Which Hedge Fund Styles Hedge Against Bad Times?

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Abstract

We investigate an important question for institutional investors—namely, which hedge fund investing styles help to hedge against bad times? We define good versus bad times as (1) up and down equity market regimes derived from the 200-day moving average of the S&P 500 price index or (2) nonstressed and stressed financial market regimes determined endogenously using the Federal Reserve Bank of Kansas City Financial Stress Index and threshold estimation. Our findings reveal that only a few hedge fund styles limit or alter their risk exposures to provide valuable hedges against bad times; in contrast, other styles remain substantially exposed to—or become more exposed to—particular risk factors and correspondingly suffer large losses during bad times. In the context of "balanced" 40-30-30 portfolios that allocate across U.S. stocks, bonds, and individual hedge fund styles, we find that the Global Macro, Managed Futures, and Multi-Strategy styles provide large investors with especially valuable hedges against bad times.

JEL classification: C24, G11, G12, G23

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Hedge fund growth has been dramatic. With only $540 billion in assets under management (AUM) in 2001, hedge funds currently manage more than $2.5 trillion. Academic research on hedge funds has also grown dramatically during this time, from a limited number of extant studies in 2001 to a now voluminous literature. An important component of the hedge fund literature uncovers a diversity of relevant risk factors. For example, Asness, Krail, and Liew (2001) and Patton (2009) show that many hedge funds are exposed to aggregate equity market risk, including putatively "market neutral" funds. Building on Fung and Hsieh (1997), Fung and Hsieh (2001) develop unique trend-following risk factors for hedge fund styles that pursue dynamic strategies, while Fung and Hsieh (2002a,b, 2004) propose a broad array of asset-based style factors to account for the manifold risks faced by different hedge fund styles. Other studies analyzing relevant risk factors for hedge funds include Mitchell and Pulvino (2001), Agarwal and Naik (2004), Bali, Brown, and Caglayan (2011, 2012, 2014), and Buraschi, Kosowski, and Trojani (2015).

The identification of relevant risk factors in the literature significantly improves our understanding of hedge fund strategies. However, it does not directly answer a question of keen interest to academic researchers and institutional investors—namely, which hedge fund investment styles help to hedge against bad times? This question is of further interest because hedge funds often market themselves as investment vehicles that deliver superior performance in bad as well as good times. However, not all hedge fund styles are the same, so that large investors, as well as researchers, need to know *which* hedge fund styles hedge against bad times.[1]

In this paper, we provide an answer to the above question. To do so, we first need a precise working definition of good and bad times. A common classification of good and bad times is business-cycle expansions and recessions, respectively, as dated by the National Bureau of Economic Research (NBER). However, the expansion/recession dichotomy appears insufficient for defining good and bad times in financial markets per se—which is of keen interest to institutional investors—because times of severe market stress often occur during cyclical expansions (i.e., during "good" macroeconomic times). For example, the October 1987 stock market crash occurred

[1]In practice, after identifying which hedge fund styles provide hedges against bad times, institutional investors can invest in a portfolio of hedge funds within the style or in a fund of certain styles.

well after the preceding NBER-dated cyclical trough in November 1982 and well in advance of the subsequent cyclical peak in July 1990; the Mexican, Long-Term Capital Management (LTCM), and East Asian crises all occurred between the cyclical trough in March 1991 and subsequent peak in March 2001; and the Global Financial Crisis was already causing serious financial market disruptions throughout 2007, while the Great Recession did not officially begin until January 2008. The NBER also dates cyclical peaks and troughs ex post and with a considerable lag, so that NBER business-cycle phases cannot provide timely assessments of current market conditions.

Instead of relying on NBER-dated business-cycle phases, we use two approaches that are directly related to financial market conditions to identify good and bad times. First, we employ a technical indicator based on the 200-day moving average of the S&P 500 price index to define up and down equity market regimes (corresponding to good and bad times, respectively) in real time. Many fund managers and investors have long viewed the stock market as having up and down trends, and the 200-day moving average is a popular metric for defining such trends, where an up (down) market prevails when the S&P 500 index is above (below) its 200-day moving average. According to Siegel (2013), the use of moving averages to define trends dates back at least to the 1930s. In practice, the 200-day moving average has been plotted for years in investment letters and newspapers (such as *Investor's Business Daily*), and it is a standard tool in trading software.[2] For our purposes, this equity market indicator provides highly plausible regimes for identifying good and bad times. For example, up and down markets defined by the 200-day moving average correspond well to "risk-on" and "risk-off" environments, respectively. Moreover, the annualized average equity market excess return and volatility are 11.6% and 12.9% (−6.5% and 21.1%), respectively, during an up (down) market over our sample period.

Our second approach for defining good and bad times in financial markets relies on the Federal Reserve Bank of Kansas City Financial Stress Index (FSI). The FSI is the first principal component extracted from eleven financial market variables that capture a wide array of information in the financial sector, and elevated levels of the FSI signal heightened stress in financial markets. The

[2] Brock, Lakonishok, and LeBaron (1992), Lo, Mamaysky, and Wang (2000), and Neely, Rapach, Tu, and Zhou (2014) provide additional references and evidence on the value of the 200-day moving average.

FSI provides a very plausible picture of stress in financial markets. For example, the FSI clearly elevates during the LTCM crisis in 1998 and spikes sharply upward during the height of the Global Financial Crisis in the Fall of 2008. In addition, the FSI for a given month is reported eight to ten days after the end of the month, so that it is available in a timely manner.[3]

For each of our two approaches for defining good and bad times, we estimate regime-switching multifactor models for eleven hedge fund style returns, where we permit the model parameters to vary across up and down equity market regimes or nonstressed and stressed financial market regimes. For the up and down equity market regimes, we straightforwardly estimate the regime-switching models using predefined dummy variables corresponding to the two market states. Because our second approach relies on the FSI, which is a continuous variable, we define nonstressed and stressed financial market regimes endogenously via threshold estimation (Tong, 1983, 1990; Chan, 1993; Hansen, 2000). Endogenous threshold estimation allows us to optimally identify the threshold defining nonstressed and stressed regimes from the data.[4] The regime-switching multifactor model estimation results shed light on whether hedge fund managers dynamically adjust risk exposures to hedge against poor performance during bad times in financial markets, as well as whether they generate alpha in bad times. We also analyze which hedge fund styles are the most beneficial in "balanced" portfolios that allocate across stocks, bonds, and hedge funds, and we compare the performances of balanced portfolios across good and bad times. This problem is of significant practical value because an increasing number of institutional investors, such as government pension funds and university endowments, invest in hedge funds.[5]

Previewing our results, we find that a number of hedge fund styles exhibit significant changes

[3] Release dates for the FSI are available at http://www.kc.frb.org/research/indicatorsdata/kcfsi/.

[4] To the best of our knowledge, ours is the first study to apply threshold estimation to regime-switching multifactor models. Because we need to estimate the threshold defining nonstressed and stressed regimes, the FSI-based approach does not provide a real-time indicator. However, once an estimate of the threshold is available and deemed to be reasonably stable, going forward we can compare the value of the FSI to the threshold to readily determine the current regime.

[5] Many of the largest pension funds substantially increased their hedge fund investments in 2012 (Pensions and Investments, 2013), and hedge fund allocations for university endowments were above 19% in 2012 (National Association of College and University Business Officers, 2013). Ang, Ayala, and Goetzmann (2014) analyze recent trends in hedge fund investing by university endowments and their implications for the investment beliefs of endowments.

in risk exposures across good and bad times. In certain instances, changes in risk exposures coincide with valuable hedging during bad times. For example, the Equity Market Neutral, Fund of Funds, Global Macro, and Multi-Strategy styles are exposed to the aggregate equity market factor during an up equity market regime. During a down market regime, these styles evince statistically and economically significant decreases in their exposure to the aggregate market factor. Because the aggregate market factor typically experiences losses during a down market regime, these adjustments in risk exposure substantially attenuate losses for these hedge fund styles during bad times. In addition, the Global Macro, Managed Futures, and Multi-Strategy styles generate statistically and economically significant alpha during both up and down market regimes, so that these styles provide additional hedging benefits.

In other instances, particular hedge fund styles remain substantially exposed to—or become even more exposed to—relevant risk factors during bad times in a manner that leads to large losses. For example, the Convertible Arbitrage, Event Driven, and Fixed Income Arbitrage styles display statistically and economically significant exposure to a credit risk factor during nonstressed financial conditions. These styles show no significant change or a significant increase in their exposure to the credit risk factor during a stressed regime. Because the credit risk factor suffers large negative returns during a stressed regime, these styles experience large losses during stressed financial conditions, as is readily apparent at the height of the Global Financial Crisis in the Fall of 2008, which severely limits their value as hedges against bad times.

In the context of balanced portfolios, we find that Global Macro, Managed Futures, and Multi-Strategy provide especially useful complements to traditional stock and bond holdings. According to a variety of metrics, including these styles in a balanced 40-30-30 portfolio that allocates 40% to stocks, 30% to bonds, and 30% to an individual hedge fund style substantially improves performance relative to a balanced 60-40 benchmark portfolio that allocates 60% to stocks and 40% to bonds. Moreover, the outperformance of the 40-30-30 portfolios is particularly sizable during bad times, further demonstrating the value of Global Macro, Managed Futures, and Multi-Strategy as hedges against bad times.

Fung and Hsieh (2004), Fung, Hsieh, Naik, and Ramadorai (2008), and Bollen and Whaley (2009) also test for time variation in hedge fund risk exposures. These studies assume one-off structural breaks in multifactor model parameters. In contrast, we permit the multifactor model parameters to assume different values as financial markets alternate between good and bad times; in other words, we treat bad times in financial markets as *recurrent* phenomena, which is consistent with the occurrence of, for example, the East Asian and Long-Term Capital Management (LTCM) crises in the late 1990s, the technology stock price collapse in the early 2000s, and the Global Financial Crisis in the late 2000s.[6]

The rest of the paper is organized as follows. Section 1 describes the data for the hedge fund style returns and risk factors, as well as the unsmoothing procedure that we use to purge spurious serial correlation from the hedge fund returns. Section 2 discusses the methodologies for defining good and bad times. Section 3 reports multifactor model estimation results during good and bad times, while Section 4 reports performance measures for balanced portfolios that allocate across stocks, bonds, and individual hedge fund styles. Section 5 concludes.

1. Data Description

We analyze hedge fund style performance in good versus bad times using the Lipper TASS hedge fund database. TASS constitutes one of the most comprehensive hedge fund databases and provides data on both active and defunct funds beginning in 1994. The hedge fund literature has identified several biases associated with hedge fund databases, including self-selection, survivorship, and backfill biases (e.g., Brown, Goetzmann, and Ibbotson, 1999; Fung and Hsieh, 1997, 2000; Liang, 2000). To minimize the impact of these biases, we select the sample funds based on the following

[6] Avramov, Kosowski, Naik, and Teo (2011) model time variation in multifactor models for individual hedge fund returns by assuming that alpha and the risk exposures are linear functions of a small set of lagged macroeconomic variables. They use this specification to construct fund-of-hedge-funds portfolio strategies, while we adopt a regime-switching approach to directly analyze hedge fund performance during good versus bad times. Sun, Wang, and Zheng (2013) examine whether individual hedge funds that outperform their peers during market downturns continue to outperform their peers over the next year, while we investigate how different hedge fund styles perform during bad times to identify which styles are good hedges against bad times. Patton and Ramadorai (2013) employ a novel approach to model within-month variation in hedge fund risk exposures.

criteria.

First, we start our sample in 1994 and analyze both live and defunct funds. The inclusion of defunct funds mitigates the impact of survivorship bias.[7] Second, we include funds that report monthly net-of-fee returns and have AUM of at least $10 million. Smaller funds with AUM below $10 million are of less concern from an institutional investor's perspective, and they have less impact on the market. Third, we require each fund to have at least 36 monthly observations to be included in the sample.[8] Our sample period extends from January 1994 through December 2011, and the selection criteria yield 7,456 hedge funds, comprised of 5,000 live and 2,456 defunct funds.

TASS divides funds into ten style categories designed to reflect popular investment strategies pursued by hedge funds: Convertible Arbitrage, Dedicated Short Bias, Event Driven, Fixed Income Arbitrage, Emerging Markets, Equity Market Neutral, Global Macro, Long/Short Equity Hedge, Managed Futures, and Multi-Strategy. Funds of hedge funds invest in individual hedge funds and appear as a separate style. For each style, we construct an equal-weighted return index.

Monthly returns for many individual hedge funds and style indices display substantial serial correlation. Getmansky, Lo, and Makarov (2004) show that such serial correlation is primarily an artifact of infrequent trading in the securities held by many funds. A key concern is that spurious serial correlation in hedge fund returns overly smooths returns and makes them appear less volatile, which overstates performance measures (such as the Sharpe ratio) and understates risk exposures (Asness, Krail, and Liew, 2001; Lo, 2002; Getmansky, Lo, and Makarov, 2004). To address this concern, we use the econometric model of Getmansky, Lo, and Makarov (2004) to unsmooth the

[7]TASS began collecting data for defunct funds in 1994, so that data starting before 1994 are subject to significant survivorship bias.

[8]Our results are robust to alternative filters (e.g., a minimum of 24 monthly observations). To address backfill bias concerns, we checked the robustness of our results by, in turn, excluding the first twelve months of return data for each fund, excluding the first 24 months of return data for each fund (the median backfill period of our sample is about 23 months), and discarding the backfill period for each fund and only using fund returns recorded after the date when the fund is added to the TASS database. The empirical results for these samples are qualitatively similar to those for the baseline sample.

hedge fund style index returns. The model is given by

$$
\begin{aligned}
R_t^{\mathrm{o}} &= \theta_0 R_t + \theta_1 R_{t-1} + \theta_2 R_{t-2}, && (1)\\
\theta_j &\in [0,1] \;\text{ for }\; j = 0,1,2, && (2)\\
1 &= \theta_0 + \theta_1 + \theta_2, && (3)
\end{aligned}
$$

where R_t^{o} (R_t) is the month-t observed smoothed (unobserved unsmoothed) excess return for $t = 1,\ldots,T$. According to (1), observed smoothed returns are a weighted average of the unobserved true economic unsmoothed returns. This specification permits the information in true excess returns to be fully reflected in observed excess returns with a delay, in recognition of the frictions associated with infrequent trading. Funds that deal primarily with highly liquid assets will display relatively limited smoothing of true returns and thus have θ_0 values near one; funds that deal more extensively in infrequently traded securities will presumably exhibit substantially more smoothing, as reflected by smaller θ_0 values.

To estimate the unobserved unsmoothed excess returns, we first express the smoothed excess return in deviation form as

$$
r_t^{\mathrm{o}} = R_t^{\mathrm{o}} - \mu, \tag{4}
$$

where μ is the mean of R_t^{o}; given (1) and (3), μ is also the mean of R_t. We then cast the model in state-space form:

$$
\begin{aligned}
r_t^{\mathrm{o}} &= H\tilde{\eta}_t, && (5)\\
\tilde{\eta}_t &= F\tilde{\eta}_{t-1} + \tilde{v}_t, && (6)
\end{aligned}
$$

where

$$
\begin{aligned}
\tilde{\eta}_t &= (\eta_t\,,\, \eta_{t-1}\,,\, \eta_{t-2})', && (7)\\
H &= (1-\theta_1-\theta_2\,,\, \theta_1\,,\, \theta_2), && (8)\\
F &= \begin{pmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}, && (9)\\
\tilde{v}_t &= (v_t\,,\, 0\,,\, 0)', && (10)
\end{aligned}
$$

$v_t =$ i.i.d. $N(0, \sigma_v^2)$, and $\theta_0 = 1 - \theta_1 - \theta_2$. Equations (5) and (6) are the measurement and transition equations, respectively, and we assume that v_t is normally distributed to operationalize estimation. After demeaning R_t^o, we use the prediction error decomposition and Kalman filter to estimate the parameters of the model (θ_0, θ_1, θ_2, and σ_v^2) via maximum likelihood. Armed with these parameter estimates, we form an estimate of η_t based on information through t, $\eta_{t|t}$, for $t = 1, \ldots, T$ using the Kalman filter. We subsequently compute an estimate of η_t based on information through T, $\eta_{t|T}$, for $t = 1, \ldots, T$ using the Kalman smoother, which provides a more efficient measure of the latent state variable. Finally, our estimate of the unsmoothed excess return based on information through T is given by $R_{t|T} = \hat{\mu} + \eta_{t|T}$ for $t = 1, \ldots, T$, where $\hat{\mu}$ is the sample mean of R_t^o.[9]

Table 1 reports summary statistics for 1994:01 to 2011:12 for smoothed and unsmoothed hedge fund excess returns for the eleven styles. Excess returns are computed relative to the one-month Treasury bill return from Ibbotson Associates. The average monthly smoothed excess returns in the second column range from 0.02% (Dedicated Short Bias) to 0.78% (Emerging Markets and Long/Short Equity Hedge). The monthly autocorrelation coefficients for the smoothed excess returns in the fifth column are sizable for many styles—eight are 0.25 or higher—highlighting the need to unsmooth the observed returns.

[9] Getmansky, Lo, and Makarov (2004) implement maximum likelihood estimation using the Brockwell and Davis (1991) "innovations algorithm." The Kalman filter allows us to subsequently apply the Kalman smoother to obtain more efficient estimates of the unsmoothed excess returns.

The sixth through eighth columns of Table 1 report the $\hat{\theta}_j$ estimates, which appear quite plausible in light of the types of securities typically held by the various styles. For example, Convertible Arbitrage has the smallest $\hat{\theta}_0$ estimate (0.56) among the eleven style categories, while Managed Futures has the highest $\hat{\theta}_0$ estimate (0.97). Convertible Arbitrage funds frequently have sizable holdings of relatively infrequently traded securities, which possibly gives rise to extensive return smoothing. In contrast, Managed Futures funds typically transact in highly liquid futures markets, so that this style is much less prone to return smoothing.

Based on (1) and (3), the mean unsmoothed excess returns in the ninth column of Table 1 match the mean smoothed excess returns in the second column. As expected, the standard deviations for the unsmoothed excess returns in the tenth column are greater than the corresponding standard deviations for the smoothed excess returns in the third column, and the proportional increases in standard deviation are larger for styles with smaller θ_0 estimates (i.e., more return smoothing). Because the mean excess returns are the same for the smoothed and unsmoothed excess returns, the higher standard deviations for the unsmoothed returns reduce their annualized Sharpe ratios in the last column of Table 1 vis-á-vis the Sharpe ratios for the smoothed returns in the fourth column.

Figure 1 depicts unsmoothed excess returns for the eleven styles. A number of styles experience sizable negative returns in 1998 near the LTCM crisis and in the Fall of 2008 at the height of the Global Financial Crisis. These outcomes raise concerns about the ability of certain hedge fund styles to hedge against bad times.

Due to the variety of hedge fund styles in our analysis, we consider a wide array of risk factors for the mutlifactor models in Section 3. The factors, which expand the well-known set of seven Fung and Hsieh (2004) factors, are listed in Table 2, along with the abbreviations by which we refer to the factors. All of the factors are expressed as excess returns.[10] Equity-related factors include the Center for Research in Security Prices (CRSP) market excess return, Fama and French (1993) size and value premiums, and Carhart (1997) momentum factor. The ten-year Treasury bond excess

[10]Data for the risk factors are from the Federal Reserve Economic Database, Global Financial Data, Morgan Stanley Capital International, Ibbotson Associates, Bloomberg, Kenneth French's Data Library, David Hsieh's Hedge Fund Data Library, and Ľuboš Pástor's webpage.

return and a credit return spread—the Bank of America Merrill Lynch (BofA ML) 10–15-year corporate bond index return minus the ten-year Treasury bond return—appear as fixed-income factors. We also consider the bond, currency, and commodity trend-following factors from Fung and Hsieh (2001), which they identify as relevant for hedge funds in the Managed Futures space.[11] To capture other strategies pursued by particular styles, we include emerging market, currency, and commodity factors. The emerging market factor is the excess return (in U.S. dollars) on the Morgan Stanley Capital International (MSCI) emerging markets index, the currency factor is a factor-mimicking portfolio corresponding to the Bloomberg DXY U.S. dollar index,[12] and the commodity factor is the excess return on the Standard & Poor's Goldman Sachs commodity index. Our final factor is the Pástor and Stambaugh (2003) liquidity factor. The last three columns of Table 2 report summary statistics for the risk factor excess returns for 1994:01 to 2011:12.

2. Defining Good and Bad Times

2.1. Up and down equity markets

We first identify good and bad times with up and down equity market regimes, respectively. We define up and down equity markets using the 200-day moving average of the S&P 500 price index. Specifically, we compare the close of the S&P 500 price index on the last trading day of the month with its 200-day moving average; if the end-of-month value is greater than or equal to (less than) the moving average, then we classify the subsequent month as an up (down) equity market.[13] As discussed in the introduction, the 200-day moving average is a popular indicator among practitioners that is available in real time.

[11] Each trend-following factor is the excess return on a lookback straddle. Because Managed Futures funds often target their volatility to broad equity market volatility, we scale the trend-following factors to have the same volatility as the market excess return. Moskowitz, Ooi, and Pedersen (2012) follow a similar procedure.

[12] Specifically, we regress the DXY U.S. dollar return on the U.S. dollar excess returns of the MSCI Europe, Australasia, and Far East (EAFE) equity index and BofA ML global (excluding the United States) government bond index and use the estimated slope coefficients to generate the factor-mimicking portfolio excess return. The DXY return and factor-mimicking portfolio excess return are very highly correlated (0.92).

[13] Alternative moving-average lengths (e.g., 150 or 250 days) produce qualitatively similar results.

The up and down equity market regimes are shown in Panel A of Figure 2. The regimes plausibly represent good and bad equity market conditions and accord well with risk-on and risk-off environments. For example, an up equity market prevails throughout much of the mid-to-late 1990s, in line with the strong bear market during this period, while a down market characterizes much of the early 2000s, signaling the bear market associated with the sharp decline in technology stock prices. After an up market for much of the mid 2000s, an extended down market begins at the end of 2007 near the start of the Global Financial Crisis. Further corroborating the plausibility of the up and down equity market regimes identified by the 200-day moving average, the average monthly excess returns for the equity market factor are 0.97% (11.6% annualized return) and -0.55% (-6.5% annualized return) during up and down market regimes, respectively.[14] Of the 216 months from 1994:01 to 2011:12, 68% (32%) belong to the up (down) equity market regime.

Panels A and B of Table 3 report summary statistics for hedge fund style excess returns during up and down equity market regimes, respectively. Comparing the second and fifth columns, the average excess return is higher during an up relative to a down equity market for nine of the eleven styles; the exceptions are Dedicated Short Bias and Managed Futures. Dedicated Short Bias funds bet on declines in equity market indices and individual firms' share prices, so that they earn more during a down equity market. Managed Futures funds primarily pursue trend-following strategies that take long and short positions that pay off in the presence of both positive and negative trends. They can thus produce relatively high average excess returns during a down market when there are strong downward price trends. Furthermore, Managed Futures funds trade in a variety of asset classes, including bond, currency, and commodity futures, which can exhibit trends of their own during a strong downward trend in the equity market.

There is less uniformity in the volatility differences across the two regimes in the third and sixth columns: volatility is lower (higher) during a down market for six (five) of the styles. Because a number of hedge fund styles often place contrarian bets, these styles can produce reasonably

[14] We reject the null hypothesis that the mean equity market excess return is the same across regimes in favor of the one-sided alternative that it is greater during an up market regime at the 5% significance level (heteroskedasticity-robust t-statistic equals 1.92).

consistent returns in down equity markets when these bets pay off, helping to explain the lower volatility during a down market for certain styles. According to the fourth and seventh columns, the annualized Sharpe ratio decreases for nine styles during a down market, with Dedicated Short Bias and Managed Futures again being the exceptions. Nevertheless, the annualized Sharpe ratio remains above one for Global Macro and Multi-Strategy during a down market. The results in Panels A and B of Table 3 suggest that not all hedge fund styles provide effective hedges against bad times in the equity market. We examine this issue more extensively in the context of multifactor models and balanced portfolios in Sections 3.2 and 4.2, respectively.[15]

2.2. Nonstressed and stressed financial conditions

Our second approach for defining good and bad times in financial markets utilizes the Federal Reserve Bank of Kansas City Financial Stress Index (FSI). The FSI is the first principal component extracted from eleven financial variables that capture defining aspects of heightened stress in financial markets, including flight to quality/liquidity, increased uncertainty, and magnified information asymmetries.[16] Panel B of Figure 2 portrays the FSI. It elevates in the latter half of 1998 during the LTCM crisis and remains relatively high through the bear equity market of the early 2000s. The FSI also rises significantly in 2007 and spikes sharply in the Fall of 2008 during the height of the Global Financial Crisis. Overall, the FSI represents a highly plausible measure of financial stress.

The FSI is a continuous variable, so that we need a procedure for defining the two regimes: nonstressed (good times) and stressed (bad times). One option is to define a stressed regime as FSI

[15]Note that we may expect certain hedge fund styles to provide hedges against bad times defined in term of a down equity market regime. Nevertheless, we are interested in the extent to which a wide variety of different styles hedge against bad times in the equity market and their portfolio impacts, so that we include all the hedge fund styles in our analysis of performance across up and down equity market regimes.

[16]The variables are the three-month TED spread, two-year swap spread, off-the-run/on-the-run ten-year Treasury spread, Aaa/ten-year Treasury spread, Baa/Aaa spread, high-yield bond/Baa spread, consumer ABS/five-year Treasury spread, correlation between stock and Treasury bond returns, VIX, idiosyncratic volatility of excess stock returns in the banking sector, and cross-sectional dispersion of excess stock returns in the banking sector; see Hakkio and Keeton (2009) for detailed definitions of the variables and data sources. In the wake of the Global Financial Crisis, financial stress or condition indices have grown in popularity. Kliesen, Owyang, and Vermann (2012) show that the Federal Reserve Bank of Kansas City FSI performs well along multiple dimensions compared to other indices.

observations in, say, the top quintile. Defining regimes in this manner appears somewhat arbitrary, however. Instead, we employ threshold regression to allow the data to select the FSI level that demarcates nonstressed and stressed regimes. We use the following threshold model to examine differences in the mean and volatility of hedge fund style excess returns across nonstressed and stressed regimes:

$$R_t = \mu_1 + \sigma_1 u_t \text{ for } q_t \leq \gamma \text{ (nonstressed financial conditions),} \tag{11}$$

$$R_t = \mu_2 + \sigma_2 u_t \text{ for } q_t > \gamma \text{ (stressed financial conditions),} \tag{12}$$

where q_t is the level of the FSI in month t; u_t is a zero-mean, unit-variance variate; and γ is the threshold parameter. When the FSI moves above the threshold γ, financial conditions enter a stressed regime, and they remain in a stressed state until the FSI falls back to or below γ. For a given threshold, it is straightforward to compute ordinary least squares (OLS) estimates of μ_1 and μ_2 (as well as σ_1 and σ_2) using dummy variables to define the two regimes; the threshold estimate is the value of γ that minimizes the sum of squared OLS residuals across all permissible γ values (Tong, 1983, 1990; Chan, 1993; Hansen, 2000). We allow γ to vary across hedge fund styles, as differences in the types of securities held by various styles potentially generate different thresholds for stressed financial conditions.

The last column of Table 3 reports $\hat{\gamma}$ estimates for (11) and (12) and each of the eleven hedge fund styles.[17] The $\hat{\gamma}$ estimates range from 0.37 to 1.01, so that the stressed regimes include many months from the LTCM crisis, technology stock price collapse, and Global Financial Crisis in Figure 2, Panel B. At the lower end of the range of $\hat{\gamma}$ estimates (0.37, Long/Short Equity Hedge and Managed Futures), 29% of the months from 1994:01 to 2011:12 represent stressed conditions; at the upper end of the range (1.01, Equity Market Neutral and Fixed Income Arbitrage), 10% of the months constitute stressed conditions.

[17] We restrict γ to lie between the 50% and 90% percentiles of the FSI observations. The lower bound requires that at least half of the observations are treated as good times (which seems economically reasonable), while the upper bound ensures that enough observations are available in the stressed regime to estimate the parameters specific to this regime with a reasonable degree of reliability.

Stark differences emerge in the average excess returns and volatilities across the nonstressed and stressed regimes in Panels C and D of Table 3. The average excess return decreases as we move from a nonstressed to a stressed regime for all of the hedge fund styles, with the exception of Dedicated Short Bias. For six of the styles, the average excess return goes from positive during a nonstressed regime to negative during a stressed regime. The fact that Dedicated Short Bias has a higher average excess return during a stressed market makes sense, as this strategy bets on declines in security prices. Volatility is higher during a stressed regime for all of the styles, with the exception of Global Macro, and volatility more than doubles (triples) for Fixed Income Arbitrage (Convertible Arbitrage). The substantial increase in volatility during stressed financial conditions for Convertible Arbitrage and Fixed Income Arbitrage is perhaps not surprising, as these styles primarily pursue convergent strategies that provide relatively stable performance during normal conditions, but that can become much more volatile during stressed financial conditions.

The differences in average excess returns and volatilities across regimes produce a lower annualized Sharpe ratio for all of the styles during a stressed regime, with the exception of Dedicated Short Bias. Although the annualized Sharpe ratio for Global Macro and Multi-Strategy declines during a stressed regime, it remains positive and sizable for both styles (0.51 and 0.96, respectively). The results in Panels C and D of Table 3 provide preliminary evidence that many hedge fund styles suffer a substantial deterioration in performance during stressed financial conditions and thus do not provide effective hedges against bad times, while the performance of some styles does appear robust to stressed conditions. We further analyze hedge fund style performance across nonstressed and stressed financial conditions in terms of multifactor models and balanced portfolios in Sections 3.3 and 4.3, respectively.

Overall, Table 3 reveals important differences in hedge fund performance across good and bad times. Whether we demarcate good and bad times in terms of up and down equity markets (Panels A and B) or nonstressed and stressed financial conditions (Panels C and D), the picture is similar: hedge fund styles typically generate a lower Sharpe ratio during bad times vis-á-vis good times; the decline in the Sharpe ratio during bad times is substantial for a number of styles, while some styles are still able to provide a sizable Sharpe ratio in bad times. We turn next to our analysis of hedge fund alphas and betas across good and bad times.

3. Multifactor Model Estimation Results

3.1. Baseline specification

As a baseline for our multifactor model analysis, we first estimate models with constant alphas and risk exposures over the 1994:01 to 2011:12 period. We subsequently estimate regime-switching multifactor models that allow the alphas and risk exposures to differ across up and down equity markets, as well as nonstressed and stressed financial conditions.

We face a tradeoff in selecting the set of risk factors for a given hedge fund style. While we want to include as many factors as needed to account for all of the relevant risk exposures, we also want to avoid overly parameterized models that substantially reduce estimation precision. Overly parameterized models are of particular concern in our context, as the number of parameters at least doubles when we estimate the regime-switching models. To accommodate a reasonably large number of relevant risk factors while maintaining a reasonable degree of parsimony, we select the set of factors for a given style as follows. We first identify a set of candidate factors from Table 2 that we deem to be the most relevant for a given style. We then use the corrected AIC (Hurvich and Tsai, 1989) to select the final model from the set of regression models that include all possible combinations of the candidate factors (where all of the regressions include an intercept term). For each hedge fund style, Table 4 reports full-sample OLS estimation results for the multifactor model,

$$R_t = \alpha + f_t'\beta + \varepsilon_t, \tag{13}$$

where f_t is the vector of selected factors and β is the vector of corresponding risk exposures. For brevity, we use asterisks to highlight coefficient estimates that are significant at conventional levels according to heteroskedasticity-robust t-statistics.

Beginning with the equity factors, eight of the eleven styles exhibit significant exposure to the market factor (MKT) in Table 4. Despite its name, Equity Market Neutral displays significant exposure to MKT ($\hat{\beta}^{\text{MKT}} = 0.12$). Convertible Arbitrage, Event Driven, and Long/Short Equity Hedge have relatively large exposure to MKT, with $\hat{\beta}^{\text{MKT}}$ estimates ranging from 0.18 to 0.39. As expected, Dedicated Short Bias has a substantial negative exposure to MKT ($\hat{\beta}^{\text{SP}} = -0.62$). Event Driven and Long/Short Equity Hedge (Dedicated Short Bias) evince significant positive (negative) exposure to the size factor (SMB), while Dedicated Short Bias, Equity Market Neutral, and Managed Futures (Fund of Funds, Long/Short Equity Hedge, and Multi-Strategy) exhibit significant positive (negative) exposure to the value factor (HML). Dedicated Short Bias, Emerging Markets, Equity Market Neutral, Fixed Income Arbitrage, Fund of Funds, Global Macro, and Managed Futures display significant exposure to the momentum factor (UMD). As anticipated, Emerging Markets shows significant and sizable exposure to the emerging market factor (EM, $\hat{\beta}^{\text{EM}} = 0.71$). Fund of Funds, Global Macro, Long/Short Equity Hedge, Managed Futures, and Multi-Strategy also display significant exposure to EM, but the $\hat{\beta}^{\text{EM}}$ estimates are substantially smaller, ranging from 0.07 to 0.17.

With respect to the fixed-income factors, Convertible Arbitrage, Event Driven, Fixed Income Arbitrage, Fund of Funds, Global Macro, Managed Futures, and Multi-Strategy all exhibit significant exposure to the Treasury bond factor (BOND), with $\hat{\beta}^{\text{BOND}}$ estimates ranging from 0.10 to 0.41. Convertible Arbitrage, Event Driven, Fixed Income Arbitrage, Fund of Funds, Global Macro, and Multi-Strategy also evince significant exposure to the credit factor (CREDIT). In line with their predominant strategies, the first three of these styles have sizable exposure to the credit factor, with $\hat{\beta}^{\text{CREDIT}}$ estimates of 1.32, 0.60, and 0.53, respectively.

Similarly to Fung and Hsieh (2001), Managed Futures has significant exposures to the bond, currency, and commodity trend-following factors (TFBOND, TFCURR, and TFCOMM, respectively). Fund of Funds and Global Macro have significant exposures to both the currency and commodity trend-following factors, while Multi-Strategy has significant exposure to the currency trend-following factor. Emerging Markets, Fund of Funds, Global Macro, and Multi-Strategy display significant exposure to the currency factor (CURR), while Fund of Funds, Long/Short Equity Hedge, Managed Futures, and Multi-Strategy exhibit significant exposure to the commodity factor (COMM). Finally, Equity Market Neutral shows significant exposure to the liquidity factor (LIQ).

Nine of the eleven styles generate significant alpha in Table 4, with Convertible Arbitrage and Fund of Funds as the exceptions. The monthly $\hat{\alpha}$ estimate is above 50 basis points (6% annualized return) for Global Macro, Managed Futures, and Multi-Strategy, so that these styles provide economically sizable alpha. The substantial alpha for Managed Futures accords with the recent findings of Moskowitz, Ooi, and Pedersen (2012), who show that time-series momentum in a broad array of assets helps trend-following strategies to deliver alpha.

The adjusted R^2 statistics for the multifactor models range from 28.93% (Fixed Income Arbitrage) to 82.51% (Long/Short Equity Hedge). Broadly consistent with the results for individual hedge funds in Titman and Tiu (2011), a number of funds with relatively low adjusted R^2 statistics below 50% provide relatively sizable alpha (most notably, Global Macro and Managed Futures), while other funds with relatively high adjusted R^2 statistics above 50% fail to generate significant alpha (Convertible Arbitrage and Fund of Funds). However, a relatively low adjusted R^2 is not a necessary condition for sizable alpha; for example, Multi-Strategy produces a very sizable alpha despite having a relatively large adjusted R^2 of 59.82%.

The results in Table 4 confirm that hedge fund styles are exposed to a variety of risk factors. The results also demonstrate that many hedge fund styles generate statistically significant and economically sizable alpha on average over the 1994:01 to 2011:12 period. Next, we examine whether hedge fund style risk exposures change significantly across good and bad regimes and whether hedge fund styles deliver substantial alpha across regimes.

3.2. Alpha and betas across up and down equity markets

Table 5 reports estimation results for the regime-switching multifactor model,

$$R_t = \alpha_1 + f_t'\beta_1 + \sigma_1 u_t \text{ for an up equity market,} \tag{14}$$

$$R_t = \alpha_2 + f_t'\beta_2 + \sigma_2 u_t \text{ for a down equity market,} \tag{15}$$

for each of the eleven hedge fund styles. We use the same set of factors from the baseline model for each style, and we report OLS estimates of alpha and the risk exposures during up and down equity markets, as well as the changes in alpha and exposures during a down equity market ($\alpha_2 - \alpha_1$ and $\beta_2 - \beta_1$, respectively). We again use asterisks to highlight coefficient estimates that are significant at conventional levels according to heteroskedasticity-robust t-statistics. To test for the existence of regime switching, Table 5 also reports a heteroskedasticity-robust F-statistic version of the Wald statistic for testing H_0: $\alpha_1 = \alpha_2$, $\beta_1 = \beta_2$ for each style.

Table 5 indicates that a number of hedge fund styles substantially reduce their exposure to broad equity market risk during a down market. In particular, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Fund of Funds, Global Macro, Long/Short Equity Hedge, and Multi-Strategy all have significant exposure to the MKT factor during an up equity market, while they exhibit significant declines in exposure during a down equity market. Recalling that the average monthly excess returns for the equity market factor are 0.97% and -0.55% during up and down equity markets, respectively, such reductions in market exposure represent beneficial hedging behavior.

Equity Market Neutral's exposure to MKT is a significant 0.18 during an up market and declines to an insignificant 0.02 during a down market, so that Equity Market Neutral's actual behavior matches its name during a down market. Fixed Income Arbitrage, Fund of Funds, and Multi-Strategy also appear to essentially eliminate any exposure to MKT during a down market. Although Event Driven and Long/Short Equity Hedge significantly reduce their exposure to MKT during a down market, they retain significant exposure to MKT during this regime. Global Macro actually moves from a significant exposure of 0.18 during an up market to a significant negative exposure of -0.10 during a down market. In contrast, Dedicated Short Bias significantly reduces the magnitude of its negative exposure to MKT during a down market, which reduces the hedging value of its MKT exposure.

Long/Short Equity Hedge exhibits significant exposure to the size factor during an up equity market, which declines significantly during a down market. The $\hat{\beta}^{\text{SMB}}$ estimate is 0.28 for Long/Short Equity Hedge during an up market and an insignificant 0.07 during a down market. Similarly to the pattern for the market factor, Dedicated Short Bias significantly reduces the magnitude of its negative exposure to SMB in a down market. Dedicated Short Bias and Managed Futures (Dedicated Short Bias) significantly reduce their exposure to the value (momentum) factor during a down market. These results indicate that certain hedge fund styles have sizable exposures to size, value, and momentum premiums during good times, which they substantially reduce during bad times.

Interesting patterns emerge with respect to the remaining equity market factor, EM. Emerging Markets significantly reduces its substantial exposure to EM during a down market, although the magnitude of the decline is limited (0.77 to 0.67), and its exposure to EM remains significant during a down market. Managed Futures also significantly reduces its exposure to EM from 0.17 during an up market to -0.09 during a down market (both of which are significant). Equity Market Neutral and Long/Short Equity Hedge follow a different tack: they significantly increase their exposure to EM during a down market. Recalling that Equity Market Neutral and Long/Short Equity Hedge also significantly reduce their exposure to MKT during a down market, these styles thus appear to reallocate from the U.S. market to emerging markets during a down market regime, perhaps reflecting a belief in "decoupling." The emerging market factor has average monthly excess returns of 0.72% and -0.13% during up and down equity markets, respectively, so that the EM exposure adjustments enhance returns for Emerging Markets and Managed Futures but lower returns for Equity Market Neutral and Long/Short Equity Hedge.

Convertible Arbitrage and Event Driven experience significant increases in exposure to the Treasury bond factor during a down equity market, while Global Macro significantly reduces its exposure to BOND during a down market. There are no significant changes in exposure to the credit factor, and Convertible Arbitrage, Event Driven, and Fixed Income Arbitrage exhibit substantial exposure to CREDIT during both up and down markets. Fund of Funds, Global Macro, and Managed Futures significantly reduce their exposure to the commodity, currency, and bond trend-following factors, respectively, during a down market. Global Macro and Multi-Strategy display significant exposure to the currency factor during an up equity market (0.22 and 0.11, respectively), and both styles significantly reduce their exposure to CURR to become essentially neutral with respect to CURR during a down market. These adjustments help to hedge against bad times, as CURR has average monthly excess returns of -0.13% and -1.61% during up and down equity markets, respectively, consistent with the "safe-haven" status of the U.S. dollar during bad times. Managed Futures significantly increases its exposure to the commodity factor during a down market, while Long/Short Equity Hedge and Multi-Strategy significantly decrease their exposure to this factor. Finally, Equity Market Neutral displays a significant increase in its exposure to the liquidity factor during a down market.

Figure 3 provides a general perspective on the extent to which risk exposure adjustments help to hedge against bad times in the equity market. Each panel depicts the cumulative log excess return due to systemic risk exposure alone for the style given in the panel heading. The solid line in each panel corresponds to the estimated regime-switching exposures reported in Table 5, while the dashed line assumes that the exposures remain constant at their values during an up equity market. The vertical bars in Figure 3 delineate down equity market regimes.

According to Figure 3, the adjustments in risk exposures by Equity Market Neutral, Fund of Funds, Global Macro, and Multi-Strategy are quite useful for limiting drawdowns in cumulative wealth during a down equity market, including the down market accompanying the Global Financial Crisis. If these styles did not alter their risk exposures during a down market, the dashed lines indicate that wealth would have fallen considerably more in 2008. This advantageous hedging behavior largely reflects the previously discussed reductions in exposure to the market factor exhibited by these styles during a down market. Adjustments in risk exposures do not help

Convertible Arbitrage, Emerging Markets, Event Driven, and Long/Short Equity Hedge avoid very sizable drawdowns during the down market accompanying the Global Financial Crisis. While some of these styles reduce their exposure to the market factor during a down market, they retain substantial exposures to the credit and emerging market factors during a down market, and these factors experienced severe losses during the Global Financial Crisis. In addition, the adjustments in risk exposures help Equity Market Neutral, Fund of Funds, Global Macro, and Multi-Strategy to limit losses during the down market periods of the early 2000s, again reflecting their reductions in exposure to the market factor during a down equity market. The adjustments in risk exposures also mitigate losses during the early 2000s for Convertible Arbitrage, but, as previously discussed, Convertible Arbitrage suffers a very large drawdown during the Global Financial Crisis, so that Convertible Arbitrage does not consistently hedge against bad times in the equity market.

Returning to Table 5, nine of the eleven styles generate significant alpha during an up equity market (the exceptions are Convertible Arbitrage and Fund of Funds), with Global Macro, Managed Futures, and Multi-Strategy delivering the three largest monthly alphas (46, 47, and 53 basis points, respectively) during an up market. Interestingly, none of the nine styles with significant alpha during an up equity market experiences a significant decrease in alpha during a down equity market, and Emerging Markets, Global Macro, Long/Short Equity Hedge, Managed Futures, and Multi-Strategy generate significant alpha during both up and down equity markets (despite the reduced number of observations during a down market), with Managed Futures producing the largest monthly alpha during a down market (72 basis points). A number of hedge fund styles thus produce significant alpha in good times that persists in bad times. Apart from Convertible Arbitrage, Equity Market Neutral, Event Driven, and Fixed Income Arbitrage, the idiosyncratic variance only increases modestly or decreases during a down market in Table 5.

Figure 4 shows the risk-adjusted cumulative log excess return for each style, which removes the influence of the risk exposures to isolate the impact of alpha and the idiosyncratic component on the cumulative return. Analogously to Figure 3, the solid lines in each panel in Figure 4 correspond to the estimated regime-switching alphas and betas in Table 5, while the dashed lines assume that the alphas and betas remain constant at their values during an up equity market.

For Global Macro, Managed Futures, and Multi-Strategy, the solid lines are predominantly positively sloped during down equity markets in Figure 4, so that these styles provide good hedges against bad times in terms of their risk-adjusted return when we account for regime switching in alpha and the risk exposures. Observe that the solid and dashed lines are relatively close to each other for these styles. This is consistent with the estimated alphas across regimes in Table 5 for Global Macro, Managed Futures, and Multi-Strategy, which are sizable and similar across regimes. The solid lines are often flat or negatively sloped during a down equity market for the other styles in Figure 4, so that these styles do not hedge as well against bad times in the equity market with respect to risk-adjusted returns. The divergence between the solid and dashed lines for Convertible Arbitrage indicates that it provides a much weaker hedge against bad times when we account for regime switching in alpha and the risk exposures.

Comparing the adjusted R^2 statistics across Tables 4 and 5, allowing for regime switching across up and down equity markets in the multifactor model produces the largest increases in explanatory power for Fund of Funds, Global Macro, and Multi-Strategy. The adjusted R^2 statistics increase by approximately five to seven percentage points for these three styles, which reflects the significant adjustments in a number of risk exposures across up and down equity markets by these styles. The Wald statistic is significant at conventional levels for ten of the styles in Table 5 (the exception is Fixed Income Arbitrage), so that there is extensive evidence of changes in risk exposures across up and down equity market regimes.

3.3. Alpha and betas across nonstressed and stressed financial markets

Table 6 reports estimation results for the threshold multifactor model,

$$R_t = \alpha_1 + f_t'\beta_1 + \sigma_1 u_t \quad \text{for} \quad q_t \leq \gamma \quad \text{(nonstressed financial conditions)}, \tag{16}$$

$$R_t = \alpha_2 + f_t'\beta_2 + \sigma_2 u_t \quad \text{for} \quad q_t > \gamma \quad \text{(stressed financial conditions)}. \tag{17}$$

Recall that q_t is the level of the FSI. As described in Section 2.2, we estimate the threshold parameter by selecting the value of γ that minimizes the sum of squared residuals across all permissible γ values, and we allow γ to vary across styles, as different styles potentially have different thresholds for defining stressed financial conditions. Similarly to Table 5, we report OLS estimates of alpha and the risk exposures during nonstressed and stressed financial conditions, as well as the changes in alpha and risk exposures during stressed conditions ($\alpha_2 - \alpha_1$ and $\beta_2 - \beta_1$, respectively).[18] Asterisks again highlight significant coefficient estimates based on heteroskedasticity-robust t-statistics. To get a sense of the evidence for the existence of thresholds, we follow Gonzalo and Pitarakis (2002) and select between models with and without a threshold using an information criterion. Specifically, we report the difference in corrected AICs for the multifactor model without a threshold and the multifactor model with a threshold; a positive difference indicates that the corrected AIC selects the model with a threshold.[19]

The $\hat{\gamma}$ estimates in Table 6 range from -0.27 to 1.01, so that, like the corresponding estimates in Table 3, the stressed regimes include numerous months from the LTCM crisis, technology stock price collapse, and Global Financial Crisis in Figure 2, Panel B. For the lowest $\hat{\gamma}$ estimate (-0.27, Fund of Funds), 50% of the months from 1994:01 to 2011:12 are classified as stressed financial conditions; for the highest $\hat{\gamma}$ estimate (1.01, Convertible Arbitrage, Equity Market Neutral, and Fixed Income Arbitrage), 10% of the months represent stressed conditions.

Reminiscent of the results in Table 5, Table 6 indicates that Equity Market Neutral, Fund of Funds, Global Macro, Long/Short Equity Hedge, and Multi-Strategy exhibit significant exposure to MKT during a nonstressed regime, which they significantly reduce during a stressed regime. Since the equity market typically performs relatively poorly during a stressed regime, these adjustments again represent useful hedges against bad times. Dedicated Short Bias significantly decreases the

[18]Note that the asymptotic distributions of the OLS estimates of α_1, α_2, β_1, β_2, σ_1, and σ_2 are not affected by the estimation of the threshold parameter γ. Chan (1993) and Hansen (2000), among others, provide analytical results for the asymptotic distribution of γ.

[19]Testing for the existence of a threshold raises thorny issues for classical hypothesis testing, as the threshold parameter is unidentified under the null hypothesis of no threshold (e.g., Hansen, 2000). We conducted Monte Carlo experiments to analyze the ability of the corrected AIC to select between models with and without a threshold, and this approach selects the proper model the vast majority of the time. Details are available upon request from the authors.

magnitude of its negative exposure to MKT during a stressed regime, but it still retains a very sizable negative exposure during bad times. The differences in corrected AICs are positive for Dedicated Short Bias, Equity Market Neutral, Fund of Funds, Global Macro, Long/Short Equity Hedge, and Multi-Strategy, so that there is evidence for the existence of thresholds for these styles.

Event Driven and Long/Short Equity Hedge evince significant exposure to SMB during a nonstressed regime, which they significantly reduce to negative or essentially no exposure during a stressed regime. Long/Short Equity Hedge and Multi-Strategy have significant negative exposure to HML during a nonstressed regime; these styles significantly reduce the magnitude of their HML exposure during a stressed regime, leaving them with effectively no exposure. Dedicated Short Bias significantly reduces its exposure to HML during a stressed regime, but retains significant exposure during this regime. These reductions in exposures to size, value, and momentum factors during bad times are also reminiscent of the results in Table 5. In contrast, Fund of Funds moves from insignificant exposure to UMD during nonstressed conditions to significant exposure during stressed conditions.

Table 6 shows that Equity Market Neutral, Long/Short Equity Hedge, and Multi-Strategy significantly increase their exposure to EM during stressed financial conditions. These styles also significantly reduce their exposure to MKT during a stressed regime, so that they appear to reallocate from the U.S. market to emerging markets during bad times. This reallocation is similar to the pattern in Table 5 and again possibly reflects a belief in decoupling. Managed Futures, in contrast, significantly decreases its EM exposure to essentially zero during a stressed regime. However, because the difference in corrected AICs is negative for Managed Futures, the multifactor model without a threshold is favored over the model with a threshold for Managed Futures. Emerging Markets is the only other style for which the multifactor model without a threshold is favored.

Convertible Arbitrage and Fixed Income Arbitrage experience significant and sizable increases in their exposure to BOND during a stressed financial regime in Table 6. In addition, Convertible Arbitrage shows a significant and sizable increase in its exposure to CREDIT during a stressed regime, with a $\hat{\beta}^{\mathrm{CREDIT}}$ estimate of 1.79 during stressed conditions. Because CREDIT tends to experience large negative returns during crises—especially during the Global Financial Crisis—Convertible Arbitrage does not offer a good hedge against bad times; indeed, it magnifies losses during such times. Although there is not significant evidence of a change in exposure to CREDIT across regimes, Event Driven and Fixed Income Arbitrage exhibit substantial exposure to CREDIT during both nonstressed and stressed regimes. Consequently, like Convertible Arbitrage, these styles are poor hedges against bad times as measured by stressed market conditions.

With respect to the remaining factors, Fund of Funds (Global Macro) significantly reduces its exposure to the TFCOMM (TFCURR) to essentially zero during a stressed regime. Long/Short Equity Hedge significantly reduces its exposure to COMM to near zero during a stressed regime, while Equity Market Neutral exhibits a significant increase in exposure to LIQ during stressed financial conditions.

Figure 5 shows the cumulative log excess return due to systemic risk exposure for each hedge fund style. The solid line in each panel corresponds to the estimated regime-switching risk exposures reported in Table 6; the dashed line assumes that the exposures are constant at their values during a nonstressed regime. The vertical bars in Figure 5 delineate periods of stressed financial conditions defined by the $\hat{\gamma}$ estimates in Table 6.

In line with their failure to reduce their sizable exposure to CREDIT during stressed conditions in Table 6, Convertible Arbitrage, Event Driven, and Fixed Income Arbitrage suffer substantial drawdowns during the Global Financial Crisis in Figure 5, so that these styles constitute poor hedges against bad times in terms of their risk exposures. Emerging Markets and Long/Short Equity Hedge also realize large drawdowns in terms of their risk exposures during the stressed conditions associated with the Global Financial Crisis, and the adjustments to risk exposures do little to limit the losses. In contrast, Funds of Funds and Multi-Strategy adjust their exposures in a manner that helps to significantly limit drawdowns during stressed financial conditions, including the Global Financial Crisis.

Ten styles in Table 6 generate significant alpha in a nonstressed regime—Fund of Funds is the exception—with Managed Futures providing the highest monthly alpha of 65 basis points (7.8% annualized return) during nonstressed conditions. For eight of these styles, alpha does not decrease significantly during a stressed regime. Equity Market Neutral and Fixed Income Arbitrage, however, experience significant declines in alpha during stressed financial conditions, which limits the ability of these styles to hedge against bad times.

Figure 6 shows the risk-adjusted log cumulative excess return for each style. Reinforcing the results in Figure 4, Global Macro, Managed Futures, and Multi-Strategy deliver consistent risk-adjusted gains during stressed financial conditions, so that they provide effective hedges against bad times from this perspective. These gains and the reasonably close proximity of the solid and dashed lines for Global Macro, Managed Futures, and Multi-Strategy are consistent with the substantial alphas across both nonstressed and stressed regimes for these styles in Table 6. The remaining styles generally fail to produce consistent risk-adjusted gains during stressed conditions in Figure 6.

When we allow for regime switching across nonstressed and stressed financial conditions, the explanatory power of the multifactor model increases considerably for Convertible Arbitrage and Equity Market Neutral, as the adjusted R^2 increases by approximately six to eight percentage points for these styles as we move from Table 4 to Table 6. A number of other styles experience adjusted R^2 improvements of three to five percentage points.

In sum, the results in Table 6 and Figures 5 and 6 based on the financial stress index generally match up well with those in Table 5 and Figures 3 and 4 based on the 200-day moving average equity market indicator. We again see that certain styles adjust their risk exposures in a manner that provides an effective hedge against bad times. Furthermore, Global Macro, Managed Futures, and Multi-Strategy again deliver consistent risk-adjusted returns during bad times. However, Table 6 and Figure 5 also reveal that particular strategies—Convertible Arbitrage, Event Driven, and Fixed Income Arbitrage—are vulnerable to large losses during bad times due to their exposure to the credit factor. These styles primarily pursue convergent strategies and hold relatively illiquid securities. They perform well much of the time, but are susceptible to large losses during periods of financial stress.

4. Balanced Portfolio Performance

In this section, we analyze the hedging benefits of hedge fund styles in the context of balanced portfolios. A 60-40 portfolio that allocates 60% to the CRSP equity market index and 40% to ten-year U.S. Treasury bonds serves as the benchmark portfolio. The 60-40 portfolio is a popular balanced portfolio among individual and institutional investors, and many investment companies offer 60-40 funds (e.g., Fidelity, Janus, Charles Schwab, Vanguard, and Wells Fargo). To investigate the effects of hedge fund holdings on portfolio performance, we compare the 60-40 portfolio to balanced 40-30-30 portfolios that allocate 40% to the CRSP equity market index, 30% to ten-year U.S. Treasury bonds, and 30% to one of the eleven hedge fund styles.

4.1. Baseline results

Table 7 reports performance metrics for the balanced portfolios for 1994:01 to 2011:12. The table reports the mean and standard deviation for each of the portfolio monthly excess returns, along with the Sharpe ratio. In addition, we report the maximum drawdown in wealth over 1994:01 to 2011:12, assuming that all proceeds are reinvested. The Calmar ratio is the geometric average portfolio return divided by the maximum drawdown. Because investment managers are frequently judged relative to a benchmark, we also report outperformance statistics. Average outperformance (tracking error) is the mean (standard deviation) of the difference between the 40-30-30 and 60-40 portfolio returns. The information ratio is the ratio of the average outperformance to the tracking error.

The last column of Table 7 reports the Goetzmann, Ingersoll, Spiegel, and Welch (2007) manipulation-proof performance measure (MPPM) gain. The MPPM gain represents the increase in certainty equivalent return for an investor who holds a 40-30-30 portfolio instead of the 60-40 benchmark portfolio; the annualized MPPM gain can be interpreted as the annual portfolio management fee that an investor would be willing to pay to have access to the 40-30-30 portfolio instead of the 60-40 benchmark.

Eight of the eleven 40-30-30 portfolios in Table 7 generate an average excess return equal to or greater than the 60-40 benchmark's average monthly excess return of 0.42%; the exceptions are Convertible Arbitrage (0.41%), Dedicated Short Bias (0.30%), and Fund of Funds (0.37%). Emerging Markets and Long/Short Equity Hedge produce the highest average monthly excess return, 0.52%, while Global Macro, Managed Futures, and Multi-Strategy deliver average excess returns greater than or equal to 0.49%. With the exception of Emerging Markets, all of the 40-30-30 portfolios are less volatile than the 60-40 benchmark. The average excess returns and volatilities for the 40-30-30 portfolios translate into annualized Sharpe ratios ranging from 0.56 to 0.82, all of which are higher than the annualized Sharpe ratio of 0.52 for the 60-40 benchmark portfolio. Managed Futures generates the largest annualized Sharpe ratio in Table 7 (0.82), followed by Dedicated Short Bias and Multi-Strategy (0.81). Equity Market Neutral, Fixed Income Arbitrage, and Global Macro also produce very sizable annualized Sharpe ratios above 0.70.

With the exception of Emerging Markets, all of the 40-30-30 portfolios have a maximum drawdown below 28.64%, the maximum drawdown for the 60-40 benchmark portfolio. Dedicated Short Bias provides the smallest maximum drawdown (11.47%), followed by Managed Futures (15.93%) and Global Macro (18.30%). The maximum drawdown is also below 25% for Equity Market Neutral, Fixed Income Arbitrage, Fund of Funds, and Multi-Strategy. Note that the maximum drawdown for Convertible Arbitrage and Event Driven is near that of the benchmark. These are two styles that experience sizable losses during stressed financial conditions in Table 6 and Figure 5, which apparently limits the ability of these styles to help investors guard against large drawdowns in wealth. Dedicated Short Bias and Managed Futures produce the largest annualized Calmar ratios (0.59 and 0.57, respectively) in Table 7, more than twice that of the 60-40 benchmark portfolio (0.28). The annualized Calmar ratio is also well above that of the 60-40 benchmark for Multi-Strategy and Global Macro.

With respect to the outperformance measures, Global Macro, Long/Short Equity Hedge, and

Multi-Strategy stand out, as all of these styles deliver an annualized information ratio above 0.30. These large information ratios result from tracking errors below 1% and average outperformances ranging from 0.08% to 0.10%. Although the tracking error is relatively high for Emerging Markets and Managed Futures, the relatively large average outperformance for these two styles enables them to generate respectable annualized information ratios of 0.29 and 0.18, respectively.

All eleven of the hedge fund styles provide positive MPPM gains relative to the 60-40 benchmark portfolio in the last column of Table 7. The annualized MPPM gain is well above 100 basis points for seven styles (Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Global Macro, Long/Short Equity Hedge, Managed Futures, and Multi-Strategy). Global Macro, Managed Futures, and Multi-Strategy generate especially large MPPM gains: an investor would be willing to pay an annual management fee of 189 basis points or more to have access to the 40-30-30 portfolios based on these styles relative to the 60-40 benchmark portfolio.

4.2. Performance across up and down equity markets

Table 8 reports outperformance measures computed separately during up and down equity markets. Only five of the styles produce positive average outperformance during an up equity market, and, with the exception of Long/Short Equity Hedge, the degree of outperformance is limited. Similarly, only seven of the styles provide positive MPPM gains during an up equity market, with a maximum annualized gain of 1.19% (Long/Short Equity Hedge). Even the styles that offer the largest MPPM gains for the full 1994:01 to 2011:12 sample in Table 7 provide limited or no gains during an up equity market; indeed, despite generating one of the largest MPPM gains for the full sample, the annualized MPPM gain for Managed Futures is only 0.02% during an up equity market in Table 8. By focusing on performance during good times only—and recall that nearly 70% of the months in our sample are classified as an up equity market—potential investors could easily conclude that these styles offer limited or no value added.

In sharp contrast to an up equity market, all eleven styles generate positive average outperformance during a down equity market in Table 8. The degree of outperformance is often substantial during a down market. For example, Emerging Markets, Global Macro, Long/Short Equity Hedge, Managed Futures, and Multi-Strategy produce annualized information ratios equal to or above 0.56 during a down market. Moreover, Dedicated Short Bias, Equity Market Neutral, Fixed Income Arbitrage, Global Macro, Managed Futures, and Multi-Strategy generate substantial annualized MPPM gains of more than 300 basis points during a down market. Managed Futures delivers a remarkable annualized MPPM gain of over 600 basis points during a down equity market regime.

Overall, Table 7 shows that Global Macro, Managed Futures, and Multi-Strategy provide the largest utility gains to investors. By demarcating good and bad times in the equity market, our analysis in Table 8 indicates that the significant value added by these styles stems primarily from their substantial outperformance during bad times.

4.3. Performance across nonstressed and stressed financial markets

Finally, Table 9 reports outperformance metrics computed separately during nonstressed and stressed financial conditions. We use the $\hat{\gamma}$ estimates from Table 6 to define the nonstressed and stressed regimes for the different hedge fund styles. Reinforcing the results in Table 8, Table 9 demonstrates that the performance gains provided by the 40-30-30 portfolios are strongly concentrated during stressed financial conditions for a number of styles. For example, Global Macro, Long/Short Equity Hedge, Managed Futures, and Multi-Strategy generate very sizable annualized information ratios during stressed conditions, ranging from 0.45 to 1.28. With the exceptions of Convertible Arbitrage and Emerging Markets, the MPPM gains increase as we move from nonstressed to stressed financial conditions. Dedicated Short Bias, Equity Market Neutral, Global Macro, Managed Futures, and Multi-Strategy all provide annualized MPPM gains above 300 basis points during stressed conditions, with Managed Futures and Multi-Strategy generating particularly large gains well in excess of 500 basis points.

5. Conclusion

Our investigation of hedge fund performance during good versus bad times reveals that certain hedge fund styles provide very effective hedges against bad times, while other styles are vulnerable to large losses during bad times. In the context of multifactor models, we show that hedge fund styles such as Equity Market Neutral, Fund of Funds, Global Macro, and Multi-Strategy adjust their exposures to key risk factors during bad times in a manner that substantially buffers against losses during bad times. Furthermore, styles such as Global Macro, Managed Futures, and Multi-Strategy—which rely extensively on divergent strategies—generate statistically significant and economically sizable alpha during both good and bad times. These styles exhibit adroit hedging behavior whether we define bad times by a down equity market or stressed financial conditions, strengthening the robustness of our results. Instead of hedging against bad times, styles which rely almost exclusively on convergent strategies—including Convertible Arbitrage, Event Driven, and Fixed Income Arbitrage—remain substantially exposed to or become more exposed to risk factors in a manner that leads to large losses during bad times.

We also find that particular hedge fund styles provide valuable complements to traditional asset holdings in balanced portfolios. Balanced portfolios that augment traditional holdings with individual hedge fund styles often substantially outperform a conventional 60-40 stock-bond portfolio according to a variety of metrics. The degree of outperformance is highly concentrated during bad times for the styles that provide the largest performance gains. In particular, Global Macro, Managed Futures, and Multi-Strategy constitute especially beneficial complements to traditional holdings in balanced portfolios, further highlighting the value of these hedge fund styles as hedges against bad times.

Our study of hedge fund style performance in bad times raises interesting issues for future research in asset pricing theory; for example, what economic forces lead investors to hold particular hedge fund styles during identifiably bad times in equilibrium despite higher risk and lower (even negative) expected returns? Additionally, Ang, Ayala, and Goetzmann (2014) recently estimate the implied investment beliefs of university endowments regarding hedge funds as a broad asset class.

Along this line, another interesting topic for future research is to investigate the implied investment beliefs of endowments about individual hedge fund styles and to analyze these beliefs in light of the results reported in the present paper.

References

Agarwal, V., and N. Y. Naik. 2004. Risks and Portfolio Decisions Involving Hedge Funds. *Review of Financial Studies* 17:63–98.

Ang, A., A. Ayala, and W. N. Goetzmann. 2014. Investment Beliefs of Endowments. Working Paper, Columbia University.

Asness, C. S., R. Krail, and J. Liew. 2001. Do Hedge Funds Hedge? *Journal of Portfolio Management* 28:6–19.

Avramov, D., R. Kosowski, N. Y. Naik, and M. Teo. 2011. Hedge Funds, Managerial Skill, and Macroeconomic Variables. *Journal of Financial Economics* 99:672–692.

Bali, T. G., S. J. Brown, and M. O. Caglayan. 2011. Do Hedge Funds' Exposures to Risk Factors Explain Their Future Returns? *Journal of Financial Economics* 101:36–68.

Bali, T. G., S. J. Brown, and M. O. Caglayan. 2012. Systematic Risk and the Cross Section of Hedge Fund Returns. *Journal of Financial Economics* 106:114–131.

Bali, T. G., S. J. Brown, and M. O. Caglayan. 2014. Macroeconomic Risk and Hedge Fund Returns. *Journal of Financial Economics* 114:1–19.

Bollen, N. P. B., and R. E. Whaley. 2009. Hedge Fund Risk Dynamics: Implications for Performance Appraisal. *Journal of Finance* 64:985–1035.

Brock, W., J. Lakonishok, and B. LeBaron. 1992. Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. *Journal of Finance* 47:1731–1764.

Brockwell, P. J., and R. A. Davis. 1991. *Time Series: Theories and Methods*, Second Edition. New York: Springer.

Brown, S. J., W. N. Goetzmann, and R. G. Ibbotson. 1999. Offshore Hedge Funds: Survival and Performance, 1989–95. *Journal of Business* 72:91–117.

Buraschi, A., R. Kosowski, and F. Trojani. 2015. When There is No Place to Hide: Correlation Risk and the Cross-Section of Hedge Fund Returns. *Review of Financial Studies*, forthcoming.

Carhart, M. M. 1997. On Persistence in Mutual Fund Performance. *Journal of Finance* 52:57–82.

Chan, K. S. 1993. Consistency and Limiting Distribution of the Least Squares Estimator of a

Threshold Autoregressive Model. *Annals of Statistics* 21:520–533.

Fama, E. F., and K. R. French. 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33:3–56.

Fung, W. H., and D. A. Hsieh. 1997. Empirical Characteristics of Dynamic Trading Strategies. *Review of Financial Studies* 10:275–302.

Fung, W. H., and D. A. Hsieh. 2000. Performance Characteristics of Hedge Funds and CTA Funds: Natural Versus Spurious Biases. *Journal of Financial and Quantitative Analysis* 35:291–307.

Fung, W. H., and D. A. Hsieh. 2001. The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers. *Review of Financial Studies* 14:313–341.

Fung, W. H., and D. A. Hsieh. 2002a. Asset-Based Style Factors for Hedge Funds. *Financial Analysts Journal* 58:16–27.

Fung, W. H., and D. A. Hsieh. 2002b. Risks in Fixed-Income Hedge Fund Styles. *Journal of Fixed Income* 12:6–27.

Fung, W. H., and D. A. Hsieh. 2004. Hedge Fund Benchmarks: A Risk-Based Approach. *Financial Analysts Journal* 60:65–80.

Fung W. H., D. A. Hsieh, N. Y. Naik, and T. Ramadorai. 2008. Hedge Funds: Performance, Risk, and Capital Formation. *Journal of Finance* 63:1777–1803.

Getmansky, M., A. W. Lo, and I. Makarov. 2004. An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns. *Journal of Financial Economics* 74:529–609.

Goetzmann, W. N., J. E. Ingersoll, M. I. Spiegel, and I. Welch. 2007. Portfolio Performance Manipulation and Manipulation-Proof Performance Measures. *Review of Financial Studies* 20:1503–1546.

Gonzalo, J. and J.-Y. Pitarakis. 2002. Estimation and Model Selection Based Inference in Single and Multiple Threshold Models. *Journal of Econometrics* 110:319–352.

Hakkio, C. S., and W. R. Keeton. 2009. Financial Stress: What Is It, How Can It Be Measured, and Why Does It Matter? Federal Reserve Bank of Kansas City *Economic Review* Second

Quarter:5–50.

Hansen, B. E. 2000. Sample Splitting and Threshold Estimation. *Econometrica* 68:575–603.

Hurvich, C. M., and C.-L. Tsai. 1989. Regression and Time Series Model Selection in Small Samples. *Biometrika* 76:297–307.

Kliesen, K. L., M. T. Owyang, and K. Vermann. 2012. Disentangling Diverse Measures: A Survey of Financial Stress Indexes. Federal Reserve Bank of St. Louis *Review* 94:369–397.

Liang, B. 2000. Hedge Funds: The Living and the Dead. *Journal of Financial and Quantitative Analysis* 35:309–326.

Lo, A. W. 2002. The Statistics of Sharpe Ratios. *Financial Analysts Journal* 58:36–52.

Lo, A. W., H. Mamaysky, and J. Wang. 2000. Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation. *Journal of Finance* 55:1705–1765.

Mitchell, M. L., and T. C. Pulvino. 2001. Characteristics of Risk and Return in Risk Arbitrage. *Journal of Finance* 56:2135–2176.

Moskowitz, T. J., Y. H. Ooi, and L. H. Pedersen. 2012. Time Series Momentum. *Journal of Financial Economics* 104:228–250.

National Association of College and University Business Officers. 2013. *2012 NACUBO Commonfund Study of Endowments*. Issue Date: February 1, 2013.

Neely, C. J., D. E. Rapach, J. Tu, and G. Zhou. 2014. Forecasting the Equity Risk Premium: The Role of Technical Indicators. *Management Science* 60:1772–1791.

Pástor, L., and R. F. Stambaugh. 2003. Liquidity Risk and Expected Stock Returns. *Journal of Political Economy* 111:642–685.

Patton, A. J. 2009. Are 'Market Neutral' Hedge Funds Really Market Neutral? *Review of Financial Studies* 22:2495–2530.

Patton, A. J., and T. Ramadorai. 2013. On the High-Frequency Dynamics of Hedge Fund Risk Exposures. *Journal of Finance* 68:597–635.

Pensions and Investments. 2013. *P&I's Top 1,000 Largest Retirement Plans*. Issue Date: February

4, 2013.

Siegel, J. J. 2013. *Stocks for the Long Run*, Fifth Edition. New York: McGraw-Hill.

Sun, Z., A. W. Wang, and L. Zheng. 2013. Only When the Tide Goes Out: Downside Returns and Hedge Fund Performance. Working Paper, University of California at Irvine.

Titman, S., and C. Tiu. 2011, Do the Best Hedge Funds Hedge? *Review of Financial Studies* 24:123–168.

Tong, H. 1983. Threshold Models in Nonlinear Time Series Analysis. *Lecture Notes in Statistics*. Berlin: Springer.

Tong, H. 1990. Nonlinear Time Series. *Oxford Statistical Science Series*, Vol. 6. New York: The Clarendon Press, Oxford University Press.

Table 1
Summary statistics for smoothed and usmoothed hedge fund excess returns, 1994:01—2011:12

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Smoothed excess returns				Unsmoothed excess returns					
Style	Mean (%)	Standard deviation (%)	Annualized Sharpe ratio	ρ	$\hat{\theta}_0$	$\hat{\theta}_1$	$\hat{\theta}_2$	Mean (%)	Standard deviation (%)	Annualized Sharpe ratio
Convertible Arbitrage	0.39	2.12	0.63	0.55	0.56	0.34	0.10	0.39	3.16	0.43
Dedicated Short Bias	0.02	3.81	0.02	0.10	0.89	0.11	0.00	0.02	4.25	0.02
Emerging Markets	0.78	4.34	0.62	0.36	0.75	0.25	0.00	0.78	5.44	0.49
Equity Market Neutral	0.46	0.85	1.87	0.38	0.66	0.19	0.15	0.46	1.19	1.34
Event Driven	0.57	1.60	1.24	0.47	0.62	0.28	0.11	0.57	2.30	0.85
Fixed Income Arbitrage	0.44	1.06	1.44	0.38	0.68	0.26	0.06	0.44	1.45	1.06
Fund of Funds	0.27	1.50	0.63	0.32	0.70	0.20	0.10	0.27	2.03	0.46
Global Macro	0.68	1.82	1.30	0.07	0.94	0.06	0.00	0.68	1.94	1.22
Long/Short Equity Hedge	0.78	2.54	1.06	0.25	0.76	0.18	0.05	0.78	3.21	0.84
Managed Futures	0.66	2.98	0.77	0.02	0.97	0.03	0.00	0.66	3.06	0.75
Multi-Strategy	0.72	1.06	2.35	0.40	0.65	0.24	0.10	0.72	1.49	1.67

The second through fifth columns report summary statistics for observed smoothed hedge fund index excess returns for the style given in the first column. Excess returns are measured relative to the one-month Treasury bill return. ρ is the first-order autocorrelation coefficient. Unsmoothed excess returns are related to smoothed excess returns via $R_t^o = \theta_0 R_t + \theta_1 R_{t-1} + \theta_2 R_{t-2}$, where R_t^o is the observed smoothed excess return, R_t is the unobserved unsmoothed excess return, $\theta_j \in [0,1]$ $(j = 0,1,2)$, and $\sum_{j=0}^{2} \theta_j = 1$. The parameters θ_j $(j = 0,1,2)$ and unsmoothed excess returns are estimated using maximum likelihood and the Kalman filter. The sixth through eighth columns report estimates of θ_j $(j = 0,1,2)$. The final three columns report summary statistics for the estimated unobserved unsmoothed excess returns based on the Kalman smoother. Hedge fund data are from the Lipper TASS hedge fund database.

Table 2
Abbreviations and summary statistics for hedge fund risk factor excess returns, 1994:01—2011:12

(1) Description	(2) Abbeviation	(3) Mean (%)	(4) Standard deviation (%)	(5) Annualized Sharpe ratio
CRSP equity market excess return	MKT	0.48	4.64	0.36
Fama-French size factor	SMB	0.26	3.28	0.27
Fama-French value factor	HML	0.12	4.20	0.10
Carhart momentum factor	UMD	0.49	5.50	0.31
Treasury bond excess return	BOND	0.32	2.24	0.50
BofA ML corporate bond return − Treasury bond return	CREDIT	0.06	1.53	0.14
Fung-Hsieh bond lookback straddle excess return	TFBOND	−0.46	4.64	−0.34
Fung-Hsieh currency lookback straddle excess return	TFCURR	−0.10	4.64	−0.08
Fung-Hsieh commodity lookback straddle excess return	TFCOMM	−0.22	4.64	−0.16
MSCI emerging market excess return	EM	0.45	7.10	0.22
Currency factor	CURR	−0.24	2.19	−0.38
S&P GSCI excess return	COMM	0.35	6.48	0.18
Pástor-Stambaugh liquidity factor	LIQ	0.77	4.08	0.65

The table describes the risk factor excess returns used to explain hedge fund style index excess returns. Excess returns are measured relative to the one-month Treasury bill return. Data are from the Federal Reserve Economic Database, Global Financial Data, Morgan Stanley, Ibbotson Associates, Bloomberg, Kenneth French's Data Library, David Hsieh's Hedge Fund Data Library, and Ľuboš Pástor's webpage. Abbreviations in the first column are as follows: CRSP = Center for Research in Security Prices, BofA ML = Bank of America Merrill Lynch, MSCI = Morgan Stanley Capital International, S&P GSCI = Standard and Poor's Goldman Sachs commodity index. The Fung-Hsieh lookback straddle excess returns are scaled to have the same volatility as the CRSP equity market excess return.

Table 3
Summary statistics for unsmoothed hedge fund excess returns during up/down equity markets and nonstressed/stressed financial conditions, 1994:01—2011:12

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Style	Mean (%)	Standard deviation (%)	Annualized Sharpe ratio	Mean (%)	Standard deviation (%)	Annualized Sharpe ratio	$\hat{\gamma}$
	A. Up Equity Market			*B. Down Equity Market*			
Convertible Arbitrage	0.47	2.15	0.75	0.22	4.64	0.16	
Dedicated Short Bias	−0.17	4.39	−0.13	0.44	3.94	0.38	
Emerging Markets	0.90	5.46	0.57	0.52	5.44	0.33	
Equity Market Neutral	0.57	1.04	1.92	0.22	1.44	0.53	
Event Driven	0.73	1.97	1.28	0.22	2.86	0.26	
Fixed Income Arbitrage	0.52	1.27	1.41	0.28	1.77	0.55	
Fund of Funds	0.43	2.14	0.70	−0.08	1.74	−0.16	
Global Macro	0.79	2.13	1.29	0.44	1.43	1.07	
Long/Short Equity Hedge	1.06	3.25	1.13	0.18	3.08	0.21	
Managed Futures	0.57	2.98	0.67	0.85	3.24	0.90	
Multi-Strategy	0.82	1.54	1.85	0.51	1.39	1.27	
	C. Nonstressed Conditions			*D. Stressed Conditions*			
Convertible Arbitrage	0.46	2.01	0.79	0.02	6.52	0.01	0.79
Dedicated Short Bias	−0.18	4.19	−0.15	1.09	4.48	0.84	0.72
Emerging Markets	1.18	5.25	0.78	−0.75	5.93	−0.44	0.59
Equity Market Neutral	0.55	1.02	1.86	−0.34	2.08	−0.56	1.01
Event Driven	0.75	1.97	1.31	−0.36	3.44	−0.36	0.72
Fixed Income Arbitrage	0.53	1.19	1.53	−0.34	2.83	−0.42	1.01
Fund of Funds	0.48	1.95	0.85	−0.47	2.18	−0.75	0.56
Global Macro	0.84	2.01	1.44	0.25	1.67	0.51	0.44
Long/Short Equity Hedge	1.09	2.99	1.26	−0.01	3.63	−0.01	0.37
Managed Futures	0.79	3.06	0.89	0.33	3.05	0.38	0.37
Multi-Strategy	0.79	1.42	1.92	0.48	1.72	0.96	0.56

Panel A (B) reports summary statistics for unsmoothed hedge fund index excess returns for the style given in the first column during an up (down) equity market. A given month is designated as an up (down) equity market if the S&P 500 price index is greater than or equal to (less than) its 200-day moving average on the last day of the preceding month. Panel C (D) reports summary statistics for unsmoothed excess returns during nonstressed (stressed) financial conditions. The nonstressed/stressed regimes are determined from the threshold regression model,

$$R_t = \mu_1 + \sigma_1 u_t \text{ for } q_t \leq \gamma \quad \text{(nonstressed financial conditions)},$$
$$R_t = \mu_2 + \sigma_2 u_t \text{ for } q_t > \gamma \quad \text{(stressed financial conditions)},$$

where R_t is the unsmoothed hedge fund index excess return; u_t is a zero-mean, unit-variance variate; q_t is the Federal Reserve Bank of Kansas City Financial Stress Index; and γ is the threshold parameter. The last column reports the estimate of γ.

Table 4
Multifactor model estimation results for unsmoothed hedge fund excess returns, 1994:01—2011:12

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Coeff.	Estimate	Coeff.	Estimate	Coeff.	Estimate	Coeff.	Estimate	Coeff.	Estimate	Coeff.	Estimate
A. Convertible Arbitrage		*B. Dedicated Short Bias*		*C. Emerging Markets*		*D. Equity Market Neutral*		*E. Event Driven*		*F. Fixed Income Arbitrage*	
$\hat{\alpha}$	0.09	$\hat{\alpha}$	0.31**	$\hat{\alpha}$	0.49***	$\hat{\alpha}$	0.30***	$\hat{\alpha}$	0.34***	$\hat{\alpha}$	0.30***
$\hat{\beta}^{MKT}$	0.18***	$\hat{\beta}^{MKT}$	−0.62***	$\hat{\beta}^{HML}$	−0.08	$\hat{\beta}^{MKT}$	0.12***	$\hat{\beta}^{MKT}$	0.26***	$\hat{\beta}^{MKT}$	0.04
$\hat{\beta}^{BOND}$	0.41***	$\hat{\beta}^{SMB}$	−0.31***	$\hat{\beta}^{UMD}$	0.07**	$\hat{\beta}^{HML}$	0.06**	$\hat{\beta}^{SMB}$	0.13***	$\hat{\beta}^{UMD}$	0.03**
$\hat{\beta}^{CREDIT}$	1.32***	$\hat{\beta}^{HML}$	0.37***	$\hat{\beta}^{EM}$	0.71***	$\hat{\beta}^{UMD}$	0.10***	$\hat{\beta}^{BOND}$	0.10**	$\hat{\beta}^{BOND}$	0.23***
		$\hat{\beta}^{UMD}$	0.10***	$\hat{\beta}^{CURR}$	0.21**	$\hat{\beta}^{EM}$	0.02	$\hat{\beta}^{CREDIT}$	0.60***	$\hat{\beta}^{CREDIT}$	0.53***
						$\hat{\beta}^{LIQ}$	0.05*				
$\hat{\sigma}^2$	4.76	$\hat{\sigma}^2$	4.11	$\hat{\sigma}^2$	5.93	$\hat{\sigma}^2$	0.94	$\hat{\sigma}^2$	1.46	$\hat{\sigma}^2$	1.49
$\bar{R}^2$	52.29%	$\bar{R}^2$	77.32%	$\bar{R}^2$	80.01%	$\bar{R}^2$	33.82%	$\bar{R}^2$	72.47%	$\bar{R}^2$	28.93%
G. Fund of Funds		*H. Global Macro*		*I. Long/Short Equity Hedge*		*J. Managed Futures*		*K. Multi-Strategy*			
$\hat{\alpha}$	0.08	$\hat{\alpha}$	0.54***	$\hat{\alpha}$	0.44***	$\hat{\alpha}$	0.57***	$\hat{\alpha}$	0.61***		
$\hat{\beta}^{MKT}$	0.08***	$\hat{\beta}^{MKT}$	0.08**	$\hat{\beta}^{MKT}$	0.39***	$\hat{\beta}^{HML}$	0.15**	$\hat{\beta}^{MKT}$	0.10***		
$\hat{\beta}^{HML}$	−0.06**	$\hat{\beta}^{UMD}$	0.04**	$\hat{\beta}^{SMB}$	0.22***	$\hat{\beta}^{UMD}$	0.14***	$\hat{\beta}^{HML}$	−0.08**		
$\hat{\beta}^{UMD}$	0.06***	$\hat{\beta}^{BOND}$	0.26***	$\hat{\beta}^{HML}$	−0.14***	$\hat{\beta}^{BOND}$	0.18**	$\hat{\beta}^{BOND}$	0.13***		
$\hat{\beta}^{BOND}$	0.23***	$\hat{\beta}^{CREDIT}$	0.26**	$\hat{\beta}^{UMD}$	0.04	$\hat{\beta}^{TFBOND}$	0.14***	$\hat{\beta}^{CREDIT}$	0.15**		
$\hat{\beta}^{CREDIT}$	0.40***	$\hat{\beta}^{TFCURR}$	0.14***	$\hat{\beta}^{BOND}$	0.07	$\hat{\beta}^{TFCURR}$	0.17***	$\hat{\beta}^{TFCURR}$	0.03**		
$\hat{\beta}^{TFCURR}$	0.06***	$\hat{\beta}^{TFCOMM}$	0.05**	$\hat{\beta}^{EM}$	0.11***	$\hat{\beta}^{TFCOMM}$	0.16***	$\hat{\beta}^{EM}$	0.09***		
$\hat{\beta}^{TFCOMM}$	0.04**	$\hat{\beta}^{EM}$	0.13***	$\hat{\beta}^{COMM}$	0.06***	$\hat{\beta}^{EM}$	0.07**	$\hat{\beta}^{CURR}$	0.09**		
$\hat{\beta}^{EM}$	0.17***	$\hat{\beta}^{CURR}$	0.20***			$\hat{\beta}^{COMM}$	0.09***	$\hat{\beta}^{COMM}$	0.03***		
$\hat{\beta}^{CURR}$	0.19***										
$\hat{\beta}^{COMM}$	0.04***										
$\hat{\sigma}^2$	1.25	$\hat{\sigma}^2$	2.12	$\hat{\sigma}^2$	1.81	$\hat{\sigma}^2$	6.15	$\hat{\sigma}^2$	0.90		
$\bar{R}^2$	69.70%	$\bar{R}^2$	43.47%	$\bar{R}^2$	82.51%	$\bar{R}^2$	34.37%	$\bar{R}^2$	59.82%		

The table reports estimation results for the multifactor model,

$$R_t = \alpha + f_t'\beta + \varepsilon_t,$$

where R_t is the unsmoothed hedge fund index excess return for the style given in the panel heading and f_t is a vector of selected factor excess returns. Excess returns are expressed in percentage points. The superscript for $\hat{\beta}$ in the Coeff. columns denotes the risk factor from Table 2. The Estimate columns report OLS estimates of α and β; *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, according to heteroskedasticity-robust t-statistics. $\bar{R}^2$ is the adjusted R^2 statistic.

Table 5
Multifactor model estimation results for unsmoothed hedge fund excess returns during up/down equity markets, 1994:01—2011:12

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Coefficient	Up	Down	Δ	Coefficient	Up	Down	Δ	Coefficient	Up	Down	Δ
A. Convertible Arbitrage				*B. Dedicated Short Bias*				*C. Emerging Markets*			
$\hat{\alpha}$	0.10	−0.22	−0.32	$\hat{\alpha}$	0.43**	0.12	−0.32	$\hat{\alpha}$	0.37*	0.79***	0.41
$\hat{\beta}^{\text{MKT}}$	0.24***	0.18**	−0.07	$\hat{\beta}^{\text{MKT}}$	−0.73***	−0.53***	0.20***	$\hat{\beta}^{\text{HML}}$	−0.10	−0.06	0.04
$\hat{\beta}^{\text{BOND}}$	0.11*	0.93***	0.82***	$\hat{\beta}^{\text{SMB}}$	−0.36***	−0.20***	0.16*	$\hat{\beta}^{\text{UMD}}$	−0.01	0.09*	0.10
$\hat{\beta}^{\text{CREDIT}}$	1.12***	1.54***	0.42	$\hat{\beta}^{\text{HML}}$	0.44***	0.26***	−0.19**	$\hat{\beta}^{\text{EM}}$	0.77***	0.67***	−0.10**
				$\hat{\beta}^{\text{UMD}}$	0.24***	0.06	−0.18**	$\hat{\beta}^{\text{CURR}}$	0.15	0.30***	0.15
$\hat{\sigma}^2$	1.77	8.89		$\hat{\sigma}^2$	3.72	3.04		$\hat{\sigma}^2$	6.15	4.10	
$\bar{R}^2$	57.87%			$\bar{R}^2$	79.69%			$\bar{R}^2$	80.56%		
Wald	5.57***			Wald	6.36***			Wald	2.43**		
D. Equity Market Neutral				*E. Event Driven*				*F. Fixed Income Arbitrage*			
$\hat{\alpha}$	0.32***	0.13	−0.19	$\hat{\alpha}$	0.35***	0.17	−0.18	$\hat{\alpha}$	0.34***	0.10	−0.24
$\hat{\beta}^{\text{MKT}}$	0.18***	0.02	−0.16***	$\hat{\beta}^{\text{MKT}}$	0.31***	0.23***	−0.07*	$\hat{\beta}^{\text{MKT}}$	0.08***	−0.01	−0.09*
$\hat{\beta}^{\text{HML}}$	0.08***	0.05	−0.03	$\hat{\beta}^{\text{SMB}}$	0.15***	0.06	−0.09	$\hat{\beta}^{\text{UMD}}$	0.03	0.00	−0.03
$\hat{\beta}^{\text{UMD}}$	0.10***	0.09***	−0.01	$\hat{\beta}^{\text{BOND}}$	0.00	0.27***	0.27***	$\hat{\beta}^{\text{BOND}}$	0.19***	0.31***	0.12
$\hat{\beta}^{\text{EM}}$	0.00	0.08**	0.07**	$\hat{\beta}^{\text{CREDIT}}$	0.58***	0.70***	0.12	$\hat{\beta}^{\text{CREDIT}}$	0.50***	0.57***	0.08
$\hat{\beta}^{\text{LIQ}}$	0.01	0.08***	0.06*		0.12*						
$\hat{\sigma}^2$	0.61	1.33		$\hat{\sigma}^2$	0.95	1.99		$\hat{\sigma}^2$	1.15	1.95	
$\bar{R}^2$	37.11%			$\bar{R}^2$	74.53%			$\bar{R}^2$	29.77%		
Wald	2.44**			Wald	3.87***			Wald	1.33		

The table reports estimation results for the regime-switching multifactor model,

$$R_t = \alpha_1 + f_t'\beta_1 + \sigma_1 u_t \quad \text{for an up equity market,}$$
$$R_t = \alpha_2 + f_t'\beta_2 + \sigma_2 u_t \quad \text{for a down equity market,}$$

where R_t is the unsmoothed hedge fund index excess return for the style given in the panel heading; f_t is a vector of selected factor excess returns; and u_t is a zero-mean, unit-variance variate. Month t is an up (down) equity market if the S&P 500 price index is greater than or equal to (less than) its 200-day moving average on the last day of the preceding month. Excess returns are expressed in percentage points. The superscript for $\hat{\beta}$ in the Coefficient columns denotes the risk factor from Table 2. The Up (Down, Δ) columns report OLS estimates of α_1 and β_1 (α_2 and β_2, $\alpha_2 - \alpha_1$ and $\beta_2 - \beta_1$); *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, according to heteroskedasticity-robust t-statistics. $\bar{R}^2$ is the adjusted R^2 statistic. Wald is a heteroskedasticity-robust F-statistic for testing the joint null hypothesis that $\alpha_1 = \alpha_2$ and $\beta_1 = \beta_2$. 0.00 indicates less than 0.005 in absolute value.

Table 5 (continued)

G. Fund of Funds

(1) Coefficient	(2) Up	(3) Down	(4) Δ
$\hat{\alpha}$	0.03	−0.10	−0.13
$\hat{\beta}^{MKT}$	0.20***	−0.06	−0.26***
$\hat{\beta}^{HML}$	−0.04	−0.04	0.00
$\hat{\beta}^{UMD}$	0.04	0.04*	0.00
$\hat{\beta}^{BOND}$	0.17***	0.18***	0.02
$\hat{\beta}^{CREDIT}$	0.26**	0.41***	0.15
$\hat{\beta}^{TFCURR}$	0.07***	0.04	−0.03
$\hat{\beta}^{TFCOMM}$	0.05**	−0.01	−0.06*
$\hat{\beta}^{EM}$	0.16***	0.16***	0.00
$\hat{\beta}^{CURR}$	0.15***	0.13*	−0.02
$\hat{\beta}^{COMM}$	0.04***	0.03**	−0.01
$\hat{\sigma}^2$	1.04	0.75	
$\bar{R}^2$	74.48%		
Wald	5.36***		

H. Global Macro

(5) Coefficient	(6) Up	(7) Down	(8) Δ
$\hat{\alpha}$	0.46***	0.37**	−0.09
$\hat{\beta}^{MKT}$	0.18***	−0.10**	−0.28***
$\hat{\beta}^{UMD}$	0.04	−0.02	−0.06
$\hat{\beta}^{BOND}$	0.27***	0.02	−0.25**
$\hat{\beta}^{CREDIT}$	0.34**	0.11	−0.22
$\hat{\beta}^{TFCURR}$	0.17***	0.03	−0.14***
$\hat{\beta}^{TFCOMM}$	0.05**	0.02	−0.03
$\hat{\beta}^{EM}$	0.13***	0.11***	−0.02
$\hat{\beta}^{CURR}$	0.22***	−0.06	−0.28**
$\hat{\sigma}^2$	1.85	1.39	
$\bar{R}^2$	50.48%		
Wald	5.16***		

I. Long/Short Equity Hedge

(9) Coefficient	(10) Up	(11) Down	(12) Δ
$\hat{\alpha}$	0.38***	0.34**	−0.04
$\hat{\beta}^{MKT}$	0.51***	0.21***	−0.30***
$\hat{\beta}^{SMB}$	0.28***	0.07	−0.21***
$\hat{\beta}^{HML}$	−0.12***	−0.09**	0.03
$\hat{\beta}^{UMD}$	0.02	0.02	0.00
$\hat{\beta}^{BOND}$	0.04	0.02	−0.02
$\hat{\beta}^{EM}$	0.07***	0.19***	0.12***
$\hat{\beta}^{COMM}$	0.08***	0.03	−0.06**
$\hat{\sigma}^2$	1.42	1.44	
$\bar{R}^2$	85.10%		
Wald	5.93***		

J. Managed Futures

(1) Coefficient	(2) Up	(3) Down	(4) Δ
$\hat{\alpha}$	0.47**	0.72**	0.25
$\hat{\beta}^{HML}$	0.22***	0.00	−0.22*
$\hat{\beta}^{UMD}$	0.13*	0.02	−0.11
$\hat{\beta}^{BOND}$	0.14	0.34**	0.21
$\hat{\beta}^{TFBOND}$	0.18***	0.04	−0.14*
$\hat{\beta}^{TFCURR}$	0.16***	0.20***	0.04
$\hat{\beta}^{TFCOMM}$	0.18***	0.06	−0.12
$\hat{\beta}^{EM}$	0.17***	−0.09*	−0.26***
$\hat{\beta}^{COMM}$	0.05	0.17***	0.11**
$\hat{\sigma}^2$	5.07	5.58	
$\bar{R}^2$	39.05%		
Wald	2.94***		

K. Multi-Strategy

(5) Coefficient	(6) Up	(7) Down	(8) Δ
$\hat{\alpha}$	0.53***	0.48***	−0.04
$\hat{\beta}^{MKT}$	0.20***	−0.02	−0.22***
$\hat{\beta}^{HML}$	−0.06***	−0.04	0.02
$\hat{\beta}^{BOND}$	0.10**	0.03	−0.07
$\hat{\beta}^{CREDIT}$	0.03	0.19**	0.16
$\hat{\beta}^{TFCURR}$	0.01	0.01	0.00
$\hat{\beta}^{EM}$	0.09***	0.10***	0.01
$\hat{\beta}^{CURR}$	0.11***	−0.06	−0.17**
$\hat{\beta}^{COMM}$	0.05***	0.00	−0.05**
$\hat{\sigma}^2$	0.61	0.86	
$\bar{R}^2$	66.20%		
Wald	5.40***		

Table 6
Multifactor model estimation results for unsmoothed hedge fund excess returns during nonstressed/stressed financial conditions, 1994:01—2011:12

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Coefficient	Nonstressed	Stressed	Δ	Coefficient	Nonstressed	Stressed	Δ	Coefficient	Nonstressed	Stressed	Δ
A. Convertible Arbitrage				*B. Dedicated Short Bias*				*C. Emerging Markets*			
$\hat{\alpha}$	0.18*	−0.24	−0.42	$\hat{\alpha}$	0.50**	0.22	−0.27	$\hat{\alpha}$	0.53***	0.38	−0.15
$\hat{\beta}^{\text{MKT}}$	0.17***	0.18	0.01	$\hat{\beta}^{\text{MKT}}$	−0.78***	−0.58***	0.20***	$\hat{\beta}^{\text{HML}}$	−0.14**	0.03	0.17
$\hat{\beta}^{\text{BOND}}$	0.18***	1.36***	1.18***	$\hat{\beta}^{\text{SMB}}$	−0.39***	−0.27***	0.12	$\hat{\beta}^{\text{UMD}}$	0.01	0.13*	0.12
$\hat{\beta}^{\text{CREDIT}}$	1.04***	1.79***	0.75*	$\hat{\beta}^{\text{HML}}$	0.60***	0.32***	−0.27**	$\hat{\beta}^{\text{EM}}$	0.74***	0.69***	−0.05
				$\hat{\beta}^{\text{UMD}}$	0.19**	0.08*	−0.12	$\hat{\beta}^{\text{CURR}}$	0.12	0.38**	0.26
$\hat{\sigma}^2$	2.14	20.08		$\hat{\sigma}^2$	3.26	3.96		$\hat{\sigma}^2$	5.84	4.36	
$\bar{R}^2$	59.57%			$\bar{R}^2$	79.13%			$\bar{R}^2$	80.35%		
$\hat{\gamma}$	1.01			$\hat{\gamma}$	−0.23			$\hat{\gamma}$	0.62		
$\text{IC}_0 - \text{IC}_1$	26.91			$\text{IC}_0 - \text{IC}_1$	11.15			$\text{IC}_0 - \text{IC}_1$	−1.28		
D. Equity Market Neutral				*E. Event Driven*				*F. Fixed Income Arbitrage*			
$\hat{\alpha}$	0.36***	−0.26	−0.62*	$\hat{\alpha}$	0.38***	−0.03	−0.41	$\hat{\alpha}$	0.39***	−0.55	−0.94**
$\hat{\beta}^{\text{MKT}}$	0.15***	−0.11	−0.26**	$\hat{\beta}^{\text{MKT}}$	0.26***	0.24***	−0.02	$\hat{\beta}^{\text{MKT}}$	0.04*	−0.03	−0.06
$\hat{\beta}^{\text{HML}}$	0.08***	0.06	−0.02	$\hat{\beta}^{\text{SMB}}$	0.17***	−0.18	−0.34***	$\hat{\beta}^{\text{UMD}}$	0.02	−0.02	−0.04
$\hat{\beta}^{\text{UMD}}$	0.11***	0.08	−0.03	$\hat{\beta}^{\text{BOND}}$	0.12***	0.22	0.10	$\hat{\beta}^{\text{BOND}}$	0.18***	0.53***	0.35**
$\hat{\beta}^{\text{EM}}$	0.01	0.16**	0.16**	$\hat{\beta}^{\text{CREDIT}}$	0.68***	0.73***	0.04	$\hat{\beta}^{\text{CREDIT}}$	0.47***	0.67***	0.20
$\hat{\beta}^{\text{LIQ}}$	0.01	0.12**	0.11**								
$\hat{\sigma}^2$	0.63	2.13		$\hat{\sigma}^2$	1.09	2.67		$\hat{\sigma}^2$	1.15	3.20	
$\bar{R}^2$	42.26%			$\bar{R}^2$	74.98%			$\bar{R}^2$	32.54%		
$\hat{\gamma}$	1.01			$\hat{\gamma}$	0.97			$\hat{\gamma}$	1.01		
$\text{IC}_0 - \text{IC}_1$	18.59			$\text{IC}_0 - \text{IC}_1$	17.65			$\text{IC}_0 - \text{IC}_1$	3.38		

The table reports estimation results for the threshold multifactor model,

$$R_t = \alpha_1 + f_t'\beta_1 + \sigma_1 u_t \ \text{ for } \ q_t \leq \gamma \quad \text{(nonstressed financial conditions)},$$
$$R_t = \alpha_2 + f_t'\beta_2 + \sigma_2 u_t \ \text{ for } \ q_t > \gamma \quad \text{(stressed financial conditions)},$$

where R_t is the unsmoothed hedge fund index excess return for the style given in the panel heading; f_t is a vector of selected factor excess returns; u_t is a zero-mean, unit-variance variate; and q_t is the Federal Reserve Bank of Kansas City Financial Stress Index. Excess returns are expressed in percentage points. The superscript for $\hat{\beta}$ in the Coefficient columns denotes the risk factor from Table 2. The Nonstressed (Stressed, Δ) columns report OLS estimates of α_1 and β_1 (α_2 and β_2, $\alpha_2 - \alpha_1$ and $\beta_2 - \beta_1$); *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, according to heteroskedasticity-robust t-statistics. $\bar{R}^2$ is the adjusted R^2 statistic. $\text{IC}_0 - \text{IC}_1$ is the difference between the corrected AICs for the model without a threshold and the model with a threshold. 0.00 indicates less than 0.005 in absolute value.

Table 6 (continued)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Coefficient	Nonstressed	Stressed	Δ	Coefficient	Nonstressed	Stressed	Δ	Coefficient	Nonstressed	Stressed	Δ
G. Fund of Funds				*H. Global Macro*				*I. Long/Short Equity Hedge*			
$\hat{\alpha}$	0.00	−0.02	−0.02	$\hat{\alpha}$	0.50***	0.41***	−0.09	$\hat{\alpha}$	0.32***	0.44*	0.13
$\hat{\beta}^{\text{MKT}}$	0.26***	0.00	−0.26***	$\hat{\beta}^{\text{MKT}}$	0.19***	−0.06	−0.25***	$\hat{\beta}^{\text{MKT}}$	0.46***	0.07	−0.39***
$\hat{\beta}^{\text{HML}}$	−0.04	−0.07**	−0.03	$\hat{\beta}^{\text{UMD}}$	0.08**	0.03	−0.05	$\hat{\beta}^{\text{SMB}}$	0.26***	0.08	−0.18**
$\hat{\beta}^{\text{UMD}}$	−0.03	0.06***	0.09*	$\hat{\beta}^{\text{BOND}}$	0.28***	0.13	−0.14	$\hat{\beta}^{\text{HML}}$	−0.15***	0.00	0.15*
$\hat{\beta}^{\text{BOND}}$	0.19***	0.24***	0.06	$\hat{\beta}^{\text{CREDIT}}$	0.34	0.12	−0.22	$\hat{\beta}^{\text{UMD}}$	0.07**	0.10	0.03
$\hat{\beta}^{\text{CREDIT}}$	0.50*	0.40***	−0.10	$\hat{\beta}^{\text{TFCURR}}$	0.19***	0.03	−0.16***	$\hat{\beta}^{\text{BOND}}$	0.10**	−0.03	−0.13
$\hat{\beta}^{\text{TFCURR}}$	0.07***	0.04	−0.03	$\hat{\beta}^{\text{TFCOMM}}$	0.07**	0.03	−0.03	$\hat{\beta}^{\text{EM}}$	0.09***	0.31***	0.22***
$\hat{\beta}^{\text{TFCOMM}}$	0.07***	0.01	−0.06*	$\hat{\beta}^{\text{EM}}$	0.11***	0.18***	0.07	$\hat{\beta}^{\text{COMM}}$	0.06***	−0.01	−0.07*
$\hat{\beta}^{\text{EM}}$	0.14***	0.19***	0.05	$\hat{\beta}^{\text{CURR}}$	0.20***	0.10	−0.10				
$\hat{\beta}^{\text{CURR}}$	0.18***	0.18***	0.00								
$\hat{\beta}^{\text{COMM}}$	0.04**	0.04**	−0.01								
$\hat{\sigma}^2$	0.89	1.09		$\hat{\sigma}^2$	1.84	1.62		$\hat{\sigma}^2$	1.33	1.84	
$\bar{R}^2$	73.31%			$\bar{R}^2$	48.84%			$\bar{R}^2$	85.23%		
$\hat{\gamma}$	−0.27			$\hat{\gamma}$	0.25			$\hat{\gamma}$	0.79		
$\text{IC}_0 - \text{IC}_1$	13.16			$\text{IC}_0 - \text{IC}_1$	9.21			$\text{IC}_0 - \text{IC}_1$	28.16		
J. Managed Futures				*K. Multi-Strategy*							
$\hat{\alpha}$	0.65***	0.44	−0.21	$\hat{\alpha}$	0.53***	0.64***	0.11				
$\hat{\beta}^{\text{HML}}$	0.12	0.13*	0.01	$\hat{\beta}^{\text{MKT}}$	0.14***	−0.05	−0.18***				
$\hat{\beta}^{\text{UMD}}$	0.02	0.12*	0.10	$\hat{\beta}^{\text{HML}}$	−0.09***	−0.04	0.06*				
$\hat{\beta}^{\text{BOND}}$	0.20**	0.14	−0.06	$\hat{\beta}^{\text{BOND}}$	0.11***	0.16*	0.05				
$\hat{\beta}^{\text{TFBOND}}$	0.13***	0.15**	0.03	$\hat{\beta}^{\text{CREDIT}}$	0.11	0.18**	0.07				
$\hat{\beta}^{\text{TFCURR}}$	0.17***	0.15**	−0.02	$\hat{\beta}^{\text{TFCURR}}$	0.03*	0.01	−0.02				
$\hat{\beta}^{\text{TFCOMM}}$	0.19***	0.10	−0.09	$\hat{\beta}^{\text{EM}}$	0.08***	0.16***	0.07*				
$\hat{\beta}^{\text{EM}}$	0.17***	−0.03	−0.20***	$\hat{\beta}^{\text{CURR}}$	0.07**	0.11	0.03				
$\hat{\beta}^{\text{COMM}}$	0.06	0.13***	0.07	$\hat{\beta}^{\text{COMM}}$	0.04***	0.01	−0.03				
$\hat{\sigma}^2$	4.86	6.26		$\hat{\sigma}^2$	0.76	0.88					
$\bar{R}^2$	36.79%			$\bar{R}^2$	61.96%						
$\hat{\gamma}$	0.18			$\hat{\gamma}$	0.72						
$\text{IC}_0 - \text{IC}_1$	−3.59			$\text{IC}_0 - \text{IC}_1$	3.18						

Table 7
Balanced portfolio performance, 1994:01—2011:12

(1) Style	(2) Mean (%)	(3) Standard deviation (%)	(4) Annualized Sharpe ratio	(5) Maximum drawdown (%)	(6) Annualized Calmar ratio	(7) Average outperformance (%)	(8) Tracking error (%)	(9) Annualized information ratio	(10) Annualized MPPM gain (%)
60-40 benchmark	0.42	2.76	0.52	28.64	0.28				
40-30-30 portfolios:									
Convertible Arbitrage	0.41	2.48	0.57	27.78	0.28	−0.01	0.90	−0.05	0.28
Dedicated Short Bias	0.30	1.27	0.81	11.47	0.59	−0.12	2.06	−0.20	0.57
Emerging Markets	0.52	3.14	0.58	30.27	0.30	0.10	1.25	0.29	0.38
Equity Market Neutral	0.43	2.03	0.73	21.68	0.38	0.01	0.82	0.04	1.30
Event Driven	0.46	2.38	0.67	26.39	0.33	0.04	0.63	0.23	1.14
Fixed Income Arbitrage	0.42	2.04	0.72	21.34	0.39	0.00	0.87	0.02	1.20
Fund of Funds	0.37	2.27	0.56	24.20	0.31	−0.05	0.72	−0.23	0.25
Global Macro	0.49	2.18	0.78	18.30	0.50	0.08	0.83	0.32	1.89
Long/Short Equity Hedge	0.52	2.66	0.68	25.49	0.37	0.10	0.61	0.59	1.45
Managed Futures	0.49	2.06	0.82	15.93	0.57	0.07	1.32	0.18	2.00
Multi-Strategy	0.51	2.17	0.81	20.19	0.46	0.09	0.70	0.43	2.03

The table reports performance metrics for balanced 40-30-30 portfolios that allocate 40% to the CRSP equity market portfolio, 30% to ten-year U.S. Treasury bonds, and 30% to the hedge fund style index given in the first column. The balanced benchmark portfolio allocates 60% to the CRSP equity market index and 40% to ten-year U.S. Treasury bonds. The second through fourth columns report statistics for portfolio excess returns. The annualized Calmar ratio is the annualized geometric average portfolio return divided by the maximum drawdown. Average outperformance (tracking error) is the arithmetic average (standard deviation) of the difference between the 40-30-30 portfolio return and 60-40 benchmark portfolio return. The information ratio is the average outperformance divided by the tracking error. The MPPM gain is the difference in the Goetzmann, Ingersoll, Spiegel, and Welch (2007) manipulation-proof performance measures for the 40-30-30 and benchmark portfolios. 0.00 indicates less than 0.005 in absolute value.

Table 8
Balanced portfolio outperformance during up/down equity markets, 1994:01—2011:12

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Up equity market				Down equity market			
40-30-30 portfolio	Average outperformance (%)	Tracking error (%)	Annualized information ratio	Annualized MPPM gain (%)	Average outperformance (%)	Tracking error (%)	Annualized information ratio	Annualized MPPM gain (%)
Convertible Arbitrage	−0.07	0.64	−0.39	−0.38	0.11	1.29	0.31	1.63
Dedicated Short Bias	−0.26	1.96	−0.46	−1.72	0.18	2.24	0.28	5.31
Emerging Markets	0.06	1.31	0.16	−0.36	0.20	1.11	0.63	1.90
Equity Market Neutral	−0.04	0.64	−0.21	0.32	0.11	1.12	0.35	3.34
Event Driven	0.01	0.55	0.05	0.55	0.11	0.78	0.50	2.35
Fixed Income Arbitrage	−0.06	0.69	−0.28	0.10	0.13	1.15	0.40	3.45
Fund of Funds	−0.08	0.54	−0.52	−0.58	0.02	0.99	0.08	1.97
Global Macro	0.03	0.65	0.14	0.79	0.18	1.11	0.56	4.14
Long/Short Equity Hedge	0.11	0.62	0.59	1.19	0.10	0.61	0.58	2.01
Managed Futures	−0.04	1.00	−0.14	0.02	0.30	1.80	0.58	6.11
Multi-Strategy	0.03	0.52	0.23	0.98	0.20	0.98	0.71	4.21

The table reports outperformance metrics for balanced 40-30-30 portfolios that allocate 40% to the CSRP equity market index, 30% to ten-year U.S. Treasury bonds, and 30% to the hedge fund style index given in the first column relative to a balanced benchmark portfolio that allocates 60% to the CRSP equity market index and 40% to ten-year U.S. Treasury bonds. Average outperformance (tracking error) is the arithmetic average (standard deviation) of the difference between the 40-30-30 portfolio return and 60-40 benchmark portfolio return. The information ratio is the average outperformance divided by the tracking error. The MPPM gain is the difference in the Goetzmann, Ingersoll, Spiegel, and Welch (2007) manipulation-proof performance measures for the 40-30-30 and benchmark portfolios. The second through fifth (sixth through ninth) columns report results for an up (down) equity market. Month t is an up (down) equity market if the S&P 500 price index is greater than or equal to (less than) its 200-day moving average on the last day of the preceding month.

Table 9
Balanced portfolio outperformance during nonstressed/stressed financial conditions, 1994:01—2011:12

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Nonstressed financial conditions				Stressed financial conditions			
40-30-30 portfolio	Average outperformance (%)	Tracking error (%)	Annualized information ratio	Annualized MPPM gain (%)	Average outperformance (%)	Tracking error (%)	Annualized information ratio	Annualized MPPM gain (%)
Convertible Arbitrage	−0.02	0.70	−0.12	0.35	0.10	1.98	0.17	−0.35
Dedicated Short Bias	−0.34	1.61	−0.73	−3.11	0.10	2.42	0.15	4.28
Emerging Markets	0.15	1.24	0.42	0.82	−0.08	1.27	−0.22	−1.32
Equity Market Neutral	0.01	0.72	0.06	1.07	−0.01	1.49	−0.01	3.35
Event Driven	0.05	0.57	0.29	1.11	−0.01	1.00	−0.02	1.38
Fixed Income Arbitrage	0.01	0.80	0.02	1.03	−0.01	1.37	−0.02	2.66
Fund of Funds	−0.11	0.47	−0.83	−1.10	0.02	0.90	0.07	1.59
Global Macro	0.02	0.62	0.09	0.50	0.18	1.09	0.57	4.19
Long/Short Equity Hedge	0.10	0.58	0.58	1.19	0.15	0.78	0.64	2.80
Managed Futures	−0.04	0.86	−0.16	−0.31	0.23	1.78	0.45	5.29
Multi-Strategy	0.03	0.59	0.16	1.01	0.39	1.07	1.28	7.04

The table reports outperformance metrics for balanced 40-30-30 portfolios that allocate 40% to the CSRP equity market index, 30% to ten-year U.S. Treasury bonds, and 30% to the hedge fund style index given in the first column relative to a balanced benchmark portfolio that allocates 60% to the CRSP equity market index and 40% to ten-year U.S. Treasury bonds. Average outperformance (tracking error) is the arithmetic average (standard deviation) of the difference between the 40-30-30 portfolio return and 60-40 benchmark portfolio return. The information ratio is the average outperformance divided by the tracking error. The MPPM gain is the difference in the Goetzmann, Ingersoll, Spiegel, and Welch (2007) manipulation-proof performance measures for the 40-30-30 and benchmark portfolios. The second through fifth (sixth through ninth) columns report results for nonstressed (stressed) financial conditions. Month t is characterized by nonstressed (stressed) financial conditions if the Federal Reserve Bank of Kansas City Financial Stress Index for month t is less than or equal to (greater than) a threshold value. The threshold value for each hedge fund style is the $\hat{\gamma}$ estimate reported in Table 6.

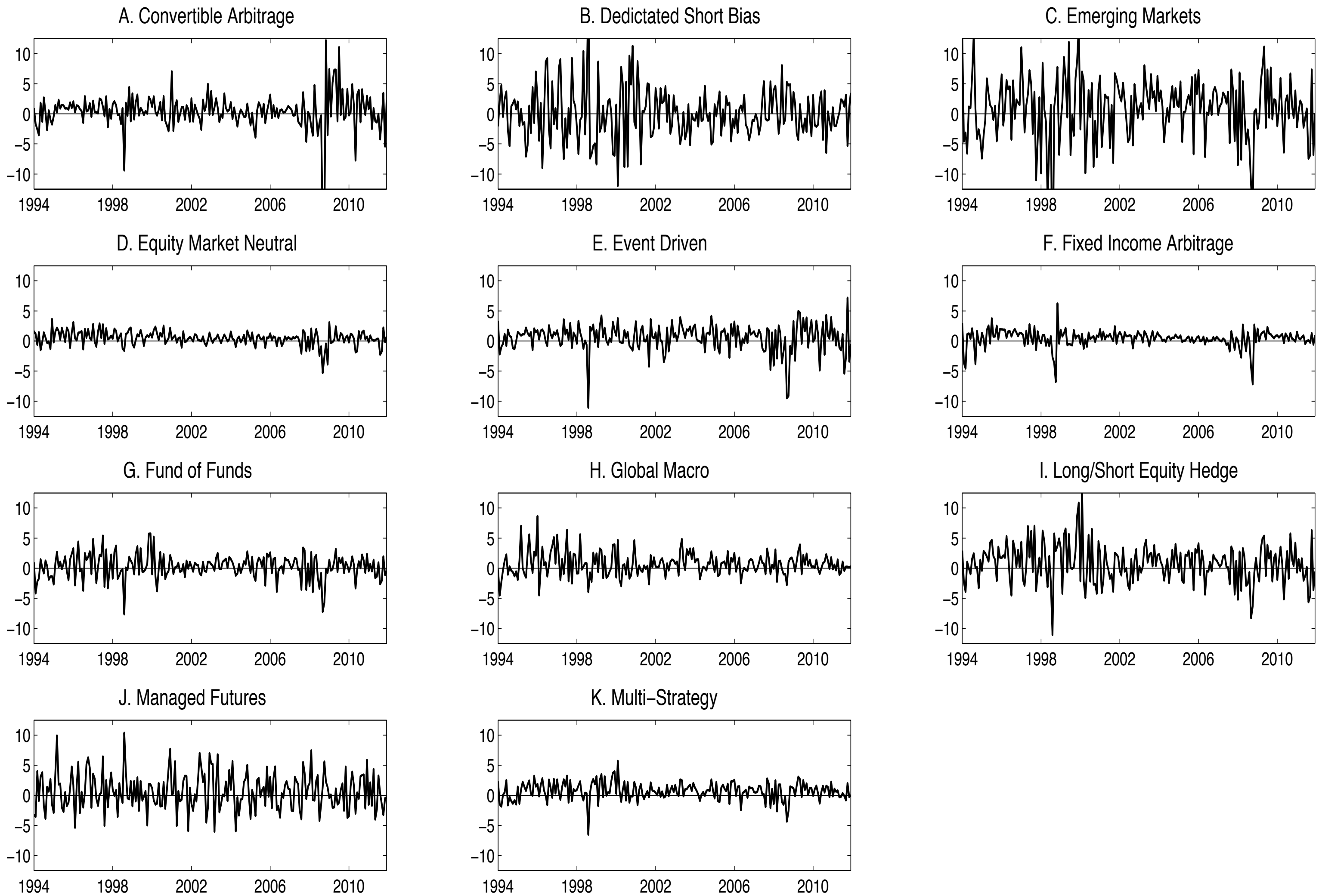

Figure 1
Unsmoothed hedge fund excess returns, 1994:01—2011:12

Each panel depicts the unsmoothed hedge fund index excess return in percentage points for the style given in the panel heading.

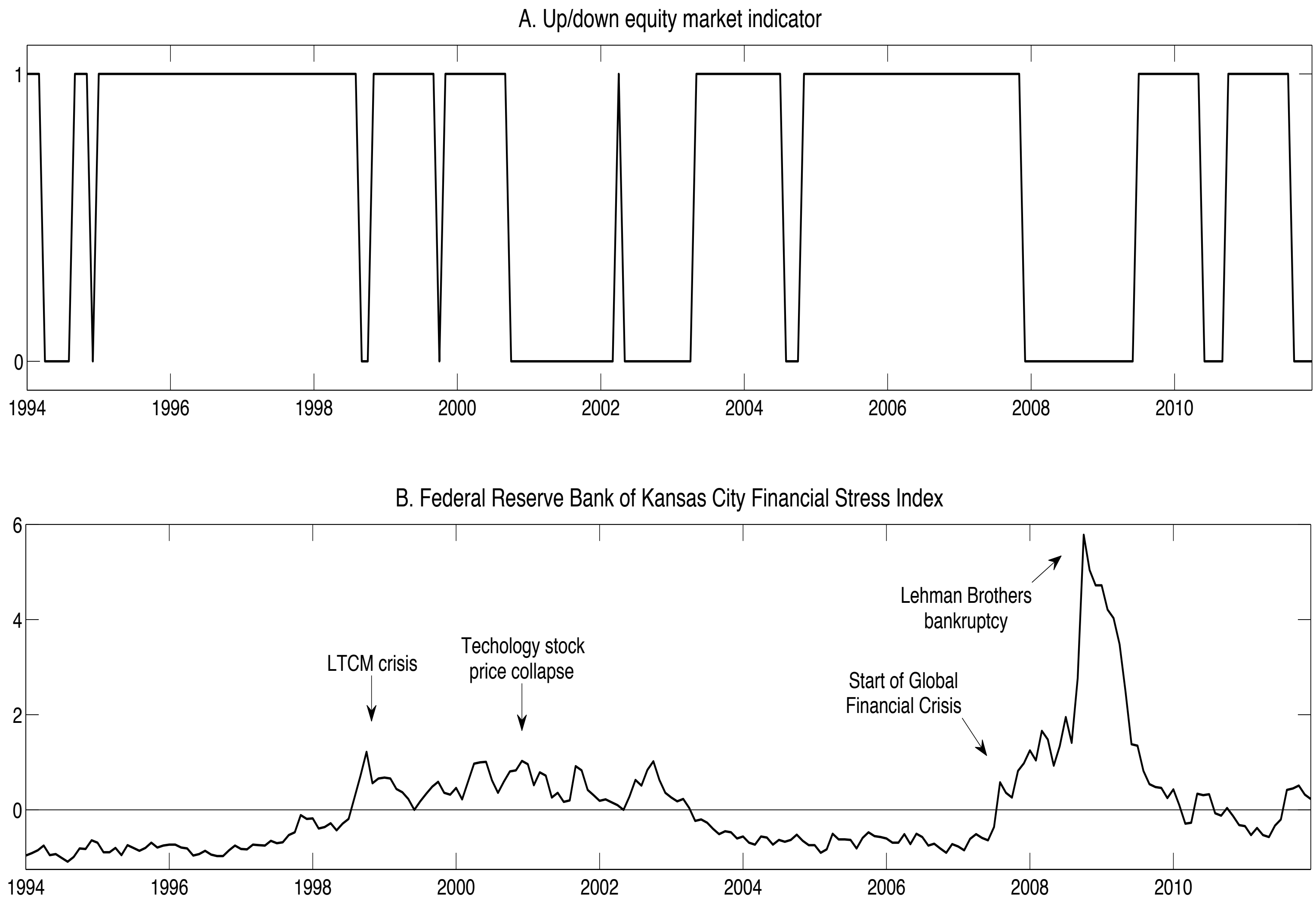

Figure 2
Equity market and financial conditions indicators, 1994:01—2011:12

Panel A shows the up/down equity market indicator that is equal to one (zero) when the S&P 500 price index is greater than or equal to (less than) its 200-day moving average on the last day of the preceding month. Panel B depicts the Federal Reserve Bank of Kansas City Financial Stress Index based on eleven financial variables.

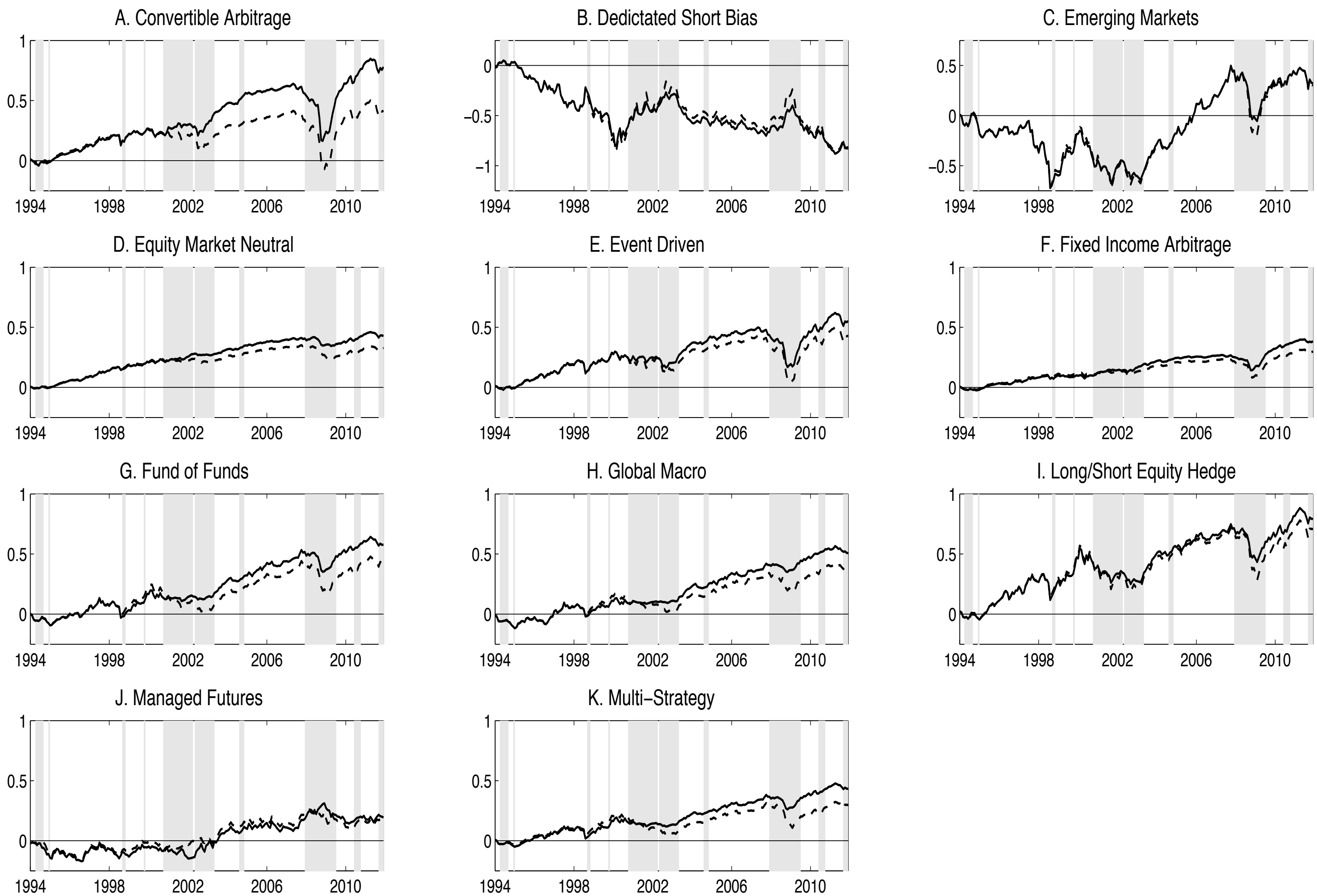

Figure 3
Hedge fund cumulative log excess returns due to systematic risk exposures across up and down equity markets, 1994:01—2011:12

Each panel depicts the component of the unsmoothed hedge fund index cumulative log excess return due to systematic risk exposures for the style given in the panel heading. The solid line in each panel corresponds to the estimated regime-switching betas reported in Table 5; the dashed line assumes that the betas are constant at their values during an up equity market. Vertical bars delineate down equity market regimes.

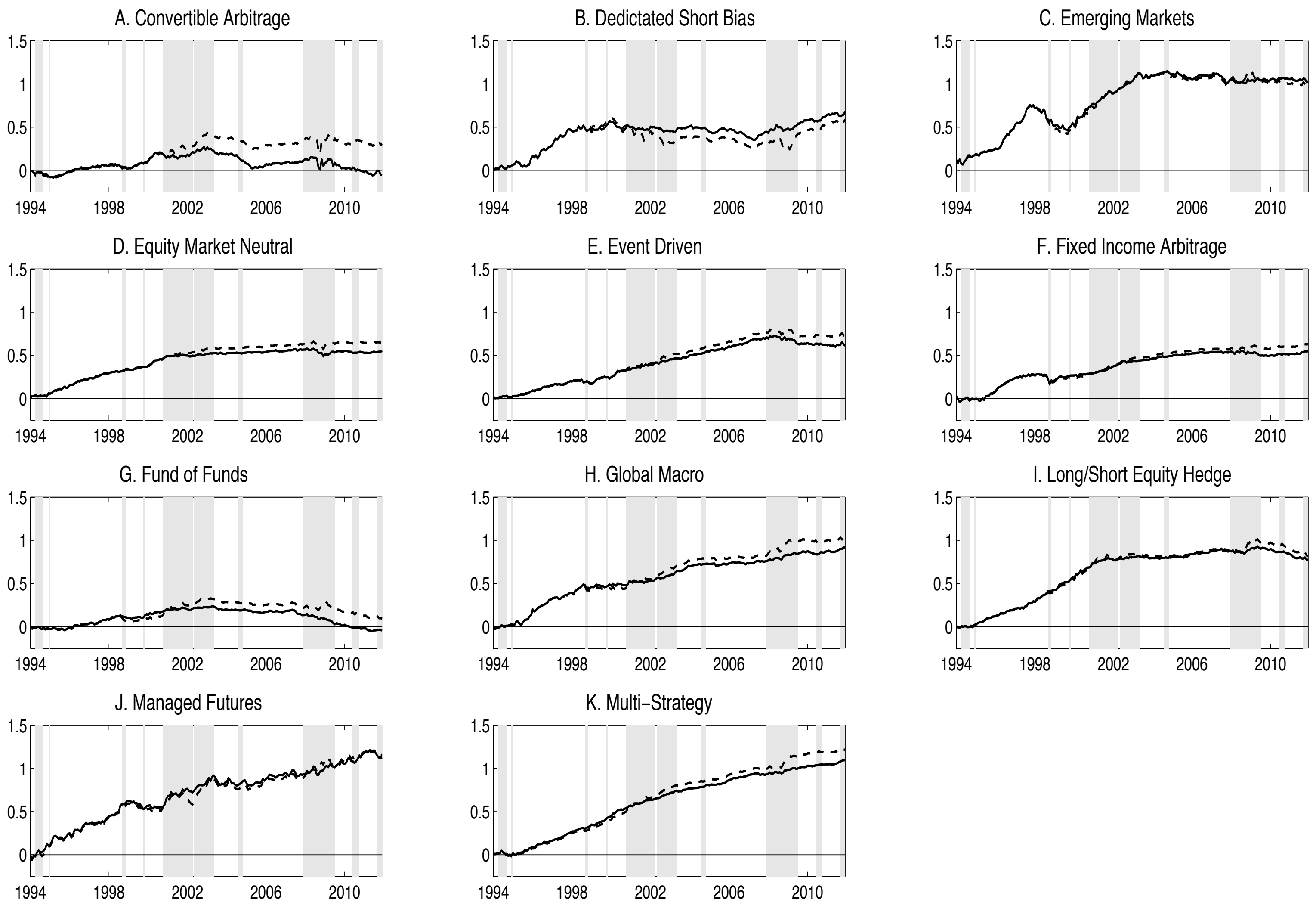

Figure 4
Hedge fund cumulative risk-adjusted log excess returns across up and down equity markets, 1994:01—2011:12

Each panel depicts the risk-adjusted component of the unsmoothed hedge fund index cumulative log excess return for the style given in the panel heading. The solid line in each panel corresponds to the estimated regime-switching alphas and betas reported in Table 5; the dashed line assumes that the alphas and betas are constant at their values during an up equity market. Vertical bars delineate down equity market regimes.

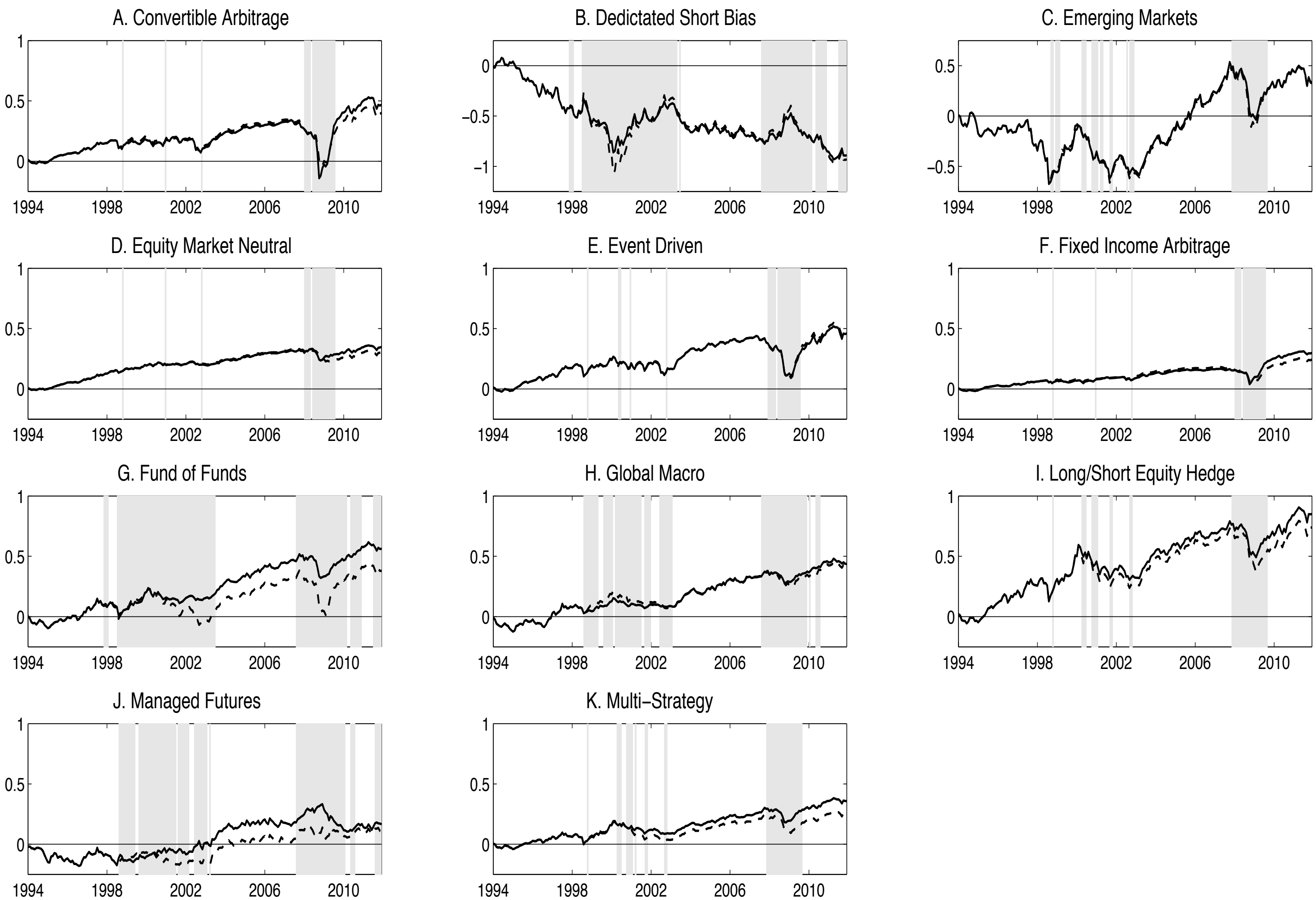

Figure 5
Hedge fund cumulative log excess returns due to systematic risk exposures across nonstressed and stressed financial conditions, 1994:01—2011:12

Each panel depicts the component of the unsmoothed hedge fund index cumulative log excess return due to systematic risk exposures for the style given in the panel heading. The solid line in each panel corresponds to the estimated regime-switching betas reported in Table 6; the dashed line assumes that the betas are constant at their values during nonstressed financial conditions. Vertical bars delineate stressed financial conditions regimes.

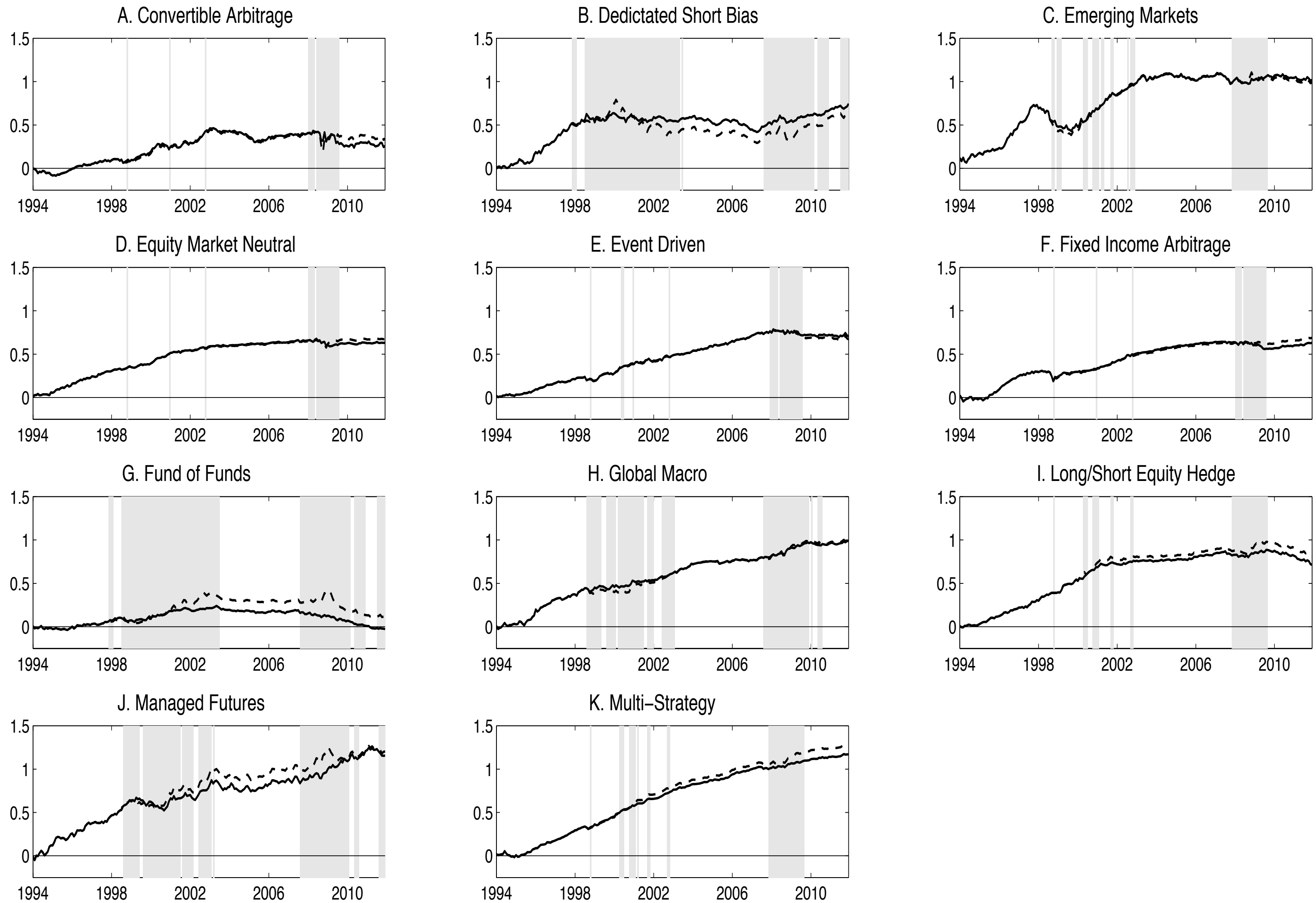

Figure 6
Hedge fund cumulative risk-adjusted log excess returns across nonstressed and stressed financial conditions, 1994:01—2011:12.

Each panel depicts the risk-adjusted component of the unsmoothed hedge fund index cumulative log excess return for the style given in the panel heading. The solid line in each panel corresponds to the estimated regime-switching alphas and betas reported in Table 6; the dashed line assumes that the alphas and betas are constant at their values during nonstressed financial conditions. Vertical bars delineate stressed financial conditions regimes.