50	0.50	0.07	0.51	0.52	0.49	0.20	1.00	-0.01	-0.60	1.00	0.62
0.5-0.2-0.8	-1.30	0.51	0.50	0.50	0.04	0.47	0.29	0.49	0.21	0.79	-0.00	-0.59	0.59	0.52
0.5-0.2-0.5	-22.71	0.48	0.50	0.50	-0.02	0.44	0.09	0.49	0.20	0.50	0.00	-0.60	-0.00	0.47
0.5-0.2-0.2	-43.53	0.44	0.49	0.50	-0.11	0.46	0.98	0.49	0.20	0.19	-0.01	-0.60	-0.62	0.53
0.2-1-1	73.31	0.28	0.50	0.50	-0.44	0.62	0.11	0.19	1.00	1.00	-0.60	1.00	1.00	0.83
0.2-1-0.8	58.69	0.26	0.51	0.50	-0.47	0.56	-0.12	0.20	1.01	0.79	-0.59	1.00	0.59	0.69
0.2-1-0.5	37.27	0.23	0.50	0.50	-0.54	0.53	-0.33	0.19	1.00	0.50	-0.59	1.00	0.00	0.62
0.2-1-0.2	16.46	0.19	0.50	0.50	-0.62	0.57	0.57	0.19	0.99	0.19	-0.60	1.00	-0.61	0.69
0.2-0.8-1	58.15	0.27	0.50	0.50	-0.47	0.56	0.00	0.19	0.80	1.00	-0.61	0.59	1.01	0.69
0.2-0.8-0.8	43.52	0.25	0.50	0.50	-0.50	0.51	-0.23	0.20	0.80	0.80	-0.60	0.60	0.60	0.58
0.2-0.8-0.5	22.11	0.22	0.50	0.50	-0.56	0.49	-0.43	0.19	0.80	0.50	-0.60	0.60	0.01	0.52
0.2-0.8-0.2	1.30	0.18	0.50	0.50	-0.64	0.52	0.46	0.19	0.79	0.19	-0.61	0.59	-0.61	0.58
0.2-0.5-1	35.30	0.25	0.51	0.50	-0.48	0.53	-0.46	0.20	0.51	1.00	-0.60	0.01	1.00	0.62
0.2-0.5-0.8	20.67	0.23	0.51	0.50	-0.52	0.49	-0.69	0.20	0.52	0.79	-0.59	0.01	0.59	0.52
0.2-0.5-0.5	-0.74	0.20	0.50	0.50	-0.58	0.47	-0.90	0.19	0.51	0.50	-0.59	0.01	0.00	0.47
0.2-0.5-0.2	-21.56	0.16	0.50	0.49	-0.66	0.49	-0.00	0.19	0.51	0.19	-0.60	0.01	-0.61	0.53
0.2-0.2-1	13.28	0.23	0.50	0.50	-0.53	0.57	0.43	0.19	0.21	0.99	-0.61	-0.59	0.99	0.68
0.2-0.2-0.8	-1.35	0.21	0.50	0.50	-0.56	0.52	0.20	0.19	0.21	0.79	-0.60	-0.58	0.58	0.57
0.2-0.2-0.5	-22.76	0.18	0.50	0.50	-0.62	0.49	-0.00	0.19	0.21	0.49	-0.60	-0.59	-0.01	0.52
0.2-0.2-0.2	-43.58	0.14	0.49	0.50	-0.70	0.51	0.89	0.19	0.20	0.19	-0.61	-0.59	-0.62	0.58

Note: The exhibit reports mean values of the coefficients obtained by performing two tests of market timing skill on simulated data for a range of forecasting ability. The portfolio manager is assumed to have forecasting ability in timing any of the three Fama-French factors. The first test is the standard test of market timing with a Henriksson-Merton timing variable ( $\tilde{r}_t = \alpha_{it} + \beta_{1it} \text{RMRF}_t + \beta_{2it} \text{SMB}_t + \beta_{3it} \text{HML}_t + \gamma_{it} \text{TIMING}_t + \epsilon_{it}$ ,  $t = 1, 2, \dots, T$ ), while the second test is a timing test with three factors to allow for timing of any of the three Fama-French factors ( $\tilde{r}_t = \alpha_{it} + \beta_{1it} \text{RMRF}_t + \beta_{2it} \text{SMB}_t + \beta_{3it} \text{HML}_t + \gamma_{1it} \text{TRMRF}_t + \gamma_{2it} \text{TSMB}_t + \gamma_{3it} \text{THML}_t + \epsilon_{it}$ ,  $t = 1, 2, \dots, T$ ). One thousand simulations were performed for each skill level combination as depicted in the exhibit. The factor returns were generated with means of 0.50, 0.17, and 0.43% for  $\text{RMRF}_t$ ,  $\text{SMB}_t$ , and  $\text{HML}_t$  and a correlation matrix shown in Exhibit 1 as retrieved from historical data. Skill level for each factor ranges from 0 (absolutely no ability) to 1 (perfect foresight). At a level of 0.5, the forecaster's ability is equivalent to an unbiased coin flip. Thus, a value of 0.6 indicates that the forecaster has a 60% chance of correctly calling the return of that factor for the next month. Values of  $\alpha$  are expressed in percent per month.



equation is misspecified. With misspecification it is not always clear which direction the bias will go for the estimated coefficients. However, in the case of a perfect timer of all factors, alpha will be positively biased if the estimated coefficients on the remaining variables are negative, that is, that  $\hat{\gamma}$  is smaller than its true value in the correctly specified equation. This can happen if the true value of the omitted coefficients are positive, while the correlation between the omitted variables and the remaining timing variable is negative. This is the case when the true process is a perfect market timer in all three factors. The multi-factor timing test correctly concludes that the manager has an exposure to all factors and also perfectly times all factors. It also estimates an inability for selection with a value of  $\hat{\alpha}$  equal to 0.

Let's now take a more varied case of 0.2–0.8–1. In this case, the manager is very poor at timing the market factor but actually quite good at timing the size and value factors. In this case, the standard technique measures a negative timing ability and again a very strong  $\hat{\alpha}$ . This occurs as described earlier, because the omitted coefficients are positive (i.e., the SMB and HML true timing coefficients are positive), and the correlation between the omitted factors are intuitively negative (i.e., the correlation between the SMB and HML timing factor and the market timing factor). The multi-factor timing technique, instead, measures correctly, perfect timing ability on the value factor, very good timing ability on the size factor, and negative timing ability on the market factor with an  $\hat{\alpha}$  equal to 0. Thus, the multi-factor timing factor estimation is able to accurately capture the true manager, while the standard technique does not. The results in other parts of the exhibit are similar. When the hedge fund manager is engaging in market timing across a broad set of factors, the multi-factor timing technique captures much more precisely the performance of the hedge fund manager.

Now that we have shown the use of such a tool for capturing the more detailed behavior of hedge fund managers, we examine actual hedge fund returns.

## DATA

The hedge fund data used for this article was obtained from HFR, one of the most extensive and reliable hedge fund databases for practitioners. It is also used by academics, but to a lesser extent than TASS. The data cover the period January 1970 to June 2009.

## Database Biases

There are many biases with any hedge fund database. This is also true for the HFR database. The main issue is that data collection procedures of hedge funds tend to introduce biases into the data. The most common biases are survivorship bias, selection bias, backfill bias, and reporting bias.

It is well known that the leading hedge fund databases, including HFR, did not collect information on disappearing funds prior to 1994. Thus, all data before 1994 is dropped from the analysis. Although all hedge fund databases may be subject to survivorship bias (Brown et al. [1992], Brown, Goetzmann, and Ibbotson [1999], Ackermann, McEnally, and Ravenscraft [1999]), some authors have argued that this bias might be larger in HFR (Liang [2000]). In this article, we collect data on live and dead funds in the HFR database to minimize the impact of survivorship bias and use both for our analysis on the timing ability of hedge funds.

The second type of bias is selection bias. Selection bias occurs due to the voluntary nature of hedge fund reporting. It is not clear which direction the bias may affect the databases. It could result in downward estimated returns if large hedge funds perform strongly, but do not report their performance during times they do not need to raise capital. Examples of this can be seen in some of the most successful hedge funds, which have never reported their performance to database providers, including Long-Term Capital Management (before the collapse), Goldman Sachs Alpha fund and Global Opportunities fund, AQR Capital, Renaissance Technologies, and various others. Conversely, an upward bias on measured hedge fund returns could result from poorly performing hedge funds that never report their performance to the hedge fund database. Finally, selection bias can be caused by the database providers themselves due to their screening criteria. For example, they may only collect and report the returns of hedge funds with a minimum assets under management.

Backfill bias occurs when a hedge fund database adds a new hedge fund in their database on a given date and backfills their performance before this date based on return data supplied by the hedge fund. With most of the premier databases, like HFR, this is not a problem, because they only report hedge fund returns on a going-forward basis.

Reporting bias can occur when a hedge fund reports an initial performance number that may be based on illiquid instruments or preliminary estimates of value but then later wishes to update this performance. For example, the HFR database allows the trailing four months of hedge fund performance to be revised if more accurate estimates become available. A more severe form of reporting bias occurs when hedge funds report a smoothed month-to-month performance, rather than their true performance. That is, when performance is very bad for a particular month, they might report a slightly smaller decrease in assets, and on a particularly good month, the hedge fund might report slightly lower increases, making performance look less volatile (Goetzmann et al. [2007] and Jagannathan and Korajczyk [1986]).

Despite these well-known biases, we use the HFR database to examine the market timing ability of hedge funds.

### Sample Statistics

As of June 2009, the HFR database contained a total of 10,007 hedge funds (excluding funds of funds of which there are 3,798). This is comprises 5,501 dead funds (of that

total, 2,766 are liquidated funds and 2,735 are nonreporting funds) and 4,506 live funds with the live funds comprising a total of US\$ 913.54 billion in assets under management. The HFR database has recently updated the definition of their categories. There are five broad categories and sub-categories within those: equity hedge,<sup>13</sup> event-driven,<sup>14</sup> macro,<sup>15</sup> relative value,<sup>16</sup> and fund of funds.<sup>17</sup>

We further reduce the data by eliminating funds that only report quarterly (97 funds were dropped), because we are using monthly returns in our performance analysis. We also dropped funds that did not have 36 consecutive months of data, because we felt that would be a minimum number of observations to run Newey–West corrected regressions. Unfortunately, a total of 3,516 funds were dropped due to this. Across fund categories, 52% were from equity hedge, 9% from event-driven, 21% from macro, and 18% from relative value. Of the funds that were dropped, 1,288 (or 37%) came from active funds. These consist of newer funds that have existed for less than three years. Another 1,190 (34%) came from liquidated funds and 1,038 (29%) came from non-reporting, but existing, funds.<sup>18</sup> Finally, we drop funds for which the performance numbers are missing or they do not have consecutive monthly return data (44 funds).<sup>19</sup> This leaves

## EXHIBIT 3

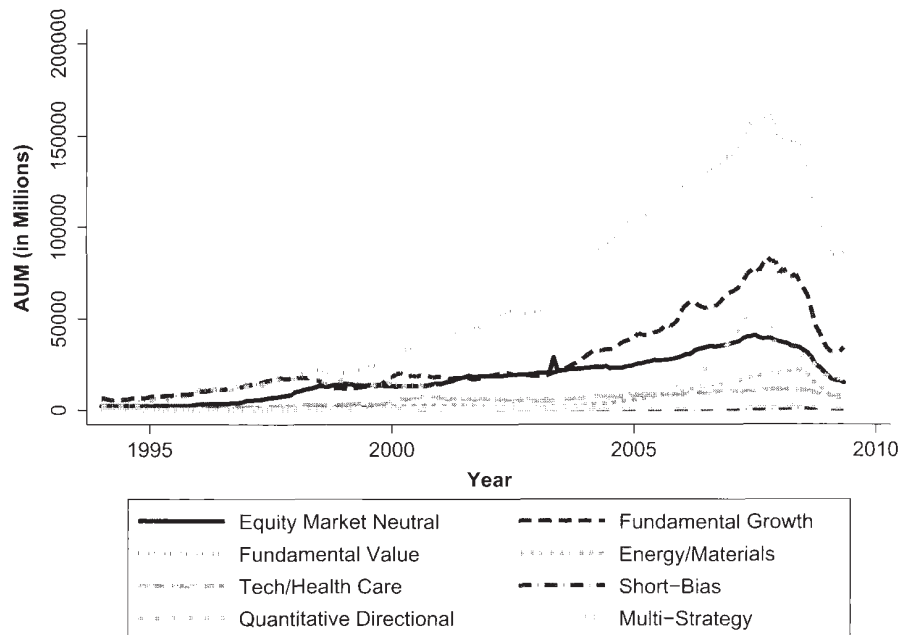
### Hedge Fund Database Characteristic Summary Statistics

Group	Total Number	Avg. Number	Avg. AUM	Avg. Growth	Avg. M. Fee	Avg. I. Fee	Avg. Age	High Water (%)	Hurdle Rate (%)
Equity Hedge	3,348	1,414.14	103.29	0.15	1.41	18.91	6.92	89.67	13.71
EH: Engy/Bmat	134	48.20	88.56	0.03	1.49	19.58	5.80	91.79	10.45
EH: EqMktNeu	472	188.17	111.39	0.19	1.39	19.18	6.50	87.50	22.67
EH: FndmtlGr	775	338.18	91.26	0.04	1.50	18.51	7.11	87.35	16.65
EH: FndmtlVal	1,337	582.12	113.78	0.25	1.38	19.24	6.99	94.02	9.80
EH: QuantDir	296	117.01	144.01	0.05	1.29	16.85	7.35	76.01	15.54
EH: Short Bias	43	20.97	25.30	0.05	1.24	18.54	8.98	81.40	4.65
EH: Tech/Hlth	235	94.27	60.46	0.03	1.38	19.58	6.43	93.19	10.21
EH: MultStrat	56	25.21	33.70	0.04	1.55	19.64	7.08	94.64	10.71
Live Funds	1,700	782.79	123.92	0.20	1.47	18.89	7.29	92.29	13.47
Dead Funds	1,648	631.35	75.53	0.08	1.33	18.92	6.54	86.95	13.96
All	6,352	2,699.83	125.45	0.11	1.49	18.95	7.02	88.27	12.96

Note: This exhibit reports the time-series averages of annual cross-sectional averages from January 1994 to June 2009, where applicable. Avg. Number is the average number of hedge funds across monthly observations, Avg. AUM represents the average assets under management across months in millions of dollars, Avg. Growth computes the average growth rate of new assets into the average hedge fund using the formula for monthly growth in flows as:  $g_t = \frac{\text{New Flows}_t}{\text{AUM}_{t-1}}$ , where  $\text{New Flows}_t = \text{AUM}_t - \text{AUM}_{t-1} \cdot (1 + r_{it})$ , where  $r_{it}$  is the net returns of fund  $i$  from  $t-1$  to  $t$ , Avg. M. Fee is the average management fee across hedge funds, Avg. I. Fee is the average incentive fee across hedge funds, Avg. Age is the average number of years of existence of a fund in a particular category, High Water (%) is the percentage of hedge funds in the database with a high water mark across funds and time, and Hurdle Rate (%) is the percentage of funds with a hurdle rate across funds and time.

## EXHIBIT 4

### Growth of Assets Under Management (AUM) of Equity Hedge Fund Strategies



Note: Each category's total assets are constructed from the values of individual hedge funds in the database.

Source: HFR.

a data set with a group of 6,353 hedge funds with about 53% from equity hedge, 10% from event-driven, 20% from macro, and 17% from relative value. Finally, we drop all observations before 1994 given the aforementioned issues with survivorship bias. We also drop all funds that are not in the equity hedge category. The final data set consists of a total of 3,348 equity hedge funds.

Exhibit 3 reports the summary statistics for all of the equity hedge fund data. The summary statistics are presented for both the live and dead equity hedge funds separately and together as well.

Exhibit 4 shows the growth in assets of the various equity hedge fund strategies for individual equity hedge funds contained in the database.<sup>20</sup>

#### Raw Performance Statistics

Exhibits 5 and 6 show the sample statistics averaged over each hedge fund in each category. Many of the hedge fund categories produce returns that are higher than the S&P 500.<sup>21</sup> However, the risk-adjusted return of

the hedge funds is much higher than both the bond and equity indices. The risk-adjusted returns of the average hedge fund is higher for every sub-category of equity hedge funds, except the short-bias category, when considering risk-adjusted measures that take into account skewness and kurtosis, that is, the Sortino, Omega, Calmar, and Sterling ratios. For example, the equity hedge category as a whole has an average Sortino ratio of 0.21 compared to the 0.16 of bonds and 0.09 of the S&P 500. This evidence is consistent with the average equity hedge fund providing a greater return per unit of risk when considering non-normal returns. The average returns in all equity hedge fund categories during the financial crisis were higher than the S&P 500.

#### EMPIRICAL RESULTS AT FUND INDEX LEVEL

Exhibit 7 and Exhibit 8 present the results from performing three sets of performance measurement tests on the hedge fund composites as constructed by HFR.<sup>22</sup> The Fama-French three-factor model  $\hat{\alpha}$ s indicate that all



## EXHIBIT 5

### Hedge Fund Database Performance Summary Statistics by Individual Fund

Group	Mean	S.D.	Max.	Min.	$\rho$	Risk-Adjusted Return Measures				
						Sharpe	Sortino	Omega	Calmar	Sterling
Equity Hedge	9.75	16.83	241.32	-90.78	0.35	0.47	0.21	1.38	4.56	6.61
EH: Engy/Bmat	13.12	22.37	101.73	-69.62	0.41	0.64	0.29	1.51	3.81	4.77
EH: EqMktNeu	6.05	8.18	36.16	-30.45	0.10	0.40	0.17	1.32	5.17	8.61
EH: FndmtlGr	10.73	21.44	172.20	-77.50	0.44	0.44	0.19	1.35	2.59	3.16
EH: FndmtlVal	9.21	14.81	97.61	-60.80	0.39	0.49	0.21	1.39	4.75	7.19
EH: QuantDir	12.27	21.58	241.32	-90.78	0.46	0.44	0.19	1.34	6.10	7.44
EH: Short Bias	3.27	23.18	66.01	-57.40	-0.58	0.04	0.02	1.04	0.95	1.12
EH: Tech/Hlth	12.68	20.38	107.01	-46.70	0.40	0.58	0.26	1.46	6.66	8.44
EH: MultStrat	11.12	16.02	61.80	-36.88	0.39	0.67	0.30	1.56	8.59	15.95
Live EH Funds	8.69	15.93	172.20	-90.78	0.38	0.44	0.19	1.35	3.18	4.04
Dead EH Funds	10.83	17.76	241.32	-84.31	0.33	0.50	0.22	1.40	6.28	9.83
Liquidated EH	8.83	16.69	241.32	-84.31	0.31	0.38	0.17	1.30	4.11	6.83
Not Reporting EH	12.91	18.88	122.46	-73.53	0.34	0.62	0.28	1.50	8.87	13.35
S&P 500 Index	7.49	15.54	9.78	-16.79	1.00	0.25	0.09	1.19	0.31	0.32
Bond Index	6.56	7.43	9.02	-6.71	-0.09	0.40	0.16	1.30	2.83	3.31

Note: This exhibit reports the averages across all hedge funds for various statistics. Mean is the average return of all the individual hedge funds' average monthly returns annualized by multiplying by 12. S.D. is the average standard deviation of the individual hedge funds' standard deviations of returns over the period annualized by multiplying by  $\sqrt{12}$ . Max. and Min. are the maximum (minimum) monthly return of any hedge fund over the period.  $\rho$  represents the correlation of the averaged series over time with the S&P 500 returns. The Risk-Adjusted measures are the standard Sharpe ratio,  $\text{Sharpe} = \frac{\bar{r}_h - \bar{r}_m}{\sigma_r}$ , the Sortino ratio is given by  $\text{Sortino} = \frac{\bar{r}_h - \bar{r}_m}{\text{LPM}_w(\tau)}$ , the Omega is given by  $\text{Omega} = \frac{\bar{r}_h - \bar{r}_m}{\text{LPM}_w(\tau)} + 1$ , where  $\text{LPM}_w(\tau) = \frac{1}{T} \sum_{t=1}^T [\max(\tau - r_t, 0)]^w$ . The latter two are similar to the Sharpe ratio but use downside-risk measures rather than variance. The Calmar ratio is given by  $\text{Calmar} = \frac{\bar{r}_h - \bar{r}_m}{-\text{MD}_{1t}}$ , and the Sterling ratio is given by  $\text{Sterling} = \frac{\bar{r}_h - \bar{r}_m}{\sum_{i=1}^N -\text{MD}_{it}}$ , where  $\text{MD}_{1t}$  is the maximum drawdown of the fund from peak to trough during the existence of the fund in percentage terms,  $\text{MD}_{2t}$  is the next largest drawdown of the fund in percentage terms, and so on. In the case of the Sterling measure, we take  $N = 4$  to represent the four largest drawdowns for the fund during the period of concern. The drawdowns are computed by creating an index series of the fund based on net returns. S&P 500 total return data and the 10-year Treasury bond total return data were obtained from Global Financial Data.

of the hedge fund categories have positive and significant  $\hat{\alpha}$ s, except for the short-bias category. This is also true when we estimate the Fama–French three-factor model with the Henriksson–Merton timing variable. However, the market timing coefficient,  $\hat{\gamma}$ , is either negative or insignificant for all hedge fund indices. This is a quite common finding in market timing literature for mutual funds (Chang and Lewellen [1984] and Ferson and Schadt [1996]).

With the multiple-factor timing model, we find similarly that the timing coefficient on the market ( $\hat{\gamma}_{\text{RMRF}}$ ) is negative or insignificant for all hedge fund categories. The timing coefficient on size ( $\hat{\gamma}_{\text{SMB}}$ ) is insignificant for most equity hedge fund categories, however it is positive and significant for several categories, including the main equity hedge strategy and the sub-strategy of technology and health care. The timing coefficient on value ( $\hat{\gamma}_{\text{IMV}}$ ) is insignificant for

most equity hedge funds but positive and statistically significant for the main strategy of equity hedge as well as that of equity market neutral.

Thus, preliminary evidence on the HFR composites suggests that some of the fund indices that appear to have no market timing ability with respect to the market factor seem to have timing ability for other risk factors. In the next section, we examine the timing characteristics of individual hedge funds in more detail.

## EMPIRICAL RESULTS AT INDIVIDUAL FUND LEVEL

### Methodology

In this section, we produce performance measurement estimates for individual hedge funds in various

## EXHIBIT 6

### Hedge Fund Database Performance Summary Statistics by Individual Funds

	Mean Returns					Non-Normality		
	Up	Down	90-00	00-09	07-09	Skewness	Kurtosis	Jarque-Bera
Equity Hedge	24.68	-15.43	25.81	6.17	-0.94	-0.14	5.42	103.34
EH: Engy/Bmat	33.3	-21.39	18.9	12.26	-2.43	-0.26	5.31	55.59
EH: EqMktNeu	8.31	2.08	12.7	4.95	1.26	-0.23	5.31	80.42
EH: FndmtlGr	32.46	-25.66	26.98	6.5	-1.47	-0.16	5.62	161.05
EH: FndmtlVal	23.33	-13.79	28.61	6.77	-2.16	-0.16	5.43	78.03
EH: QuantDir	32.97	-28.82	21.52	1.75	-2.28	-0.1	5.04	84.8
EH: Short Bias	-27.42	59.22	-5.21	8.55	13.8	0.14	4.84	63.65
EH: Tech/Hlth	33.76	-20.86	49.66	3.64	2.67	0.2	4.99	78.31
EH: MultStrat	24.63	-10.26	24.95	9.73	4.15	-0.28	7.98	449.83
Live EH Funds	24.07	-15.97	30.29	7.89	-0.84	-0.24	5.42	90.2
Dead EH Funds	25.3	-14.88	24.04	4.1	-1.22	-0.05	5.42	116.9
S&P 500 Index	39.46	-47.99	22.25	-1.83	-12.93	-0.66	3.88	193.7
Bond Index	5.6	8.23	5.68	7.12	7.96	0.16	4.18	11.56

Note: This exhibit reports the average returns of individual fund returns over the entire sample period. Mean returns are the average return of all the individual hedge funds average monthly returns annualized by multiplying by 12 for the given period. Skewness is a measure of skewness of the sample distribution of fund returns, Kurtosis is a measure of kurtosis of the sample distribution, and Jarque-Bera reports the average Jarque-Bera test statistic for the normality of the fund returns across hedge funds. The S&P 500 total return series is only available from January 1980 in our hedge fund database, hence the missing value for the 1970-1980 decade.

## EXHIBIT 7

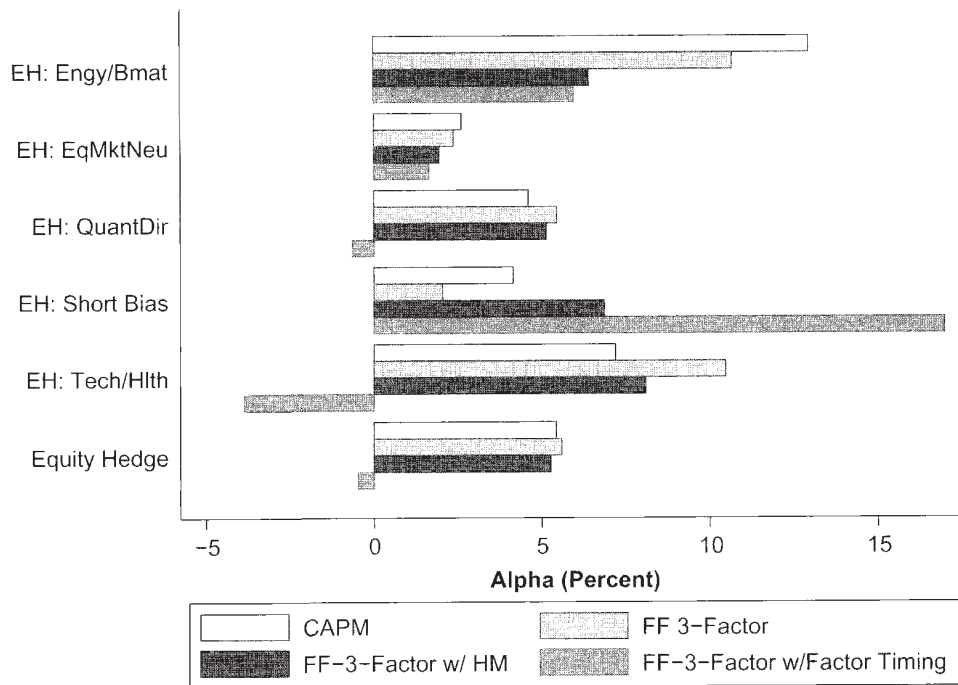
### Test of Performance at Index Level

Strategy	Fama-French 3-Factor					Fama-French 3-Factor w/Timing						Fama-French 3-Factor w/Multifactor Timing							
	$\alpha$	$\beta_{RMRF}$	$\beta_{SMB}$	$\beta_{HML}$	$\bar{R}^2$	$\alpha$	$\beta_{RMRF}$	$\beta_{SMB}$	$\beta_{HML}$	$\gamma$	$\bar{R}^2$	$\alpha$	$\beta_{RMRF}$	$\beta_{SMB}$	$\beta_{HML}$	$\gamma_{RMRF}$	$\gamma_{SMB}$	$\gamma_{HML}$	$\bar{R}^2$
Equity Hedge	0.47	0.47	0.09	-0.01	0.69	0.44	0.48	0.09	-0.01	0.01	0.69	-0.04	0.41	0.25	0.11	-0.10	0.28	0.27	0.73
	3.55	12.21	1.14	-0.18	3.05	7.95	1.14	-0.17	0.21			-0.18	8.62	2.96	1.71	-1.36	1.72	1.83	
EH: Engy/Bmat	0.89	0.61	0.14	0.39	0.26	0.53	0.71	0.15	0.40	0.18	0.26	0.50	0.71	0.18	0.39	0.19	0.06	-0.04	0.25
	2.45	7.63	1.39	3.49	0.87	4.19	1.44	3.55	0.72			0.71	4.05	0.90	1.97	0.69	0.19	-0.10	
EH: EqMktNeu	0.20	0.05	0.00	0.04	0.06	0.16	0.06	0.00	0.04	0.01	0.05	0.14	0.05	-0.03	0.10	-0.01	-0.06	0.12	0.06
	3.08	3.62	0.05	2.05	1.51	2.05	0.08	2.08	0.41			1.14	1.66	-0.80	2.83	-0.22	-1.07	1.98	
EH: QuantDir	0.45	0.69	0.20	-0.10	0.83	0.43	0.70	0.20	-0.10	0.01	0.83	-0.05	0.64	0.43	-0.07	-0.07	0.39	0.10	0.85
	4.03	12.31	1.80	-1.59	1.91	7.79	1.79	-1.57	0.12			-0.17	7.50	4.58	-0.86	-0.48	1.82	0.81	
EH: Short Bias	0.17	-0.87	-0.12	0.34	0.68	0.57	-1.00	-0.13	0.33	-0.21	0.68	1.41	-0.91	-0.54	0.29	-0.08	-0.71	-0.14	0.71
	0.80	-8.82	-0.61	4.27	1.87	-9.28	-0.64	4.37	-1.37			3.30	-8.09	-4.21	2.31	-0.46	-3.67	-0.61	
EH: Tech/Hlth	0.87	0.68	0.04	-0.56	0.65	0.67	0.74	0.04	-0.56	0.11	0.65	-0.32	0.62	0.45	-0.41	-0.10	0.70	0.39	0.70
	3.27	10.10	0.24	-7.44	2.08	6.99	0.26	-7.44	0.79			-0.63	6.56	2.44	-4.01	-0.54	1.74	1.53	

Note: This exhibit reports the time-series averages of hedge fund composites as computed by HFR from January 1994-June, 2009. This exhibit shows the abnormal return of HFR hedge fund indices from January 1970 to July 2009. The results are from the following ordinary least squares (OLS) regressions with standard errors corrected by the Newey-West [1997] procedure with  $\text{round}\left[4\left(\frac{n}{100}\right)^{2/5}\right]$  lags:  $\tilde{r}_t = \alpha + \sum_{i=1}^K \beta_i r_{i,t} + \gamma Z_t + \epsilon_t$ , where  $\tilde{r}_t$  is the return from  $t-1$  to  $t$  of fund  $i$  minus the risk-free rate,  $K = 1, 3$ , or 4 depending on which model is used, the CAPM, the Fama-French three-factor, or the Fama-French four factor with momentum,  $Z_t$  equals  $\max(0, -|r_{M,t} - r_{f,t}|)$  for the Henriksson-Merton model, and  $\text{TRMRF}_t = \max(0, -|r_{M,t} - r_{f,t}|)$ ,  $\text{TSMB}_t = \max(0, -\text{SMB}_t)$ , and  $\text{THML}_t = \max(0, -\text{HML}_t)$  for the Multiple Factor Timing model.  $\epsilon_t$  is the residual. The  $t$ -statistics of the estimates are presented below the coefficient estimates.

## EXHIBIT 8

The  $\alpha$ s for Various Hedge Fund Categories for Various Model Specifications from January 1994 to June 2009



Note: The  $\alpha$ s are annualized in percent.

fund categories with and without timing measures. In all of our exhibits, the performance measures are produced by linear regressions of individual hedge fund monthly returns against the respective factor model. For every hedge fund, we apply tests of heteroscedasticity and auto serial correlation on the errors with up to four lags using the Breusch–Pagan [1979] test and the Breusch [1978]–Godfrey [1978] test, respectively. In cases where the hypothesis of no heteroscedasticity or no autocorrelation is rejected, the standard errors are corrected by the Newey–West [1987] correction procedure with a number of lags computed according to the suggestion of Newey–West,  $\text{lags} = \text{round}[4(\frac{n}{100})^{2/9}]$ , where round is a function that rounds to the nearest integer and  $n$  is the number of monthly observations for each hedge fund.

After the regressions are run on each fund individually, we average the coefficients across hedge funds for each hedge fund category and report those. We also report the average  $t$ -statistics for each parameter and report the percentage of funds with positive  $t$ -statistics. The average  $t$ -statistics should not be used to make inferences about the average coefficient estimates, since another measure is

needed to make such inference, which we do not report in this article but is available from the authors.<sup>23</sup>

### Tests without Timing

Before examining the timing results in detail, we report the non-timing average  $\hat{\alpha}$ s for each fund category using the CAPM, the three-factor Fama–French, and four-factor Fama–French model. The results are contained in Exhibit 9.

The equity hedge category contains 3,348 different funds over the period. The  $\hat{\alpha}$  for the CAPM regressions is positive at 0.43% per month with 31% of the funds having a positive and significant  $\hat{\alpha}$ . The  $\hat{\alpha}$  for the three-factor regressions is 0.42% with 29% of the hedge funds having a positive and significant  $\hat{\alpha}$ . Finally, the four-factor average  $\hat{\alpha}$  is 0.37% per month with 29% of the funds having a positive and significant  $\hat{\alpha}$ .

The other sub-categories of equity hedge funds also have positive average  $\hat{\alpha}$ s. The live equity hedge funds have an  $\hat{\alpha}$  that is almost 2.5 times as large as the dead funds  $\hat{\alpha}$  for the four-factor Fama–French model.

## EXHIBIT 9

### Non-Timing-Based Tests of Performance

Strategy	N	CAPM			Fama-French 3-Factor					Fama-French 4-Factor					
		$\alpha$	$\beta$	$\bar{R}^2$	$\alpha$	$\beta_{RMRF}$	$\beta_{SMB}$	$\beta_{HML}$	$\bar{R}^2$	$\alpha$	$\beta_{RMRF}$	$\beta_{SMB}$	$\beta_{HML}$	$\beta_{MOM}$	$\bar{R}^2$
Equity Hedge	3,348	0.43	0.47	0.24	0.42	0.48	0.08	-0.02	0.28	0.37	0.51	0.08	0.00	0.08	0.32
		1.08	3.91	1.01	3.84	0.62	0.10	0.96	3.93	0.62	0.22	0.83			
		0.31	0.71	0.29	0.71	0.22	0.19	0.29	0.73	0.23	0.20	0.31			
EH: Engy/Bmat	134	0.86	0.67	0.24	0.82	0.73	-0.00	-0.06	0.27	0.77	0.78	-0.01	0.03	0.19	0.31
		1.43	4.00	1.40	3.94	-0.06	-0.20	1.35	4.12	-0.11	0.10	1.18			
		0.32	0.81	0.34	0.83	0.08	0.15	0.34	0.82	0.09	0.15	0.31			
EH: EqMktNeu	472	0.23	0.06	0.07	0.19	0.08	0.01	0.03	0.12	0.16	0.10	0.01	0.04	0.07	0.17
		0.99	1.01	0.86	1.12	0.16	0.17	0.80	1.44	0.14	0.31	1.09			
		0.26	0.29	0.25	0.28	0.13	0.17	0.24	0.35	0.14	0.19	0.38			
EH: FndmtlGr	775	0.47	0.68	0.27	0.47	0.71	0.05	-0.06	0.31	0.41	0.74	0.06	-0.03	0.10	0.34
		1.01	4.75	1.00	4.67	0.59	-0.23	0.93	4.70	0.61	-0.11	0.92			
		0.29	0.86	0.28	0.86	0.23	0.13	0.27	0.88	0.24	0.13	0.29			
EH: FndmtlVal	1,337	0.44	0.44	0.25	0.39	0.44	0.09	0.03	0.29	0.35	0.47	0.09	0.05	0.06	0.33
		1.19	4.19	1.04	4.21	0.78	0.40	1.01	4.26	0.79	0.49	0.69			
		0.36	0.75	0.32	0.76	0.25	0.23	0.32	0.78	0.26	0.25	0.30			
EH: QuantDir	296	0.21	0.74	0.34	0.29	0.71	0.26	-0.01	0.40	0.26	0.73	0.26	0.01	0.06	0.43
		0.53	6.18	0.51	5.93	1.34	0.64	0.46	6.03	1.31	0.71	0.69			
		0.19	0.83	0.18	0.79	0.35	0.26	0.17	0.79	0.35	0.27	0.27			
EH: Short Bias	43	0.45	-1.06	0.44	0.24	-0.97	-0.33	0.19	0.50	0.33	-0.99	-0.35	0.18	-0.05	0.52
		0.77	-7.98	0.54	-7.21	-1.17	1.01	0.67	-7.46	-1.31	1.07	-0.32			
		0.16	0.00	0.14	0.00	0.05	0.37	0.26	0.00	0.07	0.42	0.19			
EH: Tech/Hlth	235	0.56	0.63	0.25	0.74	0.54	0.08	-0.29	0.30	0.61	0.58	0.10	-0.26	0.14	0.34
		1.25	4.64	1.44	3.75	0.57	-1.17	1.34	3.86	0.63	-1.08	1.00			
		0.33	0.80	0.41	0.77	0.19	0.04	0.36	0.79	0.22	0.05	0.34			
EH: MultStrat	56	0.74	0.41	0.24	0.72	0.44	0.03	-0.10	0.26	0.73	0.46	0.04	-0.07	0.05	0.29
		1.88	3.78	1.81	4.20	0.46	-0.33	1.91	4.23	0.53	-0.19	0.63			
		0.48	0.79	0.48	0.77	0.18	0.16	0.48	0.77	0.20	0.13	0.32			
Live EH Funds	1,700	0.55	0.44	0.25	0.53	0.47	-0.00	-0.10	0.29	0.52	0.50	0.00	-0.07	0.08	0.33
		1.38	4.11	1.36	4.26	0.29	-0.36	1.36	4.36	0.32	-0.16	1.04			
		0.39	0.73	0.37	0.74	0.16	0.14	0.38	0.78	0.16	0.15	0.35			
Dead EH Funds	1,648	0.30	0.50	0.22	0.30	0.49	0.15	0.07	0.28	0.22	0.51	0.16	0.08	0.08	0.31
		0.77	3.70	0.65	3.41	0.96	0.58	0.55	3.50	0.94	0.61	0.61			
		0.23	0.70	0.21	0.68	0.30	0.24	0.20	0.68	0.30	0.24	0.26			

Note: This exhibit shows the abnormal returns of individual hedge funds from January 1994 to July 2009. The results are obtained from the following ordinary least squares (OLS) regressions with standard errors corrected by the Newey–West [1997] procedure with  $\text{round}[\frac{4}{\sqrt{N}}]^{259}$  lags:  $\tilde{r}_i = \alpha + \sum_{j=1}^K \beta_j r_{i,t-j} + \varepsilon_i$ , where  $\tilde{r}_i$  is the return from  $t-1$  to  $t$  of fund  $i$  minus the risk-free rate,  $K = 1, 3$ , or  $4$  depending on which model is used, the CAPM, the Fama–French three-factor, or the Fama–French four factor with momentum, and  $\varepsilon_i$  is the residual. After each fund's regression has been estimated, the parameters for each category are averaged and reported in the exhibit along with the average  $t$ -statistics and the percentage of funds with a positive and significant  $t$ -statistic.

### Timing Tests Based on the Fama–French Three-Factor Model

In this section, we investigate the timing issue using a three-factor Fama–French model. Exhibits 10 and 11 contain the results of our analysis. The standard HM measure finds average negative timing ability for the equity hedge category and for most of its sub-categories. The GII measure also finds negative timing ability for almost all equity hedge fund categories.

The multi-factor timing model (Exhibit 11) finds average negative market timing ability for almost all equity hedge fund categories, just as the standard HM

measure does. This model finds that the average size timing measure ( $\hat{\gamma}_{SMB}$ ) is positive for the main equity hedge fund category and for every one of the equity hedge sub-categories except for the short-bias category. The highest average estimate for size timing is for the quantitative directional strategy and the technology/health care strategy with average  $\hat{\gamma}_{SMB}$  equal to 0.30 and 0.49 respectively and with 15% and 22% of the funds in that category having positive and significant coefficients. It makes sense that the quantitative directional has higher timing ability than other funds, given that they change net long and short exposures over the business cycle. The average value timing coefficient ( $\hat{\gamma}_{HML}$ ) is positive

# EXHIBIT 10

## Timing Tests Based on Fama–French Three Factor Model

Strategy	N	Henrikson-Merton						GII					
		$\alpha$	$\beta_{\text{RMRF}}$	$\beta_{\text{SMB}}$	$\beta_{\text{HML}}$	$\gamma$	$\bar{R}^2$	$\alpha$	$\beta_{\text{RMRF}}$	$\beta_{\text{SMB}}$	$\beta_{\text{HML}}$	$\gamma$	$\bar{R}^2$
Equity Hedge	3,348	0.50	0.45	0.08	-0.02	-0.05	0.29	1.13	0.39	0.08	-0.05	-0.07	0.30
		0.75	1.96	0.62	0.09	-0.08		1.13	2.67	0.62	-0.03	-0.70	
		0.20	0.52	0.22	0.19	0.08		0.36	0.58	0.22	0.17	0.06	
EH: Engy/Bmat	134	1.03	0.63	0.02	-0.07	-0.13	0.28	2.16	0.52	0.06	-0.17	-0.14	0.30
		1.07	1.96	-0.03	-0.22	-0.23		1.81	2.53	0.09	-0.38	-1.22	
		0.25	0.54	0.10	0.13	0.04		0.47	0.60	0.10	0.12	0.01	
EH: EqMktNeu	472	0.18	0.08	0.01	0.03	0.02	0.13	0.40	0.05	0.02	0.02	-0.02	0.14
		0.58	0.65	0.16	0.15	0.01		0.79	0.72	0.20	0.10	-0.41	
		0.15	0.23	0.13	0.17	0.08		0.28	0.26	0.13	0.18	0.09	
EH: FndmtlGr	775	0.65	0.65	0.05	-0.06	-0.10	0.32	1.43	0.60	0.06	-0.09	-0.10	0.33
		0.80	2.33	0.58	-0.24	-0.13		1.33	3.21	0.55	-0.41	-0.92	
		0.21	0.60	0.22	0.14	0.08		0.40	0.71	0.22	0.11	0.03	
EH: FndmtlVal	1,337	0.44	0.42	0.09	0.03	-0.04	0.30	1.07	0.36	0.10	0.00	-0.07	0.32
		0.76	2.19	0.79	0.39	-0.07		1.15	2.97	0.82	0.25	-0.70	
		0.22	0.56	0.26	0.23	0.08		0.37	0.61	0.26	0.21	0.08	
EH: QuantDir	296	0.40	0.67	0.26	-0.01	-0.06	0.41	0.96	0.64	0.25	-0.03	-0.07	0.41
		0.44	3.03	1.31	0.62	-0.12		0.72	4.32	1.26	0.51	-0.48	
		0.12	0.62	0.34	0.27	0.09		0.23	0.69	0.32	0.23	0.07	
EH: Short Bias	43	0.45	-1.04	-0.34	0.18	-0.09	0.50	-0.06	-0.90	-0.33	0.18	0.08	0.52
		0.77	-4.47	-1.19	0.98	-0.44		0.33	-5.98	-1.31	1.00	-0.20	
		0.23	0.00	0.07	0.37	0.02		0.21	0.00	0.07	0.42	0.12	
EH: Tech/Hlth	235	0.69	0.56	0.08	-0.28	0.03	0.30	1.70	0.46	0.06	-0.31	-0.09	0.31
		0.92	1.92	0.56	-1.17	-0.00		1.17	2.61	0.48	-1.27	-0.54	
		0.25	0.53	0.19	0.04	0.06		0.36	0.62	0.20	0.04	0.06	
EH: MultStrat	56	0.81	0.38	0.03	-0.11	-0.08	0.28	1.35	0.35	0.05	-0.12	-0.06	0.28
		1.28	2.03	0.52	-0.35	0.00		1.87	2.86	0.52	-0.51	-0.96	
		0.46	0.45	0.20	0.16	0.13		0.55	0.52	0.14	0.11	0.05	
Live EH Funds	1,700	0.61	0.43	0.00	-0.10	-0.05	0.30	1.13	0.39	0.02	-0.13	-0.06	0.31
		1.05	2.08	0.30	-0.38	-0.15		1.54	3.03	0.33	-0.53	-0.91	
		0.27	0.55	0.16	0.14	0.08		0.46	0.64	0.16	0.12	0.06	
Dead EH Funds	1,648	0.38	0.46	0.15	0.06	-0.05	0.28	1.13	0.40	0.15	0.04	-0.09	0.29
		0.44	1.85	0.95	0.58	-0.01		0.71	2.29	0.92	0.48	-0.48	
		0.13	0.48	0.29	0.23	0.07		0.25	0.53	0.29	0.22	0.07	

Note: This exhibit shows the abnormal returns of individual hedge funds from January 1994 to July 2009. The results are from the following ordinary least squares (OLS) regressions with standard errors corrected by the Newey–West [1997] procedure with  $\text{round}[\frac{4(\frac{20}{100})^{2/3}}{100}]$  lags:  $\tilde{r}_{i,t} = \alpha + \sum_{j=1}^K \beta_j r_{j,t} + \gamma Z_i + \varepsilon_{i,t}$ , where  $\tilde{r}_{i,t}$  is the return from  $t-1$  to  $t$  of fund  $i$  minus the risk-free rate,  $K = 1, 3$ , or  $4$  depending on which model is used, the CAPM, the Fama–French three-factor, or the Fama–French four factor with momentum,  $Z_i$  equals  $\max(0, -[r_{M,t} - r_{f,t}])$  for the Henrikson–Merton model or  $[(\prod_{s \in \mathcal{E}} \max(1 + r_{M,s}, 1 + r_{f,s})) - 1] - r_{M,t}$  for the GII (Goetzmann, Ingersoll, and Iukovic) model, and  $\varepsilon_{i,t}$  is the residual. After each fund's regression has been estimated, the parameters for each category are averaged and reported in the exhibit along with the average  $t$ -statistics and the percentage of funds with a positive and significant  $t$ -statistic.

for many equity hedge fund sub-categories including the overall main category.

In all cases where there exists timing ability on factors other than the traditional market timing factor, the average  $\hat{\alpha}$  estimates from the multi-factor timing regressions are much smaller than those in the standard HM technique.<sup>24</sup> Most likely this reflects the misspecification of the standard estimation equation, which leads to higher average  $\hat{\alpha}$ s. This leads to an overemphasis on hedge fund selection ability versus factor timing ability.

Overall, the results seem to suggest that most equity hedge funds have poor ability to time the direc-

tion of the stock market; however, there are a minority group of equity funds able to time other risk factors in the economy such as whether small-cap stocks will outperform large-cap stocks or whether value stocks will outperform growth stocks.

### ON THE PERSISTENCE OF TIMING

In the previous sections, we have documented the ability for some hedge fund managers to time various risk factors in the economy. In this section, we examine more closely whether this factor timing ability is persistent. Our methodology is as follows. We construct



# EXHIBIT 11

## Timing Tests Based on Fama–French Three-Factor Timing Model

Strategy	N	Factor Timing							$\bar{R}^2$
		$\alpha$	$\beta_{\text{RMRF}}$	$\beta_{\text{SMB}}$	$\beta_{\text{HML}}$	$\gamma_{\text{RMRF}}$	$\gamma_{\text{SMB}}$	$\gamma_{\text{HML}}$	
Equity Hedge	3,348	0.24	0.42	0.17	-0.01	-0.09	0.18	0.03	0.30
		0.38	1.83	0.67	0.18	-0.18	0.37	0.06	
		0.14	0.49	0.21	0.16	0.07	0.13	0.09	
EH: Engy/Bmat	134	0.94	0.62	0.03	-0.00	-0.16	0.01	0.13	0.27
		0.82	1.83	0.08	-0.07	-0.20	0.12	-0.04	
		0.19	0.51	0.06	0.05	0.09	0.05	0.05	
EH: EqMktNeu	472	0.19	0.09	0.03	-0.05	0.04	0.05	-0.15	0.14
		0.52	0.64	0.20	-0.06	0.08	0.14	-0.26	
		0.15	0.20	0.10	0.09	0.09	0.11	0.06	
EH: FndmtlGr	775	0.24	0.61	0.18	0.00	-0.17	0.23	0.16	0.33
		0.29	2.15	0.76	0.14	-0.29	0.51	0.23	
		0.14	0.57	0.25	0.14	0.06	0.14	0.10	
EH: FndmtlVal	1,337	0.25	0.40	0.17	0.03	-0.07	0.15	-0.00	0.31
		0.39	2.04	0.77	0.40	-0.19	0.36	0.08	
		0.14	0.53	0.21	0.21	0.06	0.12	0.10	
EH: QuantDir	296	0.02	0.65	0.45	-0.01	-0.08	0.30	-0.02	0.42
		0.16	2.91	1.02	0.40	-0.17	0.35	-0.02	
		0.12	0.61	0.34	0.20	0.09	0.15	0.06	
EH: Short Bias	43	1.13	-1.13	-0.78	0.27	-0.21	-0.67	0.33	0.52
		1.19	-4.07	-1.59	0.44	-0.22	-0.89	-0.18	
		0.35	0.00	0.00	0.12	0.07	0.00	0.05	
EH: Tech/Hlth	235	-0.12	0.50	0.36	-0.22	-0.07	0.49	0.16	0.32
		0.14	1.68	1.08	-0.57	-0.26	0.80	0.22	
		0.12	0.50	0.32	0.04	0.06	0.22	0.14	
EH: MultStrat	56	0.68	0.38	0.13	-0.15	-0.07	0.18	-0.07	0.29
		0.88	1.92	0.68	-0.17	-0.12	0.45	-0.04	
		0.23	0.45	0.18	0.07	0.11	0.09	0.04	
Live EH Funds	1,700	0.45	0.41	0.07	-0.09	-0.08	0.14	0.05	0.31
		0.65	1.93	0.46	-0.09	-0.24	0.32	0.05	
		0.19	0.53	0.16	0.13	0.08	0.10	0.10	
Dead EH Funds	1,648	0.02	0.43	0.28	0.07	-0.09	0.22	0.01	0.29
		0.10	1.72	0.89	0.45	-0.12	0.42	0.07	
		0.10	0.45	0.27	0.19	0.06	0.16	0.08	

Note: This exhibit shows the abnormal returns of individual hedge funds from January 1994 to July 2009. The results are from the following ordinary least squares (OLS) regressions with standard errors corrected by the Newey–West [1997] procedure with  $\text{round}[\frac{1}{4}(\frac{K}{|m|})^{2/3}]$  lags:  $\tilde{r}_{it} = \alpha + \sum_{k=1}^K \beta_k r_{kt} + \gamma Z_t + \epsilon_{it}$ , where  $\tilde{r}_{it}$  is the return from  $t-1$  to  $t$  of fund  $i$  minus the risk-free rate,  $K = 1, 3$ , or  $4$  depending on which model is used, the CAPM, the Fama–French three-factor, or the Fama–French four factor with momentum, and  $\text{TRMRF}_t = \max(0, -[r_{M,t} - r_{f,t}])$ ,  $\text{TSMB}_t = \max(0, -\text{SMB}_t)$ , and  $\text{THML}_t = \max(0, -\text{HML}_t)$  for the Multiple Factor Timing model.  $\epsilon_{it}$  is the residual. After each fund's regression has been estimated, the parameters for each category are averaged and reported in the exhibit along with the average  $t$ -statistics and the percentage of funds with a positive and significant  $t$ -statistic.

estimation periods of 36 months starting at the beginning of the sample period and extending all the way to the period 36 months before the end of our sample in June 2009. For each 36-month period, we run a regression on each individual hedge fund using the three-factor Fama–French model including the three timing factors. We then store the estimates. Funds are then grouped

into deciles based on their timing coefficient. We do this procedure for each timing coefficient. Thus, for the timing coefficient on the market, we rank all funds by decile. We then create equal-weight portfolios of each decile and compute the monthly returns for the following one, three, six, and twelve months forward.

## EXHIBIT 12

### The Persistence of Timing

	$\gamma_{\text{RMRF}}$				$\gamma_{\text{SMB}}$				$\gamma_{\text{HML}}$			
	1	3	6	12	1	3	6	12	1	3	6	12
$\alpha$	0.51	-0.04	0.48	6.21	0.51	-0.04	0.49	6.22	0.51	-0.04	0.47	6.2
	2.45	-0.11	0.91	10.91	2.39	-0.1	0.75	5.68	2.41	-0.11	0.86	7.44
$\beta_{\text{RMRF}}$	-0.11	-0.14	-0.2	-0.82	-0.11	-0.14	-0.2	-0.83	-0.11	-0.14	-0.2	-0.82
	-2.48	-2.31	-2.42	-6.5	-2.37	-2.13	-1.77	-3.26	-2.51	-2.23	-2.21	-3.87
$\beta_{\text{SMB}}$	0.06	0.1	-0.22	-0.11	0.06	0.1	-0.22	-0.11	0.06	0.1	-0.21	-0.1
	1.44	1.51	-2.47	-1.25	1.43	1.44	-2.32	-1.27	1.44	1.49	-2.43	-1.22
$\beta_{\text{HML}}$	0.08	0.26	0.04	-1.51	0.08	0.26	0.04	-1.51	0.08	0.26	0.04	-1.51
	2.18	3.01	0.56	-10.03	2.17	3.09	0.5	-7.03	2.13	2.94	0.54	-7.85
$\hat{\gamma}_{\text{RMRF}}$	-0.1	-0.6	-0.43	-1.97	-0.14	-0.45	-0.31	-2.04	-0.14	-0.45	-0.3	-2.03
	-0.82	-1.79	-1.35	-3.88	-1.92	-3.13	-1.59	-4.16	-1.97	-3.27	-2	-5.07
$\hat{\gamma}_{\text{SMB}}$	0.08	0.25	-0.36	-1.51	0.19	0.43	-0.11	-1.23	0.08	0.25	-0.36	-1.5
	1.46	1.67	-1.8	-6.57	1.61	2.54	-0.38	-1.48	1.47	1.64	-1.82	-5.74
$\hat{\gamma}_{\text{HML}}$	0.06	0.41	0.51	-1.82	0.06	0.41	0.51	-1.82	0.17	0.56	0.91	-1.29
	0.95	3.08	3.84	-8.92	0.94	3.19	3.86	-7.14	1.22	2.36	3.62	-4.78
$D_i \times D_2$	-0.09	0.07	0.05	-0.08	-0.06	-0.07	-0.15	-0.08	-0.09	-0.11	-0.35	-0.45
	-0.63	0.2	0.13	-0.15	-0.52	-0.47	-0.59	-0.09	-0.59	-0.52	-1.22	-2.34
$D_i \times D_3$	-0.08	0.13	0.14	0.01	-0.11	-0.15	-0.22	-0.26	-0.11	-0.15	-0.42	-0.51
	-0.64	0.38	0.4	0.02	-0.98	-0.96	-0.87	-0.3	-0.78	-0.72	-1.34	-2.24
$D_i \times D_4$	-0.06	0.15	0.14	0.06	-0.12	-0.15	-0.26	-0.38	-0.08	-0.17	-0.39	-0.5
	-0.51	0.47	0.43	0.12	-1.05	-1.01	-1.08	-0.45	-0.59	-0.86	-1.32	-2.51
$D_i \times D_5$	-0.08	0.15	0.12	-0.02	-0.13	-0.14	-0.22	-0.28	-0.13	-0.18	-0.44	-0.58
	-0.67	0.46	0.37	-0.04	-1.11	-0.84	-0.87	-0.33	-0.94	-0.88	-1.59	-3
$D_i \times D_6$	-0.07	0.18	0.17	0.03	-0.14	-0.18	-0.26	-0.16	-0.11	-0.15	-0.49	-0.63
	-0.58	0.55	0.53	0.07	-1.22	-1.07	-1.07	-0.2	-0.81	-0.75	-1.55	-2.58
$D_i \times D_7$	-0.05	0.19	0.15	0	-0.16	-0.28	-0.36	-0.33	-0.1	-0.15	-0.47	-0.6
	-0.44	0.59	0.46	0	-1.42	-1.53	-1.42	-0.4	-0.77	-0.73	-1.6	-2.99
$D_i \times D_8$	-0.04	0.19	0.11	-0.19	-0.14	-0.28	-0.37	-0.4	-0.13	-0.23	-0.59	-0.76
	-0.34	0.58	0.34	-0.4	-1.17	-1.5	-1.42	-0.48	-0.89	-1.09	-1.76	-2.78
$D_i \times D_9$	0.01	0.3	0.23	-0.2	-0.15	-0.28	-0.32	-0.43	-0.11	-0.15	-0.46	-0.55
	0.06	0.89	0.68	-0.4	-1.19	-1.23	-1.14	-0.53	-0.75	-0.65	-1.34	-2.09
$D_i \times D_{10}$	0.01	0.19	0.16	-0.18	-0.13	-0.23	-0.41	-0.47	-0.21	-0.21	-0.43	-0.65
	0.04	0.51	0.43	-0.34	-0.87	-0.88	-1.2	-0.41	-1.29	-0.77	-1.04	-1.98
$N$	1,490	500	250	130	1,490	500	250	130	1,490	500	250	130
$\bar{R}^2$	0	0.02	0.02	0.55	0	0.02	0.02	0.44	0	0.02	0.03	0.5
$F$ -test	0.81	2.08	1.05	2	2.76	5.67	1.37	0.05	1.58	2.34	4.83	0.05
	0.18	0.08	0.15	0.08	0.05	0.01	0.12	0.41	0.1	0.06	0.01	0.42

Note: The exhibit contains estimates from the following procedure. We construct estimation periods of 36 months starting at the beginning of the sample period and extending all the way to the period 36 months before the end of our sample in June 2009. For each 36-month period, we run a regression on each individual hedge fund using the three-factor Fama–French model including the three timing factors. We then store the estimates and group the funds into deciles based on their timing coefficient. We do this procedure for each timing coefficient. Thus, for the timing coefficient on the market, we rank all funds by decile. We then create equal-weight portfolios of each decile and compute the returns for the following 1, 3, 6, 12, and 24 months. We then roll the period forward by 1, 3, 6, 12, or 24 months respectively and reestimate. With these equal-weighted decile returns, we re-run the regression on all of the deciles. We include 9 dummies for each timing factor for deciles 2–10. The results for each horizon (1, 3, 6, 12, and 24) and for each timing factor ( $\gamma_{\text{RMRF}}$ ,  $\gamma_{\text{SMB}}$ , and  $\gamma_{\text{HML}}$ ) are presented in the exhibit. The F-tests at the bottom of the exhibit are for the hypothesis that the timing factor + the first 4 deciles minus the last 5 deciles are equal to 0; that is,  $\gamma_t + \sum_{i=2}^5 D_i - \sum_{i=6}^{10} D_i = 0$ .

We then roll the period forward by one, three, six, or twelve months respectively and re-estimate.<sup>25</sup>

With these equal-weighted decile returns, we re-run the regression on all of the deciles. We include 9 dummies for each timing factor for deciles 2–10. The results for each horizon (1, 3, 6, and 12) and for each timing factor ( $\gamma_{RMRF}$ ,  $\gamma_{SMB}$ , and  $\gamma_{HML}$ ) are presented in Exhibit 12. The F-tests at the bottom of the exhibit are for the hypothesis that the timing factor plus the first 4 deciles minus the last 5 deciles are equal to 0.

The estimates of  $\gamma_{RMRF}$  for the top decile and other deciles are indistinguishable from 0 (compare estimates for  $\hat{\gamma}_{RMRF}$  with other deciles for the second through fifth columns). The F-test supports this for horizons from 1 to 12 months. Thus, for the entire group of equity hedge funds, there does not seem to be any persistence in timers of the market factor. One should remember, however, that there did not seem to be any timing ability for this factor anyway. It is still true, though, that the better timers (decile 10) have higher point estimates of the  $\gamma_{RMRF}$ .<sup>26</sup>

The estimates of  $\gamma_{SMB}$  reveal a similar pattern. There does not seem to be strong persistence in timing ability for the SMB factor for most individual deciles for all horizons (compare  $\gamma_{SMB}$  with the deciles in the sixth through ninth columns). However, at a horizon of three months,  $\hat{\gamma}_{SMB}$  is positive and significant suggesting a *reversal* in timing ability. That is, the equity funds with the lowest estimates of the SMB timing factor have higher estimates three months later.

The estimates of  $\gamma_{HML}$  reveal a similar pattern to the SMB timing factor. For hedge funds grouped together as a whole, at horizons of three and six months, there seem to be *reversals*. That is, higher decile timers on the HML factor are subsequently worse timers three and six months later (compare  $\hat{\gamma}_{HML}$  with other deciles in the tenth through thirteenth columns).

From this analysis, we conclude that generally, there does not seem to be timing persistence at any of the horizons for any of the timing factors. However, for the SMB and HML timing factor, it appears that there is *timing reversal* at the three- and six-month horizon. Lower decile timers begin to have better timing ability than higher deciles timers.

Exhibit 13 shows a table of timing transition matrices. This exhibit was constructed by computing the percentage of funds in decile 1–10 that remain in the same decile in the following regression period. Thus, if the horizon is one month, a multi-factor timing regression is run on each individual fund. Funds are then separated into deciles by their respective timing coefficient. The horizon is rolled forward by either one, three, six, twelve, or twenty-four months. The regression is estimated again. The exhibit produces the percentage of funds that were originally in each decile that remain in the same decile in the subsequent regression period over the entire sample period.

Generally, about 20% of funds remain in the same decile for a one-month horizon. This reduces drastically as the horizon extends. For example, for a 24-month

## EXHIBIT 13

### Timing Transition Matrices

	$\gamma_{RMRF}$					$\gamma_{SMB}$					$\gamma_{HML}$				
	1	3	6	12	24	1	3	6	12	24	1	3	6	12	24
$D_1$	20.90	12.76	11.85	9.63	9.58	21.40	12.84	11.24	10.61	9.06	20.51	13.08	11.93	9.67	8.14
$D_2$	18.05	11.83	10.56	12.54	10.71	18.32	12.32	10.65	10.56	11.62	17.21	11.71	11.05	10.08	8.11
$D_3$	16.35	12.37	10.61	8.94	10.39	15.94	11.81	10.80	9.94	10.78	15.64	11.58	9.91	10.40	10.06
$D_4$	16.34	11.25	10.07	9.16	7.05	15.53	11.48	10.29	10.02	10.19	15.44	10.48	10.23	11.65	11.08
$D_5$	15.25	10.50	10.33	7.58	8.23	14.46	10.84	9.46	9.65	8.57	15.16	11.01	11.42	10.98	11.04
$D_6$	15.21	11.12	11.43	10.24	10.26	15.90	10.93	10.34	11.81	11.31	16.06	10.57	10.10	9.70	9.05
$D_7$	15.50	10.91	10.70	9.29	10.55	15.87	11.89	9.59	9.75	9.94	15.46	10.23	10.89	10.45	7.66
$D_8$	16.11	11.44	11.56	9.35	10.86	16.87	11.64	10.34	10.06	11.51	16.03	11.29	9.50	8.83	9.66
$D_9$	17.38	12.71	10.03	8.85	9.66	17.91	12.49	9.69	11.08	13.37	17.51	10.82	9.78	8.89	9.67
$D_{10}$	21.29	13.49	11.88	9.27	11.92	21.50	13.94	11.36	10.06	10.84	19.68	13.35	11.72	8.54	10.94

Note: This exhibit represents the percentage of funds in any given decile for a prior three-year estimation period that continue to be in the same decile when the estimation period is rolled forward by the horizon length (1, 3, 6, 12 or 24 months).

horizon, this drops to around 10% for decile 1 for  $\gamma_{RMRF}$ . The pattern also suggests that funds with poor timing ability (decile 1) are more likely to remain poor timers and funds with good timing ability (decile 10) are more likely to remain good timers than funds in other deciles. For example, for a one-month horizon, the percentage that remain in decile 1 and 10 is 20.90% and 21.29% respectively for the market timing variable. This pattern is consistent across horizons and timing factors. The persistence in timing is stronger for quantitative directional, fundamental growth, energy and materials, and technology and health care hedge fund categories. Thus, from this perspective there seems to be a small amount of timing persistence over shorter horizons, say less than one year.

## CONCLUSION

Much research has been concerned with the question of whether portfolio managers have market timing ability going probably back as far as the early work of Cowles, but certainly well popularized by Merton and Henriksson in the 1980s. Less work has been done investigating the timing ability of hedge funds. Generally, the evidence has been overwhelmingly against market timing ability among mutual fund managers and mixed among the hedge fund managers. Presumably, one characteristic that sets hedge fund managers apart from mutual fund managers is their ability to invest with fewer restrictions and consequently take positions in a variety of risk factors. These more sophisticated strategies may lead to a more refined level of market timing. That is, rather than just timing the market, these managers might be involved in timing multiple factors. In this article we show that a standard market timing test fails to capture the actual patterns of a multiple factor timer and may actually lead erroneously to the conclusion that the manager has no timing ability when in fact he does. It may also lead to concluding that the manager has a much higher selection ability, as measured by  $\alpha$ , when in fact, he does not. We use this multi-factor timing test on a sample of equity hedge funds from 1994–2009 to determine whether hedge funds exhibit any timing ability on other factors. Generally, we find that equity hedge funds are poor market timers, but some equity hedge funds do have the ability to time other Fama–French factors like size and value. In particular, 13% of equity hedge funds have size timing ability, 9% have value timing ability, and 7%

have market timing ability. The average values, however are only positive for the size and value factor.

We also examined the persistence aspects of market timing. We measure persistence two ways. The first method ordered funds by their timing coefficients and ran regressions of performance 1, 3, 6, and 12 months later. For these regressions, we found that there were actually reversals in timing ability of various funds after three months for the value and size factors. That is, funds that had high coefficients on the value timing factor would have lower coefficients on the same factor relative to funds that had very low coefficients on these factors when measured 3 to 12 months later. The second method ranked funds by their timing coefficients and then re-ran the regressions 1, 3, 6, and 12 months later and computed which of the top decile funds remained in their same decile at the later date. The general tendency was that funds that were good timers of the value and size factors tended to remain good timers and funds that were bad timers tended to remain bad timers more than funds in the middle of the distribution.

## APPENDIX

### EQUITY HEDGE FUND CATEGORY DESCRIPTIONS IN THE HFR DATABASE

**Equity Hedge (Total):** Equity hedge (EH) strategies maintain positions both long and short in primarily equity and equity derivative securities. A wide variety of investment processes can be employed to arrive at an investment decision, including both quantitative and fundamental techniques; strategies can be broadly diversified or narrowly focused on specific sectors and can range broadly in terms of levels of net exposure, leverage employed, holding period, concentrations of market capitalizations, and valuation ranges of typical portfolios. EH managers would typically maintain at least 50%, and may, in some cases, be substantially entirely invested in equities, both long and short. EH is further subdivided into 7 sub-strategies:

**EH: Energy/Basic Materials** strategies employ investment processes designed to identify opportunities in securities in specific niche areas of the market in which the manager maintains a level of expertise which exceeds that of a market generalist in identify companies engaged in the production and procurement of inputs to industrial processes, and implicitly sensitive to the direction of price trends as determined by shifts in supply and demand factors, and implicitly sensitive to the direction of broader economic trends. Energy/basic

materials strategies typically maintain a primary focus in this area or expect to maintain in excess of 50% of portfolio exposure to these sectors over a various market cycles.

***EH: Equity Market Neutral*** strategies employ sophisticated quantitative techniques of analyzing price data to ascertain information about future price movement and relationships between securities, select securities for purchase and sale. These can include both factor-based and statistical arbitrage/trading strategies. Factor-based investment strategies include strategies in which the investment thesis is predicated on the systematic analysis of common relationships between securities. In many, but not all cases, portfolios are constructed to be neutral to one or multiple variables, such as broader equity markets in dollar or beta terms, and leverage is frequently employed to enhance the return profile of the positions identified. Statistical arbitrage/trading strategies consist of strategies in which the investment thesis is predicated on exploiting pricing anomalies that may occur as a function of expected mean reversion inherent in security prices; high frequency techniques may be employed and trading strategies may also be employed on the basis on technical analysis or opportunistically to exploit new information the investment manager believes has not been fully, completely or accurately discounted into current security prices. Equity market neutral strategies typically maintain characteristic net equity market exposure no greater than 10% long or short.

***EH: Fundamental Growth*** strategies employ analytical techniques in which the investment thesis is predicated on assessment of the valuation characteristics on the underlying companies, which are expected to have prospects for earnings growth and capital appreciation exceeding those of the broader equity market. Investment theses are focused on characteristics of the firms' financial statements in both an absolute sense and relative to other similar securities and, more broadly, market indicators. Strategies employ investment processes designed to identify attractive opportunities in securities of companies which are experiencing or expected to experience abnormally high levels of growth compared with relevant benchmarks growth in earnings, profitability, sales, or market share.

***EH: Fundamental value*** strategies employ investment processes designed to identify attractive opportunities in securities of companies which trade at valuation metrics by which the manager determines them to be inexpensive and undervalued when compared with relevant benchmarks. Investment theses are focused on characteristics of the firms' financial statements in both an absolute sense and relative to other similar securities and, more broadly, market indicators. Relative to fundamental growth strategies, in which earnings growth and capital appreciation are expected as a function of expanding market share and revenue increases, fundamental value strategies typically focus on equities which currently generate high cash flow but trade at discounted valuation

multiples, possibly as a result of limited anticipated growth prospects or generally out of favor conditions, which may be specific to sector or holding.

***EH: Quantitative directional*** strategies employ sophisticated quantitative analysis of price and other technical and fundamental data to ascertain relationships among securities and to select securities for purchase and sale. These can include both factor-based and statistical arbitrage/trading strategies. Factor-based investment strategies include strategies in which the investment thesis is predicated on the systematic analysis of common relationships between securities. Statistical arbitrage/trading strategies consist of strategies in which the investment thesis is predicated on exploiting pricing anomalies that may occur as a function of expected mean reversion inherent in security prices; high frequency techniques may be employed and trading strategies may also be employed on the basis on technical analysis or opportunistically to exploit new information the investment manager believes has not been fully, completely or accurately discounted into current security prices. Quantitative directional strategies typically maintain varying levels of net long or short equity market exposure over various market cycles.

***EH: Short-biased*** strategies employ analytical techniques in which the investment thesis is predicated on assessment of the valuation characteristics on the underlying companies with the goal of identifying overvalued companies. Short Biased strategies may vary the investment level or the level of short exposure over market cycles, but the primary distinguishing characteristic is that the manager maintains consistent short exposure and expects to outperform traditional equity managers in declining equity markets. Investment theses may be fundamental or technical in nature and manager has a particular focus, above that of a market generalist, on identification of overvalued companies and would expect to maintain a net short equity position over various market cycles.

***EH: Technology/healthcare*** strategies employ investment processes designed to identify opportunities in securities in specific niche areas of the market in which the manager maintains a level of expertise that exceeds that of a market generalist in identifying opportunities in companies engaged in all development, production, and application of technology, biotechnology and as related to production of pharmaceuticals and healthcare industry. Though some diversity exists as an across sub-strategy, strategies implicitly exhibit some characteristic sensitivity to broader growth trends, or in the case of the latter, developments specific to the healthcare industry. Technology/healthcare strategies typically maintain a primary focus in this area or expect to maintain in excess of 50% of portfolio exposure to these sectors over a various market cycles.

***EH: Multi-strategy*** investment managers maintain positions both long and short in primarily equity and equity derivative securities. A wide variety of investment processes



can be employed to arrive at an investment decision, including both quantitative and fundamental techniques; strategies can be broadly diversified or narrowly focused on specific sectors and can range broadly in terms of levels of net exposure, leverage employed, holding period, concentrations of market capitalizations and valuation ranges of typical portfolios. EH multi-strategy managers do not maintain more than 50% exposure in any one equity hedge sub-strategy.

## ENDNOTES

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<sup>1</sup>The most well-known studies are Fama and French [1993, 1996], Carhart [1997], Daniel et al. [1997] Elton et al. [1996], Grinblatt and Titman [1989, 1992], Hendricks et al. [1993], and Wermers [2000].

<sup>2</sup>The most familiar work being the original contributions of Treynor and Mazuy [1966] and Henriksson and Merton [1981]. However, numerous other studies have been produced, including Merton [1981], Henriksson [1984], Jagannathan and Korajczyk [1986], Ferson and Schadt [1996], Goetzmann, Ingersoll, and Ivkovich [2000], Bollen and Busse [2001], and Jiang, Yao, and Yu [2005].

<sup>3</sup>Bollen and Busse [2001], who employ daily return data, and Jiang, Yao, and Yu [2005], who employ portfolio holding data, find supportive evidence of timing ability in mutual funds. Their findings suggest that the measurement of timing ability may be sensitive to data frequency (see Goetzmann, Ingersoll, and Ivkovich [2000]) or data type.

<sup>4</sup>The one exception is Chan, Chen, and Lakonishok [2002] who study the other timing factors for mutual funds. They find no market timing ability of the factors for mutual funds.

<sup>5</sup>This builds on the work of Chen [2007] who found that it was more accurate to study a hedge fund's timing ability in its local market rather than with respect to some broad U.S. equity index.

<sup>6</sup>Fung and Hsieh [2001, 2004] and Agarwal and Naik [2004] argue that the standard linear-factor models, like the Fama-French model, may not be suitable for measuring the performance behavior of non-equity hedge funds. Thus, in this article we restrict our analysis to the study of hedge funds in the equity category making it more appropriate to use the Fama-French three and four-factor models for performance measurement.

<sup>7</sup>Source: [http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data\\_library.html](http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

<sup>8</sup>An alternative to the GII formulation is  $[\prod_{i \in I} \max(1 + [r_{M,i,t} - r_{f,i,t}], 1)] - 1$ , which assumes that the hedge fund manager borrows at the risk-free rate to invest in the market when its return is above the risk-free rate and does nothing on other days. The two measures are correlated.

<sup>9</sup>In theory, the portfolio manager does not need to liquidate the entire portfolio, they could simply engage in a position that effectively changes the  $\beta$  from 1 to 0.

<sup>10</sup>An interesting exercise would be to mathematically determine how this value changes depending on the frequency of market timing and the distribution of returns.

<sup>11</sup>This is the same equation as used in Chan, Chen, and Lakonishok [2002].

<sup>12</sup>Future work might attempt to determine the range of possible rational combinations so as to not violate the actual relationship between the factors. For example, if factor 1 and factor 2 are highly correlated, it might not be rational to have zero forecasting ability on factor 1 and perfect forecasting ability on factor 2.

<sup>13</sup>Sub-categories are energy/basic materials, equity market neutral, fundamental growth, fundamental value, quantitative directional, short bias, technology/health care, and multi-strategy.

<sup>14</sup>Sub-categories are activist, credit arbitrage, distressed/restructuring, merger arbitrage, private issue/regulation D, special situations, and multi-strategy.

<sup>15</sup>Sub-categories are active trading, commodity discretionary, commodity systematic, currency discretionary, commodity systematic, discretionary thematic, systematic diversified, and multi-strategy.

<sup>16</sup>Sub-categories are fixed income-asset backed, fixed income-convertible arbitrage, fixed income-corporate, fixed income-sovereign, volatility, yield alternatives, and multi-strategy.

<sup>17</sup>Sub-categories are conservative, diversified, market defensive, and strategy.

<sup>18</sup>In the appendix available from the authors on request, we report the summary statistics for the dropped funds.

<sup>19</sup>This can be for a variety of reasons. One of the most common reasons is that a fund begins reporting quarterly, but at a later date reports monthly. Thus, in the database, the fund is classified as a monthly reporter, even though for a portion of its existence it was a quarterly reporter.

<sup>20</sup>These calculations do not represent the assets of the entire equity hedge fund industry. They are just the aggregated values of asset levels of all funds in the database.

<sup>21</sup>In the appendix available from the authors on request, the same statistics are produced for equal-weighted hedge fund indices. These results are much better. Also contained in the

supplemental appendix are the summary statistics for equity hedge funds that were dropped from the sample either because they reported only quarterly returns or did not have 36 consecutive months of data. As compared with the funds that remained in the sample, the average returns of those that were dropped are lower than those retained (7.55% versus 9.75%).

<sup>22</sup> Indices do not exist for every hedge fund category to correspond with the individual hedge fund categories.

<sup>23</sup> To make some sense of the average value of the parameters, we construct the “average”  $t$ -statistic assuming that the coefficients of each fund are uncorrelated. If we are interested in the statistic,  $\bar{\hat{x}} = \frac{1}{N} \sum_{i=1}^N \hat{x}_i$ , then assuming normality from the central limit theorem and independence across parameter estimates, we can use  $s_{\bar{\hat{x}}} = \frac{1}{N} \sqrt{\sum_{i=1}^N s_{\hat{x}_i}^2}$ , where  $N$  is the number of hedge funds used in the average. The “average”  $t$ -statistic or the  $t$ -statistic of the average of the parameter across the hedge funds is given by  $t\text{-stat} = \frac{\bar{\hat{x}}}{s_{\bar{\hat{x}}}}$ . Although the assumptions used to create this statistic might not necessarily be true, it is not any worse than computing the average  $t$ -statistic, which is not really interpretable. Also, the number of funds in that category with positive  $t$ -statistics can be inferred by using the percentage information combined with the total of funds in that particular category, which is listed below the fund name.

<sup>24</sup> This can also be seen graphically in Exhibit 8.

<sup>25</sup> Another, perhaps more interesting method, would be to create portfolios of each timing factor by weighting hedge funds so as to achieve a zero exposure to all other factors. This would make each portfolio truly weighted on the timing factor.

<sup>26</sup> To get the additional value of the timing coefficient for any decile 2 to 10, one must add the coefficient on the dummy to the coefficient on the actual timing parameter.

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we discover that safety ranks help explain cross-sectional stock returns within optimistic timeliness ranks. The information complementarity between timeliness and safety ranks makes it advisable to formulate a better investment strategy by constructing cross-ranking portfolios to yield significant abnormal returns allowing for conventional risk factors and transaction costs.

**MEASURING HEDGE FUND TIMING ABILITY ACROSS FACTORS** 50

LUDWIG B. CHINCARINI AND ALEX NAKAO

There has been a substantial amount of research on whether mutual funds, and, to a lesser extent, hedge funds, have the ability to time the market. All of these studies have focused on market timing in the sense that they can correctly position their portfolios for a positive or negative movement in the main equity index. Since many hedge funds are sophisticated investors, one might believe that they engage in timing of more than just a single factor. This article tests this hypothesis directly by expanding the Henriksson–Merton timing factor to all of the Fama–French factors. The authors show in simulations that this may lead to incomplete inference about hedge fund timing ability. They also show, using a sample of equity hedge fund data for 1994–2009, that although many hedge funds are poor market timers, they have timing ability with respect to other risk factors in the economy. In particular, 13% of equity hedge funds have size timing ability, whereas 9% have value timing ability and 7% have market timing ability.

**THE “NEW CLASSIC” EQUITY ALLOCATION? A Discussion on the Implementation of the Global Equity Allocation and Evolving Mandate Structures** 71

FRANK NIELSEN, GIACOMO FACHINOTTI, AND XIAOWEI KANG

The recent financial crisis led many institutional investors to review their asset allocation policies and explore alternative approaches to implementation. MSCI recently held discussions around the world with major pension plans, asset

managers, and investment consultants to understand different approaches to implementing equity allocation. Following these consultations, the authors provide a framework for the implementation of global equity allocation. Our research suggests that global equity mandates, together with dedicated emerging market mandates and small-cap mandates, may be emerging as the “new classic” structure for implementing equity allocation. Investors who need to maintain a home bias can manage the domestic portfolio separately. Such a top-down mandate structure not only accrues benefits from the potential merits of an integrated global investment process, but accommodates segment-specific considerations on manager selection, legacy or mandatory home bias, and different risk and return drivers in various equity market segments.

**PORTFOLIO DIVERSIFICATION ACROSS CHARACTERISTICS** 84

ERIK HJALMARSSON

This article studies long–short portfolio strategies formed on seven different stock characteristics representing various measures of past returns, value, and size. Each individual characteristic results in a profitable portfolio strategy, but these single-characteristic strategies are dominated by a diversified strategy that places equal weight on each of the single-characteristic strategies. The benefits of diversifying across characteristic-based long–short strategies are substantial and can be attributed to the mostly low, and sometimes substantially negative, correlation between the returns on the single-characteristic strategies.

**CAN CHANGES IN THE PURCHASING MANAGERS’ INDEX FORETELL STOCK RETURNS? An Additional Forward-Looking Sentiment Indicator** 89

MARK A. JOHNSON AND KEVIN J. WATSON

This article studies whether the Purchasing Managers’ Index (PMI) can lend itself usefully to the forecasting of future stock returns. Utilizing time-series regression analyses, we find a positive relationship between changes in PMI