Original Article

The role of credit default swaps and other alternative betas in hedge fund factor analysis

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ABSTRACT Hedge fund factor analysis is growing in popularity. While some investors simply use traditional factor βs from the stock and bond markets, these factors do not fully explain hedge fund returns. Explanatory power of hedge fund factor analysis improves when illiquidity and non-linear exposures are explored. Alternative βs, such as commodity, currency and credit default swaps, also lead to more accurate estimates of α and β.

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INTRODUCTION

Fung and Hsieh (2004), among many others, perform factor analysis for the broad hedge fund universe as well as funds of hedge funds. These studies have found that various hedge fund styles have statistically significant exposures to a number of market variables, including the large and small stocks, high yield bonds, the S&P 500 Volatility Index (VIX), the 10 Year Treasury yield and look-back straddles on a number of assets. Many studies consider the role of illiquidity or traditional market βs in isolation.

This article broadens the hedge fund factor analysis literature by using updated data set through June 2009. This time period includes the market crises of 2007 and 2008, which may have changed many of the hedge fund β relationships. In addition to studying the exposure of hedge fund styles to traditional market factors, we also include alternative market factors, such as commodity, currency and volatility indices. Next, we add measures of illiquidity and market timing to the market β sources. Finally, we calculate a unique data series based on the credit default swap prices of commercial and investment banks, which proves to be a significant risk factor in a number of hedge fund strategies. Hedge funds may prefer to trade credit default swaps, as these instruments allow managers to quickly take credit positions in instruments that are often more liquid than the underlying bonds.

LITERATURE REVIEW

Hedge fund factor analysis has been studied from a number of angles across the literature. Fung and Hsieh (2004) model hedge fund returns using an arbitrage pricing model methodology and include dynamic risk factor analysis. They suggest that, rather than using peer universes (such as those calculated by Hedge Fund Research, HFR), more accurate hedge fund benchmarks can be calculated through the use of returns-based style analysis. Their seven-factor model includes the S&P 500, small-large stocks, change in the 10 Year Treasury yield, change in credit spreads, and look-back straddles on bonds, currencies and commodities. Beckers *et al* (2007) conclude that funds of funds have less factor exposure than funds tracked by hedge fund style indices. Funds of funds also exhibit negative market timing skill, as measured by the returns to traditional β factor exposures. Unique factors covered in this study include emerging markets stock and bond indices, non-US stocks, growth-value equity spreads and commodity futures. Similar factors are used by Ennis and Sebastian (2003).

Illiquidity is discussed by Till (2004), Getmansky *et al* (2004) and Kazemi and Schneeweis (2004). Till describes the costs of illiquidity, including difficulties in rebalancing, valuation risk, stale pricing and understated volatility, as well as observing that investors who purchase illiquid assets have the return profile of short put option strategies. Kazemi and Schneeweis test lagged returns to the S&P 500 as a measure of illiquidity and suggest that the proper risk measurement of factor risk is the sum of the current month coefficient and all statistically significant lagged coefficients. Hamza *et al* (2006) include squared factor βs to understand non-linearities and lagged hedge fund index data to measure illiquidity. Getmansky *et al* (2004) used serial correlation analysis to determine the illiquidity of hedge fund strategies.

Dopfel (2005) demonstrates the inclusion of hedge funds in the analysis of portfolio risk exposures. Rather than including hedge funds in a mean-variance portfolio optimization, the β exposures of hedge funds should be determined and included in the portfolio level target of β risk exposures. However, hedge fund β exposures are subject to change over time.

Finally, Kat (2004) suggests that, as of that time, no study on hedge fund performance has correctly explained the role of liquidity and credit risk as return sources. The higher moments of hedge funds must be constrained before hedge funds are added to a mean-variance analysis that is intended to justify the weights of hedge funds in an investor's portfolio.

DATA SET AND METHODOLOGY

For the time period of January 1990–June 2009, we seek to predict the return to 19 indices calculated by HFR. Sharma (2004) describes HFR indices as having minimal survivor bias, as the returns to defunct funds are not dropped from the time series of hedge fund style returns. HFR indices are equally weighted, so give a broad representation to both small and large hedge funds. Traditional β sources include the S&P 500, EAFE, Emerging Markets Stocks, Barclays Aggregate Bond Index and the Merrill Lynch High Yield Index. These risk exposures are commonly found in investor portfolios.

Those who have some understanding of hedge fund factor analysis typically include these traditional β exposures in their data set. However, several of the authors referenced above state that α estimates of hedge funds are likely overstated when only traditional β sources are included in factor analyses, as omitted variables are counted as α, even though the returns may come from alternative β sources.

Alternative, or non-traditional, β sources in this study include the GSCI Commodity Index, the small stock premium as measured by the difference between the return to the S&P 500 and the Russell 2000 stock indices, the value premium as determined by the difference between the Russell 1000 value and growth indices, the monthly percentage change in the VIX and the US Dollar Index, which measures the currency market risk of hedge fund portfolios.

Negative coefficients on the Treasury market return (7–10 year maturity) show the cash leverage inherent in a hedge fund portfolio. Lagged returns to the S&P 500 Index and the High Yield Index show the illiquidity risk of varying hedge fund styles. Squared terms of the same indices demonstrate the lack of market timing skill by hedge fund managers.

Finally, and possibly new to the literature, this study contributes an analysis of credit default swaps. From August 2001 to June 2009, credit default swap data is analyzed. Daily credit default swap prices, in basis points, are reported on underlying financial institution credits, including Merrill Lynch, Wells Fargo, Wachovia, Bank America, Barclays, Credit Suisse, Deutsche Bank, HSBC, RBS, UBS, JP Morgan, Morgan Stanley, Goldman Sachs, and most interesting, Lehman Brothers and Bear Stearns. Given that hedge fund returns are reported monthly, our monthly observation for credit default swaps is simply the average of the daily CDS prices during that month, which overcomes the infrequent reporting issues of some underlying financial institution CDS prices. While data is sparse in 2001 and 2002, later data shows between 264 and 368 observations each month. Clearly, credit default swap prices on underlying financial credits demonstrate changes in systemic risk, especially during the tumultuous period of 2007–2009. While CDS spreads never reached 70 basis points between August 2001 and October 2007, they rose quickly during the recent crisis, trading mostly between 120 and 270 basis points between February 2008 and June 2009. Spreads narrowed in the fall of 2009 as systemic risk subsided. Surprisingly, this measure of CDS prices is relatively uncorrelated to the returns to high yield debt, −0.07, and equity volatility (VIX), 0.032.

TRADITIONAL β RESULTS

The results of factor analysis regressions using traditional β factors can be found in Tables 1 and 2, which show the results for the traditional β regressions over the time periods starting January 1990 and August 2001, respectively, while both data sets end in June 2009.

$$\begin{aligned}HFR\ \text{Index} = {} & \alpha + \beta 1 \times S\&P\ 500 + \beta 2 \times EAFE \\ & + \beta 3 \times \text{Emerging Markets} \\ & + \beta 4 \times \text{Barclays Aggregate Bond Index} \\ & + \beta 5 \times \text{High Yield}\end{aligned}$$

It is important to note that all results in this article have been calculated using stepwise regression, where all β coefficients are included in results only when they are statistically significant at the 1 per cent level. Variables included each subsequent step of the regression

Table 1 Traditional β regressions, January 1990 – June 2009, monthly observations, HFR data, all variables statistically significant at the 1 per cent level

	Monthly α	*t (α)*	*S&P 500*	*EAFE*	*Emerging markets*	*Barclays Aggregate Bond Index*	*High yield*	*Adjusted R^2*
Fund Weighted Index	0.640	8.388	0.143	—	0.140	—	0.138	0.701
Relative Value Multi-Strategy	0.446	7.957	—	—	0.047	—	0.291	0.584
Convertible Arbitrage	0.339	3.658	—	—	—	—	0.516	0.488
Distressed	0.659	7.136	—	—	0.080	—	0.370	0.498
Emerging Markets	0.641	4.756	—	—	0.533	—	—	0.772
Equity Hedge	0.800	6.859	0.281	—	0.142	—	—	0.572
Equity Market Neutral	0.604	9.853	0.040	—	—	—	—	0.031
Fixed Income Arbitrage	0.334	3.712	—	—	—	—	0.505	0.492
Event Driven	0.611	7.431	0.133	—	0.076	—	0.294	0.637
Macro	0.650	4.565	—	—	0.140	0.603	—	0.277
Systematic Diversified	0.951	7.994	0.197	—	0.107	—	−0.244	0.304
Merger Arbitrage	0.596	8.706	0.103	—	—	—	0.137	0.329
Fixed Income Corporate	0.221	2.692	—	—	0.040	—	0.536	0.625
Short Selling	1.004	3.823	−0.731	—	−0.164	—	—	0.509
Fund of Funds	0.508	5.814	—	—	0.161	—	—	0.421
Fund of Funds Conservative	0.416	6.518	—	—	0.067	—	0.123	0.357
Fund of Funds Diversified	0.459	5.067	—	—	0.168	—	—	0.425
Fund of Funds Market Defensive	0.736	6.813	−0.108	—	0.101	—	—	0.085
Fund of Funds Strategic	0.620	4.714	0.118	—	0.188	—	—	0.423
Average	0.591	6.129	—	—	—	—	—	0.449

are determined through the use of the Akaike Information Criterion (AIC), where lower scores of the AIC are preferred. The AIC declines as the number of model parameters declines and the maximum likelihood of the model increases. While some prior studies included the βs of all factors tested, this study uses only variables that are found to be highly significant. The results show that, while all factors predict the returns to some hedge fund styles, the risk drivers vary significantly by hedge fund trading style.

Table 1 shows that this model fits hedge fund style returns quite well, with an average adjusted R^2 of 0.449 and an average α of 59.1 basis points per month over the January 1990–June 2009 period. The α of each hedge fund strategy tested was statistically significant and positive over the time period from 1990 to 2009. Table 2 shows an increase in explanatory power and a decline in α in the time period since August 2001, as measured by an average adjusted R^2 of 0.599 and average monthly α of only 18.1 basis points. In fact, convertible arbitrage and fixed income arbitrage show statistically insignificant negative αs in the modern time period. Since 2001, only 8 of the 19 hedge fund styles tested earned a statistically

Table 2 Traditional β regressions, August 2001 – June 2009, monthly observations, HFR data, all variables statistically significant at the 1 per cent level

	Monthly α	*t (α)*	*S&P 500*	*EAFE*	*Emerging markets*	*Barclays Aggregate Bond Index*	*High yield*	*Adjusted R^2*
Fund Weighted Index	0.153	2.034	—	—	0.207	—	0.098	0.858
Relative Value Multi-Strategy	0.155	1.633	—	—	0.063	—	0.243	0.635
Convertible Arbitrage	−0.220	−1.180	−0.207	—	0.152	—	0.562	0.607
Distressed	0.454	3.379	—	0.141	—	—	0.250	0.565
Emerging Markets	0.370	2.926	−0.173	0.196	0.429	—	—	0.899
Equity Hedge	0.003	0.029	—	0.141	0.224	—	—	0.878
Equity Market Neutral	0.126	1.639	−0.080	—	0.081	—	—	0.192
Fixed Income Arbitrage	−0.228	−1.264	−0.194	—	0.141	—	0.551	0.609
Event Driven	0.435	3.932	—	0.218	—	−0.283	0.242	0.767
Macro	0.433	3.148	−0.224	—	0.197	—	—	0.293
Systematic Diversified	0.657	3.272	—	—	0.227	—	−0.332	0.259
Merger Arbitrage	0.230	3.181	—	—	0.113	—	—	0.588
Fixed Income Corporate	0.189	1.594	—	0.101	—	—	0.336	0.655
Short Selling	0.283	1.684	−0.715	—	—	—	—	0.800
Fund of Funds	0.043	0.422	—	—	0.178	—	—	0.642
Fund of Funds Conservative	0.063	0.619	—	—	0.124	—	—	0.467
Fund of Funds Diversified	0.051	0.489	—	—	0.171	—	—	0.611
Fund of Funds Market Defensive	0.285	2.021	−0.272	—	0.197	—	—	0.276
Fund of Funds Strategic	−0.033	−0.316	—	—	0.251	—	—	0.771
Average	0.181	1.539	—	—	—	—	—	0.599

significant positive α, measured by a *t*-statistic exceeding 2.0.

LEVERAGE TEST RESULTS

The regression results reported in Tables 3 and 4 see an increase in explanatory power and a decline in α relative to those reported in Tables 1 and 2 through the addition of the leverage factor. When the return to the 7–10 year Treasury notes has a significant negative coefficient, we suspect that the hedge funds trading a specific style have incurred leverage through cash borrowings in the prime brokerage market. (Notice how the addition of the leverage factor increases the explanatory power, reduces the α and changes β coefficients of the fixed income trading strategies.) Consider the differences between Tables 1 and 3 and those between Tables 2 and 4. The convertible arbitrage strategy since 2001 shows an adjusted R^2 of 0.607 and a negative α of 22 basis points per month, with a β to high yield bonds of 0.562. The addition of the leverage factor increases the R^2 to 0.622 while the α declined to −40 basis points per month. The β coefficients more accurately represent the trading strategy with a β to the Barclays Aggregate Bond Index of 3.25 and leverage of

Table 3 Regressions including leverage factor, January 1990 – June 2009, monthly observations, HFR data, all variables statistically significant at the 1 per cent level

	α	*t (α)*	*S&P 500*	*EAFE*	*Emerging markets*	*Barclays Aggregate Bond Index*	*High yield*	*7–10 year Treasury return*	*Adjusted R^2*
Fund Weighted Index	0.640	8.388	0.143	—	0.140	—	0.138	—	0.701
Relative Value Multi-Strategy	0.329	5.270	—	—	0.048	0.968	0.172	−0.576	0.620
Convertible Arbitrage	0.151	1.468	—	—	—	1.600	0.324	−0.961	0.534
Distressed	0.745	7.753	—	—	0.072	—	0.380	−0.138	0.512
Emerging Markets	0.641	4.756	—	—	0.533	—	—	—	0.772
Equity Hedge	0.664	4.924	0.258	—	0.129	0.890	—	−0.554	0.583
Equity Market Neutral	0.604	9.853	0.040	—	—	—	—	—	0.031
Fixed Income Arbitrage	0.161	1.594	—	—	—	1.451	0.331	−0.866	0.530
Event Driven	0.611	7.431	0.133	—	0.076	—	0.294	—	0.637
Macro	0.650	4.565	—	—	0.140	0.603	—	—	0.277
Systematic Diversified	0.951	7.994	0.197	—	0.107	—	−0.244	—	0.304
Merger Arbitrage	0.596	8.706	0.103	—	—	—	0.137	—	0.329
Fixed Income Corporate	0.221	2.692	—	—	0.040	—	0.536	—	0.625
Short Selling	1.004	3.823	−0.731	—	−0.164	—	—	—	0.509
Fund of Funds	0.330	3.320	—	—	0.139	0.902	—	−0.510	0.454
Fund of Funds Conservative	0.296	4.212	—	—	0.069	1.007	—	−0.601	0.406
Fund of Funds Diversified	0.314	3.016	—	—	0.149	0.787	—	−0.460	0.446
Fund of Funds Market Defensive	0.736	6.813	−0.108	—	0.101	—	—	—	0.085
Fund of Funds Strategic	0.620	4.714	0.118	—	0.188	—	—	—	0.423
Average	0.540	5.331	—	—	—	—	—	—	0.462

1.70x. This is consistent with the convertible arbitrage strategy, as Black (2004) reports that convertible bond arbitrage is the most highly levered of all hedge fund strategies. Similar results are found for fixed income arbitrage, with β exposures to Barclays Aggregate (2.086), High Yield (0.328) and leverage −1.085.

ALTERNATIVE β RESULTS

Tables 5 and 6 add alternative βs and yield curve trades to the analysis. Relative to the first and second regressions reported above, the average R^2 increased with the addition of a broader scope of market risks, which is consistent with the findings of Amenc and Martellini (2002) who show an increased R^2 when alternative β exposures are added to a regression containing only β exposures to traditional markets. In this regression, we add a number of variables to those used in the prior regressions. The S&P GSCI is used to represent commodity markets, the US Dollar Index to represent currency markets, the difference between the S&P 500 and Russell 2000 stock market indices to represent the

Table 4 Regressions including leverage factor, August 2001 – June 2009, monthly observations, HFR data, all variables statistically significant at the 1 per cent Level

	α	*t (α)*	*S&P 500*	*EAFE*	*Emerging markets*	*Barclays Aggregate Bond Index*	*High yield*	*7–10 year Treasury return*	*Adjusted R^2*
Fund Weighted Index	0.153	2.034	—	—	0.207	—	0.098	—	0.858
Relative Value Multi-Strategy	−0.003	−0.034	—	—	0.078	1.625	—	−0.875	0.683
Convertible Arbitrage	−0.403	−2.147	—	—	0.104	3.250	—	−1.701	0.622
Distressed	0.454	3.379	—	0.141	—	—	0.250	—	0.565
Emerging Markets	0.370	2.926	−0.173	0.196	0.429	—	—	—	0.899
Equity Hedge	0.083	0.893	—	0.142	0.215	—	—	−0.133	0.889
Equity Market Neutral	0.126	1.639	−0.080	—	0.081	—	—	—	0.192
Fixed Income Arbitrage	−0.258	−1.376	—	—	—	2.086	0.328	−1.085	0.609
Event Driven	0.435	3.932	—	0.218	—	−0.283	0.242	—	0.767
Macro	0.433	3.148	−0.224	—	0.197	—	—	—	0.293
Systematic Diversified	0.657	3.272	—	—	0.227	—	−0.332	—	0.259
Merger Arbitrage	0.230	3.181	—	—	0.113	—	—	—	0.588
Fixed Income Corporate	0.280	2.375	—	0.092	—	—	0.327	−0.163	0.681
Short Selling	0.283	1.684	−0.715	—	—	—	—	—	0.800
Fund of Funds	0.043	0.422	—	—	0.178	—	—	—	0.642
Fund of Funds Conservative	0.023	0.228	—	—	0.089	0.784	—	−0.490	0.531
Fund of Funds Diversified	0.051	0.489	—	—	0.171	—	—	—	0.611
Fund of Funds Market Defensive	0.285	2.021	−0.272	—	0.197	—	—	—	0.276
Fund of Funds Strategic	−0.033	−0.316	—	—	0.251	—	—	—	0.771
Average	0.169	1.461	—	—	—	—	—	—	0.607

return to smaller capitalization securities, the difference between the Russell 1000 value and growth indices to show the return to equity styles, the VIX to measure the implied volatility of S&P 500 options as a proxy for investor sentiment, and the difference between the 10 Year and 1 Year Treasury yields to measure the slope of the yield curve. Note that where the slope of the yield curve is determined to be a statistically significant factor, that the interpretation of the intercept is no longer α, as the slope variable does not directly correspond to a market return.

Comparing Table 3 and 5 (4 and 6), we see that the average adjusted R^2 rises from 0.462 to 0.533 (0.607 to 0.695) through the addition of a wider variety of market risks. While the traditional market βs used in Tables 1 and 2 show broad market exposures, the addition of a wider array of variables better explains the trading strategies of hedge funds. In fact, the market exposures reported in these regressions broadly matches the professed style of the hedge fund managers. It is comforting to see that macro managers take consistent bets to currency markets while fixed income and convertible

Table 5 Alternative β regressions, January 1990 – June 2009, monthly observations

	Intercept	*t (Intercept)*	*S&P GSCI Commodity*	*S&P 500*	*S&P 500 – Russell 2000*	*Russell 1000 Value – Growth*	*VIX Change*	*EAFE*	*US Dollar Index*	*Emerging markets*	*Barclays Aggregate Bond Index*	*High yield*	*10 year – 1 year Treasury yield*	*7–10 year Treasury return*	*Adjusted* R^2
Fund Weighted Index	0.550	7.847	0.041	0.179	−0.173	−0.083	—	—	0.071	0.108	0.601	—	—	−0.289	0.812
Relative Value Multi-Strategy	0.324	5.268	0.023	—	—	—	—	—	—	0.045	0.949	0.171	—	−0.563	0.631
Convertible Arbitrage	0.103	1.054	0.057	—	—	—	0.021	—	—	—	1.501	0.355	—	−0.898	0.585
Distressed	0.658	7.440	0.038	—	−0.088	—	—	—	0.098	0.069	—	0.351	—	—	0.542
Emerging Markets	0.688	5.165	—	—	—	—	−0.037	—	—	0.508	—	—	—	—	0.780
Equity Hedge	0.794	8.761	0.081	0.325	−0.262	−0.137	—	—	—	0.062	—	—	—	—	0.744
Equity Market Neutral	0.818	8.691	0.037	—	—	—	—	—	—	—	—	—	−1.850	—	0.088
Fixed Income Arbitrage	0.115	1.192	0.053	—	—	—	0.021	—	—	—	1.357	0.362	—	−0.807	0.577
Event Driven	0.673	9.288	0.029	0.165	−0.150	—	−0.026	—	—	0.040	—	0.205	—	—	0.726
Macro	0.688	5.262	—	—	−0.105	—	—	—	0.179	0.153	—	—	—	0.471	0.331
Systematic Diversified	0.988	8.698	—	0.208	−0.116	−0.122	—	—	—	0.083	—	−0.276	—	—	0.367
Merger Arbitrage	0.899	8.796	—	0.089	−0.068	—	−0.018	—	—	—	—	0.097	−2.329	—	0.409
Fixed Income Corporate	0.221	2.692	—	—	—	—	—	—	—	0.040	—	0.536	—	—	0.625
Short Selling	0.793	4.308	—	−0.879	0.716	0.524	—	—	—	—	—	0.249	—	—	0.769
Fund of Funds	0.301	3.233	0.067	—	—	−0.078	—	—	0.093	0.126	0.837	—	—	−0.429	0.528
Fund of Funds Conservative	0.287	4.291	0.044	—	—	—	—	—	—	0.062	0.958	—	—	−0.571	0.460
Fund of Funds Diversified	0.282	2.878	0.067	—	—	−0.079	—	—	0.104	0.136	0.724	—	—	−0.377	0.517
Fund of Funds Market Defensive	0.711	6.755	0.063	−0.101	—	—	—	—	—	0.085	—	—	—	—	0.136
Fund of Funds Strategic	0.624	5.079	0.057	0.134	−0.150	−0.133	—	—	—	0.138	—	—	—	—	0.502
Average	0.554	5.616	—	—	—	—	—	—	—	—	—	—	—	—	0.533

bond arbitrage managers employ the greatest degree of leverage.

THE CREDIT DEFAULT SWAP FACTOR

Besides a change in time period, the addition of credit default swap data is a key change between Tables 5 and 6. When added to the 10 traditional and alternative βs, as well as the slope and leverage factors, credit default swap spreads enter the analysis as a statistically significant factor for 12 of the 19 hedge fund styles tested. In each case, we find a negative coefficient, where hedge fund returns decline as CDS spreads widen and credit risks increase. There is an interesting interaction between CDS spreads and high yield and VIX exposures. We see that, while three strategies show short VIX exposures in Table 5, the CDS exposures in Table 6 have eliminated the significant short exposures to VIX since 2001. This means that widening credit spreads are more explanatory of hedge fund risks than rising equity market volatility. Interestingly, this is the case for funds that make minimal use of fixed income in their trading strategies, such as equity hedge or equity market neutral.

ILLIQUIDITY TEST RESULTS

We next present Tables 7 and 8, which include tests for illiquidity and market timing. Adding these additional variables increases the adjusted R^2 of the average regressions shown in Tables 5 and 6. We repressed regression results that showed a significant exposure to a lagged variable when there was not a significant exposure to the same variable in the current month. Notice that, unlike in Kazemi and Schneeweis (2004), we did not find any statistically significant exposures to 1 month lagged returns on the S&P 500 Index. This makes sense, as the equity securities tracked by this index are priced daily and are not widely regarded to incur liquidity risks. We did, however, find a number of hedge fund styles that have statistically significant exposures to 1 month, and even 2 month, lagged returns of the High Yield Index. These tables also provide the results of a Ljung-Box test, which is used to measure the degree of autocorrelation in the time series of returns. We are encouraged that the average Ljung-Box test score for strategies shown in Table 7 as having statistically significant exposure to the lagged returns of the High Yield Bond Index is 58.185, whereas strategies that do not report this degree of illiquidity have an average score of 19.855. That is, the strategies with a greater degree of autocorrelation as measured by the Ljung-Box test are those that show significant exposures to illiquidity risks.

Kazemi and Schneeweis (2004) show that the true β risk is the sum of the current month β and all statistically significant β exposures from prior months. That is, counting only the current month exposure to a given risk factor underestimates the total risk exposure to that factor when illiquidity risk is present. For example, consider the high yield risk of distressed strategies in Tables 6 and 8. While distressed strategies show a high yield β of 0.342 in the current month, the sum of the current month and the 2 lagged months in Table 8 show a total high yield β of 0.506. Disregarding illiquidity risk, then, makes hedge funds appear to have a lower degree of market risk. The difference in intercept for distressed strategies between Tables 6 and 8, then, can be used to estimate the liquidity premium of

Table 6 Alternative β regressions, August 2001 – June 2009, monthly observations, HFR data, all variables statistically significant at the 1 per cent level

	Intercept	*t (Intercept)*	*S&P GSCI Commodity*	*S&P 500*	*S&P 500 – Russell 2000*	*Russell 1000 Value – Growth*	*VIX Change*	*EAFE*
Fund Weighted Index	0.456	5.396	0.028	—	−0.075	−0.111	—	0.086
Relative Value Multi-Strategy	0.269	2.423	0.040	—	—	—	—	—
Convertible Arbitrage	−0.212	−1.199	0.072	—	—	—	0.052	—
Distressed	1.163	7.541	0.048	—	—	—	—	—
Emerging Markets	0.832	5.303	—	—	—	—	—	—
Equity Hedge	0.262	2.622	0.034	—	−0.110	−0.142	—	0.142
Equity Market Neutral	0.448	4.873	—	−0.092	—	—	—	—
Fixed Income Arbitrage	−0.148	−0.917	—	—	—	—	0.083	—
Event Driven	0.782	5.991	—	—	−0.105	—	—	0.177
Macro	0.416	3.140	—	−0.207	—	—	—	—
Systematic Diversified	0.657	3.272	—	—	—	—	—	—
Merger Arbitrage	0.536	4.887	—	—	−0.088	—	—	—
Fixed Income Corporate	0.639	4.468	0.050	—	—	—	—	—
Short Selling	0.356	2.702	—	−0.654	0.327	0.288	—	—
Fund of Funds	0.481	4.508	0.034	−0.078	—	−0.105	—	—
Fund of Funds Conservative	0.522	5.204	0.044	—	—	−0.098	—	—
Fund of Funds Diversified	0.525	4.555	—	−0.106	—	−0.097	—	—
Fund of Funds Market Defensive	0.268	1.969	—	−0.255	—	—	—	—
Fund of Funds Strategic	0.529	4.509	0.032	—	—	−0.138	—	—
Average	0.462	3.750	—	—	—	—	—	—

Black

	US Dollar Index	*Emerging markets*	*Barclays Aggregate Bond Index*	*High yield*	*CDS*	*10 year – 1 year Treasury yield*	*7–10 year Treasury return*	*Adjusted R^2*
Fund Weighted Index	—	0.128	0.493	—	−0.004	—	−0.317	0.917
Relative Value Multi-Strategy	—	0.052	1.655	—	−0.005	—	−0.887	0.762
Convertible Arbitrage	—	—	1.811	0.380	—	—	−1.005	0.681
Distressed	—	—	—	0.342	−0.011	—	−0.157	0.714
Emerging Markets	—	0.419	0.907	—	−0.009	—	−0.485	0.918
Equity Hedge	—	0.159	0.482	—	−0.004	—	−0.350	0.932
Equity Market Neutral	—	0.078	—	—	−0.006	—	—	0.370
Fixed Income Arbitrage	—	0.095	—	0.540	—	—	—	0.660
Event Driven	—	—	—	0.215	−0.007	—	−0.140	0.819
Macro	−0.163	0.167	—	—	—	—	—	0.345
Systematic Diversified	—	0.227	—	−0.332	—	—	—	0.259
Merger Arbitrage	—	0.100	—	—	—	−2.413	—	0.665
Fixed Income Corporate	—	—	—	0.387	−0.007	—	−0.161	0.749
Short Selling	—	—	—	—	—	—	—	0.879
Fund of Funds	—	0.159	0.672	—	−0.009	−0.401	—	0.819
Fund of Funds Conservative	—	0.053	0.851	—	−0.008	—	−0.503	0.756
Fund of Funds Diversified	—	0.179	0.654	—	−0.010	—	−0.414	0.778
Fund of Funds Market Defensive	−0.160	0.168	—	—	—	—	—	0.324
Fund of Funds Strategic	—	0.221	—	—	−0.009	—	—	0.860
Average	—	—	—	—	—	—	—	0.695

Table 7 Regressions with lagged factor variables, January 1990 – June 2009, monthly observations, HFR data, all variables statistically significant at the 1 per cent level

	Ljung-Box	*Intercept*	*t (Intercept)*	*S&P GSCI Commodity*	*S&P 500*	*S&P 500 – Russell 2000*	*Russell 1000 Value – Growth*	*VIX Change*	*EAFE*	*US Dollar Index*	*Emerging markets*
Fund Weighted Index	23.626	0.550	7.847	0.041	0.179	−0.173	−0.083	—	—	0.071	0.108
Relative Value Multi-Strategy	65.690	0.425	6.938	—	—	—	—	—	—	—	0.046
Convertible Arbitrage	87.593	0.200	2.092	—	—	—	—	0.021	—	—	0.042
Distressed	75.970	0.775	8.200	—	—	−0.074	—	−0.019	—	—	0.065
Emerging Markets	29.724	0.688	5.165	—	—	—	—	−0.037	—	—	0.508
Equity Hedge	16.197	0.794	8.761	0.081	0.325	−0.262	−0.137	—	—	—	0.062
Equity Market Neutral	5.580	0.818	8.691	0.037	—	—	—	—	—	—	—
Fixed Income Arbitrage	89.172	0.233	2.502	—	—	—	—	0.020	—	—	0.039
Event Driven	35.885	0.815	10.014	—	0.187	−0.144	—	−0.027	—	—	0.038
Macro	6.200	0.688	5.262	—	—	−0.105	—	—	—	0.179	0.153
Systematic Diversified	0.011	0.605	4.508	—	0.203	−0.133	−0.106	—	—	—	0.092
Merger Arbitrage	11.962	0.899	8.796	—	0.089	−0.068	—	−0.018	—	—	—
Fixed Income Corporate	54.850	0.262	2.897	—	—	—	—	−0.026	—	—	—
Short Selling	2.352	1.139	6.002	—	−0.827	0.672	0.528	—	—	—	—
Fund of Funds	32.588	0.322	3.329	0.049	—	−0.061	−0.081	—	—	0.099	0.133
Fund of Funds Conservative	49.984	0.419	6.348	0.031	—	—	−0.045	—	—	—	0.053
Fund of Funds Diversified	31.237	0.274	2.714	0.048	—	−0.069	−0.084	—	—	0.110	0.147
Fund of Funds Market Defensive	1.983	0.711	6.755	0.063	−0.101	—	—	—	—	—	0.085
Fund of Funds Strategic	24.954	0.650	3.948	—	0.115	−0.159	−0.144	—	—	—	0.151
Average	—	0.593	5.830	—	—	—	—	—	—	—	—

Black

	Barclays Aggregate Bond Index	*High yield*	*10 year – 1 year Treasury yield*	*7–10 year Treasury return*	*S&P 500*	*High yield 1*	*High yield 2*	*Lagged Index*	*High yield squared*	*S&P 500 squared*	*Adjusted R^2*
Fund Weighted Index	0.601	—	—	−0.289	—	—	—	—	—	—	0.812
Relative Value Multi-Strategy	1.077	0.138	—	−0.645	—	—	—	—	−0.013	—	0.663
Convertible Arbitrage	1.620	0.206	—	−0.910	—	0.131	—	—	−0.021	—	0.655
Distressed	—	0.209	—	—	—	0.204	0.129	—	—	−0.011	0.675
Emerging Markets	—	—	—	—	—	—	—	—	—	—	0.780
Equity Hedge	—	—	—	—	—	—	—	—	—	—	0.744
Equity Market Neutral	—	—	−1.850	—	—	—	—	—	—	—	0.088
Fixed Income Arbitrage	1.505	0.216	—	−0.844	—	0.113	—	—	−0.023	—	0.657
Event Driven	—	0.092	—	—	—	0.170	—	—	—	−0.009	0.772
Macro	—	—	—	0.471	—	—	—	—	—	—	0.331
Systematic Diversified	—	−0.212	—	—	—	—	—	—	—	0.017	0.424
Merger Arbitrage	—	0.097	−2.329	—	—	—	—	—	—	—	0.409
Fixed Income Corporate	—	0.478	—	—	—	0.119	0.157	—	—	−0.006	0.716
Short Selling	—	—	—	—	—	—	—	—	−0.030	—	0.775
Fund of Funds	1.167	−0.140	—	−0.567	—	0.089	—	—	−0.012	—	0.574
Fund of Funds Conservative	0.932	—	—	−0.562	—	—	—	—	−0.014	—	0.536
Fund of Funds Diversified	1.154	−0.178	—	−0.558	—	0.112	—	—	−0.012	—	0.570
Fund of Funds Market Defensive	—	—	—	—	—	—	—	—	—	—	0.136
Fund of Funds Strategic	1.668	−0.231	—	−0.870	—	—	—	—	—	−0.013	0.526
Average	—	—	—	—	—	—	—	—	—	—	0.571

Table 8 Regressions with lagged factor variables, August 2001 – June 2009, monthly observations, HFR data, all variables statistically significant at the 1 per cent level

	Ljung-Box	*Intercept*	*t (Intercept)*	*S&P GSCI Commodity*	*S&P 500*	*S&P 500 – Russell 2000*	*Russell 1000 Value – Growth*	*VIX Change*	*EAFE*	*US Dollar Index*	*Emerging markets*	*Barclays Aggregate Bond Index*
Fund Weighted Index	15.967	0.456	5.396	0.028	—	−0.075	−0.111	—	0.086	—	0.128	0.493
Relative Value Multi-Strategy	31.570	0.243	2.936	0.030	—	—	—	—	0.057	—	—	1.640
Convertible Arbitrage	36.079	−0.369	−1.747	—	—	—	—	0.051	—	—	0.099	3.084
Distressed	38.713	0.631	4.491	—	—	—	—	—	0.093	—	—	—
Emerging Markets	19.902	0.832	5.303	—	—	—	—	—	—	—	0.419	0.907
Equity Hedge	16.546	0.042	0.518	0.042	—	−0.107	−0.149	—	0.182	—	0.161	—
Equity Market Neutral	3.454	0.448	4.873	—	−0.092	—	—	—	—	—	0.078	—
Fixed Income Arbitrage	36.720	0.089	0.520	—	—	—	—	0.050	—	—	—	2.138
Event Driven	24.422	0.605	5.443	—	—	−0.119	−0.122	—	0.197	—	—	—
Macro	0.000	0.630	3.662	0.057	−0.181	—	—	—	—	—	0.163	—
Systematic Diversified	0.451	0.424	1.984	—	—	—	—	—	—	—	0.238	—
Merger Arbitrage	6.562	0.536	4.887	—	—	−0.088	—	—	—	—	0.100	—
Fixed Income Corporate	30.355	0.060	0.389	—	—	—	—	—	0.107	—	—	1.692
Short Selling	5.729	0.553	4.297	—	−0.691	0.331	0.301	—	—	—	—	—
Fund of Funds	18.251	0.506	4.534	—	−0.103	—	−0.098	—	—	—	0.185	0.685
Fund of Funds Conservative	29.628	0.522	5.204	0.044	—	—	−0.098	—	—	—	0.053	0.851
Fund of Funds Diversified	17.549	0.439	3.911	—	−0.174	—	−0.107	—	0.151	—	0.120	0.617
Fund of Funds Market Defensive	0.157	0.268	1.969	—	−0.255	—	—	—	—	−0.160	0.168	—
Fund of Funds Strategic	15.265	0.524	4.652	—	−0.157	—	−0.179	—	0.165	—	0.207	—
Average	—	0.391	3.327	—	—	—	—	—	—	—	—	—

	High yield	*CDS*	*10 year – 1 year Treasury yield*	*7–10 year Treasury return*	*S&P 500*	*High yield 1*	*High yield 2*	*Lagged Index*	*High yield squared*	*S&P 500 squared*	*Adjusted R^2*
Fund Weighted Index	—	−0.004	—	−0.317	—	—	—	—	—	—	0.917
Relative Value Multi-Strategy	—	—	—	−0.914	—	—	—	—	−0.013	—	0.797
Convertible Arbitrage	—	0.008	—	−1.741	—	—	—	—	−0.032	—	0.735
Distressed	0.229	−0.010	2.412	—	—	0.176	0.101	—	—	—	0.849
Emerging Markets	—	−0.009	—	−0.485	—	—	—	—	—	—	0.918
Equity Hedge	—	—	—	—	—	—	—	—	—	—	0.913
Equity Market Neutral	—	−0.006	—	—	—	—	—	—	—	—	0.370
Fixed Income Arbitrage	0.288	—	—	−1.219	—	—	—	—	−0.024	—	0.712
Event Driven	0.164	−0.006	—	—	—	0.106	0.080	—	—	—	0.874
Macro	—	−0.007	—	—	—	—	—	—	0.018	—	0.407
Systematic Diversified	−0.291	—	—	—	—	—	—	—	0.017	—	0.305
Merger Arbitrage	—	—	−2.413	—	—	—	—	—	—	—	0.665
Fixed Income Corporate	—	—	3.049	−1.112	—	—	—	—	−0.023	—	0.803
Short Selling	—	—	—	—	—	—	—	—	−0.017	—	0.899
Fund of Funds	—	−0.010	—	−0.414	—	—	—	—	—	—	0.800
Fund of Funds Conservative	—	−0.008	—	−0.503	—	—	—	—	—	—	0.756
Fund of Funds Diversified	—	−0.008	—	−0.413	—	—	—	—	−0.013	0.009	0.808
Fund of Funds Market Defensive	—	—	—	—	—	—	—	—	—	—	0.324
Fund of Funds Strategic	—	−0.009	—	—	—	—	—	—	—	—	0.872
Average	—	—	—	—	—	—	—	—	—	—	0.722

Table 9 Regressions with Lagged Index variables, January 1990 – June 2009, monthly observations, HFR data, all variables statistically significant at the 1 per cent level (1 of 2)

	Ljung-Box	*Intercept*	*t (Intercept)*	*S&P GSCI Commodity*	*S&P 500*	*S&P 500 – Russell 2000*	*Russell 1000 Value – Growth*	*VIX Change*	*EAFE*	*US Dollar Index*	*Emerging markets*
Fund Weighted Index	23.626	0.442	6.609	0.037	0.175	−0.161	−0.102	−0.014	—	—	0.100
Relative Value Multi-Strategy	65.690	0.226	3.497	—	—	—	—	—	—	—	0.052
Convertible Arbitrage	87.593	0.106	1.113	—	—	—	—	—	—	—	0.037
Distressed	75.970	0.318	4.148	—	—	−0.088	—	−0.019	—	—	0.070
Emerging Markets	29.724	0.301	2.119	—	—	—	—	−0.035	—	—	0.484
Equity Hedge	16.197	0.621	6.725	0.076	0.322	−0.259	−0.149	—	—	—	0.055
Equity Market Neutral	5.580	0.818	8.691	0.037	—	—	—	—	—	—	—
Fixed Income Arbitrage	89.172	0.129	1.400	—	—	—	—	—	—	—	0.034
Event Driven	35.885	0.699	8.069	0.203	—	−0.160	—	−0.030	—	—	0.047
Macro	6.200	0.688	5.262	—	—	−0.105	—	—	—	0.179	0.153
Systematic Diversified	0.011	0.605	4.508	—	0.203	−0.133	−0.106	—	—	—	0.092
Merger Arbitrage	11.962	0.899	8.796	—	0.089	−0.068	—	−0.018	—	—	—
Fixed Income Corporate	54.850	0.122	1.657	—	—	—	—	−0.026	—	—	0.035
Short Selling	2.352	1.139	6.002	—	−0.827	0.672	0.528	—	—	—	—
Fund of Funds	32.588	0.167	1.906	0.058	—	—	−0.091	—	—	0.095	0.138
Fund of Funds Conservative	49.984	0.225	3.206	0.028	—	—	−0.052	—	—	—	0.055
Fund of Funds Diversified	31.237	0.052	0.560	0.054	—	−0.062	−0.087	—	—	0.099	0.147
Fund of Funds Market Defensive	1.983	0.711	6.755	0.063	−0.101	—	—	—	—	—	0.085
Fund of Funds Strategic	24.954	0.346	2.159	—	0.130	−0.163	−0.155	—	—	—	0.149
Average	—	0.453	4.378	—	—	—	—	—	—	—	—

	Barclays Aggregate Bond Index	*High yield*	*10 year − 1 year Treasury yield*	*7–10 year Treasury return*	*S&P 500*	*High yield 1*	*High yield 2*	*Lagged Index*	*High yield squared*	*S&P 500 squared*	*Adjusted R^2*
Fund Weighted Index	0.158	—	—	—	—	—	—	0.209	—	—	0.845
Relative Value Multi-Strategy	1.049	0.091	—	−0.595	—	—	—	0.260	−0.008	—	0.713
Convertible Arbitrage	1.402	0.173	—	−0.770	—	—	—	0.310	−0.015	—	0.679
Distressed	—	0.239	—	—	—	—	—	0.452	—	—	0.715
Emerging Markets	0.299	—	—	—	—	—	—	0.206	—	—	0.820
Equity Hedge	—	—	—	—	—	—	—	0.163	—	—	0.769
Equity Market Neutral	—	—	−1.850	—	—	—	—	—	—	—	0.088
Fixed Income Arbitrage	1.278	0.181	—	−0.694	—	—	—	0.307	−0.016	—	0.684
Event Driven	—	—	—	—	—	—	—	0.256	—	−0.008	0.767
Macro	—	—	—	0.471	—	—	—	—	—	—	0.331
Systematic Diversified	—	−0.212	—	—	—	—	—	—	—	0.017	0.424
Merger Arbitrage	—	0.097	−2.329	—	—	—	—	—	—	—	0.409
Fixed Income Corporate	—	0.426	—	—	—	—	—	0.317	—	—	0.721
Short Selling	—	—	—	—	—	—	—	—	−0.030	—	0.775
Fund of Funds	0.237	—	—	—	—	—	—	0.308	—	—	0.600
Fund of Funds Conservative	0.807	—	—	−0.460	—	—	—	0.279	−0.008	—	0.594
Fund of Funds Diversified	1.129	−0.142	—	−0.537	—	—	—	0.300	—	—	0.615
Fund of Funds Market Defensive	—	—	—	—	—	—	—	—	—	—	0.136
Fund of Funds Strategic	1.687	−0.287	—	−0.819	—	—	—	0.270	—	−0.010	0.593
Average	—	—	—	—	—	—	—	—	—	—	0.594

Table 10 Regressions with Lagged Index variables, August 2001 – June 2009, monthly observations, HFR data, all variables statistically significant at the 1 per cent level (1 of 2)

	Ljung-Box	*Intercept*	*t (Intercept)*	*S&P GSCI Commodity*	*S&P 500*	*S&P 500 – Russell 2000*	*Russell 1000 Value – Growth*	*VIX Change*	*EAFE*	*US Dollar Index*	*Emerging markets*	*Barclays Aggregate Bond Index*
Fund Weighted Index	15.967	0.456	5.396	0.028	—	−0.075	−0.111	—	0.086	—	0.128	0.493
Relative Value Multi-Strategy	31.570	0.115	1.284	—	—	—	—	—	—	—	0.058	1.477
Convertible Arbitrage	36.079	−0.369	−1.747	—	—	—	—	0.051	—	—	0.099	3.084
Distressed	38.713	0.631	4.491	—	—	—	—	—	0.093	—	—	—
Emerging Markets	19.902	0.832	5.303	—	—	—	—	—	—	—	0.419	0.907
Equity Hedge	16.546	0.042	0.518	0.042	—	−0.107	−0.149	—	0.182	—	0.161	—
Equity Market Neutral	3.454	0.448	4.873	—	−0.092	—	—	—	—	—	0.078	—
Fixed Income Arbitrage	36.720	0.089	0.520	—	—	—	—	0.050	—	—	—	2.138
Event Driven	24.422	0.605	5.443	—	—	−0.119	−0.122	—	0.197	—	—	—
Macro	0.000	0.630	3.662	0.057	−0.181	—	—	—	—	—	0.163	—
Systematic Diversified	0.451	0.424	1.984	—	—	—	—	—	—	—	0.238	—
Merger Arbitrage	6.562	0.536	4.887	—	—	−0.088	—	—	—	—	0.100	—
Fixed Income Corporate	30.355	0.060	0.389	—	—	—	—	—	0.107	—	—	1.692
Short Selling	5.729	0.553	4.297	—	−0.691	0.331	0.301	—	—	—	—	—
Fund of Funds	18.251	0.506	4.534	—	−0.103	—	−0.098	—	—	—	0.185	0.685
Fund of Funds Conservative	29.628	0.522	5.204	0.044	—	—	−0.098	—	—	—	0.053	0.851
Fund of Funds Diversified	17.549	0.439	3.911	—	−0.174	—	−0.107	—	0.151	—	0.120	0.617
Fund of Funds Market Defensive	0.157	0.268	1.969	—	−0.255	—	—	—	—	−0.160	0.168	—
Fund of Funds Strategic	15.265	0.524	4.652	—	−0.157	—	−0.179	—	0.165	—	0.207	—
Average	—	0.385	3.241	—	—	—	—	—	—	—	—	—

	High yield	*CDS*	*10 year – 1 year Treasury yield*	*7–10 year Treasury return*	*S&P 500*	*High yield 1*	*High yield 2*	*Lagged Index*	*High yield squared*	*S&P 500 squared*	*Adjusted R^2*
Fund Weighted Index	—	−0.004	—	−0.317	—	—	—	—	—	—	0.917
Relative Value Multi-Strategy	—	—	—	−0.794	—	—	—	0.184	−0.011	—	0.804
Convertible Arbitrage	—	0.008	—	−1.741	—	—	—	—	−0.032	—	0.735
Distressed	0.229	−0.010	2.412	—	—	0.176	0.101	—	—	—	0.849
Emerging Markets	—	−0.009	—	−0.485	—	—	—	—	—	—	0.918
Equity Hedge	—	—	—	—	—	—	—	—	—	—	0.913
Equity Market Neutral	—	−0.006	—	—	—	—	—	—	—	—	0.370
Fixed Income Arbitrage	0.288	—	—	−1.219	—	—	—	—	−0.024	—	0.712
Event Driven	0.164	−0.006	—	—	—	0.106	0.080	—	—	—	0.874
Macro	—	−0.007	—	—	—	—	—	—	0.018	—	0.407
Systematic Diversified	−0.291	—	—	—	—	—	—	—	0.017	—	0.305
Merger Arbitrage	—	—	−2.413	—	—	—	—	—	—	—	0.665
Fixed Income Corporate	—	—	3.049	−1.112	—	—	—	—	−0.023	—	0.803
Short Selling	—	—	—	—	—	—	—	—	−0.017	—	0.899
Fund of Funds	—	−0.010	—	−0.414	—	—	—	—	—	—	0.800
Fund of Funds Conservative	—	−0.008	—	−0.503	—	—	—	—	—	—	0.756
Fund of Funds Diversified	—	−0.008	—	−0.413	—	—	—	—	−0.013	0.009	0.808
Fund of Funds Market Defensive	—	—	—	—	—	—	—	—	—	—	0.324
Fund of Funds Strategic	—	−0.009	—	—	—	—	—	—	—	—	0.872
Average	—	—	—	—	—	—	—	—	—	—	0.723

allocating assets to managers with exposure to distressed securities. Notice that the adjusted R^2 for this strategy rises from 0.714 to 0.849 through the addition of the lagged returns, which shows that a substantial portion of the risk of investing in distressed hedge funds is related to liquidity risk.

The change from Table 7 to Table 8 shows some interesting results. While the adjusted R^2 for the average strategy increases from 0.571 to 0.722 when testing on the same variable set over two time periods, only event-driven and distressed strategies maintain a significant exposure to illiquidity risk since August 2001. Two possible interpretations for this observation are that either (i) the CDS factor is correlated to lagged high yield returns or (ii) that hedge funds are taking more market risk and less liquidity risk in the current decade relative to the prior decade.

A different measure of liquidity risk is described by Getmansky *et al* (2004). Rather than including lagged market exposures in the regression, such as in Kazemi and Schneeweis (2004), Getmansky *et al* (2004) include the lagged returns to the hedge fund index. The regression model is now

$$\begin{aligned}\text{Hedge fund return}_t = \alpha &+ \text{Hedge Fund Return}_{t-1}\\ &+\Sigma\beta_{t,i} \times \text{Traditional Factor}_{t,i}\\ &+\Sigma\beta_{t,i} \times \text{Traditional Factor}_{t-1,i}\\ &+\Sigma\beta_{t,i} \times \text{Alternative Factor}_{t,i}\\ &+\Sigma\beta_{t,i} \times (\text{Traditional Returns})^2\end{aligned}$$

The results of adding the lagged return to the hedge fund index are shown in Tables 9 and 10. Once again, the adjusted R^2 increases, from 0.571 to 0.594 for the entire time period, and from 0.722 to 0.723 since August 2001. This adds to our observation that hedge funds have taken less illiquidity risk since 2001 than in the prior decade. Surprisingly, while 13 of the 19 hedge fund indices show statistically significant exposures to the Lagged Index over the entire time period, only relative value multi-strategy funds show a significant exposure to lagged returns since August 2001. Perhaps this is due to the illiquidity risk of CDS, which could absorb the liquidity risk of the lagged hedge fund indices.

MARKET TIMING TESTS

Hamza *et al* (2006) add squared terms to the model, where a non-linear regression is used to test market timing skill. The idea of using squared terms to detect timing ability was pioneered in Treynor and Mazuy (1966) and further explained by Coggin *et al* (1993).
A manager with perfect market timing ability will have a long position in rising markets, and a short position in declining markets. When plotted against market returns, the fund's returns would have a parabolic shape. A positive coefficient on squared factor returns shows superior market timing skill, whereas a negative coefficient shows poor market timing skill.

This return payoff could also be earned through the purchase of straddles (at-the-money calls and puts), on the underlying market index. Over long periods of time, managers regularly buying straddles would exhibit positive market timing skill. The α of that manager's strategy would be directly related to whether the options were overpriced or underpriced relative to the realized volatility experienced in the underlying market. A manager with market timing skill would be able to generate a straddle-like payoff function without paying options premium, which is quite a valuable skill.

An alternate specification for market timing skill is presented by Henriksson and Merton (1981). This article proposes the use of a dummy variable for down markets. When the market exposure in down markets is significantly less than the fund's exposure in up markets, the manager is showing market timing skill.

When the squared return to the S&P 500 coefficient is statistically significant and positive, the manager has positive market timing skill, as returns rise with larger moves in the stock market. Conversely, when the squared return to the High Yield Index is negative and statistically significant, the manager has negative market timing skill, taking larger exposures before market declines and smaller exposures before market rallies. Tables 7 and 8 show that at least six hedge fund styles have negative market timing skill in high yield bonds, while market timing skill, for better or worse, is less common in the equity markets. Once again, we are encouraged that the data back up the trading styles explained by the managers. Typically, only macro and systematic diversified (managed futures or commodity trading advisors) claim to have positive market timing skill. The data also makes this case, as both strategies have positive timing skill to high yield bonds since August 2001, while systematic diversified managers show positive timing skill to the equity markets over the entire sample period. Géhin and Vaissié (2006) estimate that while 23 per cent of the risk of hedge funds comes from dynamic β exposures, −3 per cent of the total return to hedge funds is explained by these risks. That is, hedge funds would offer higher returns and lower risks by offering static β exposures than dynamic β exposures. Should hedge funds offer more static exposures to market βs, the factor-based benchmarks suggested by Fung and Hsieh (2004) would be more reliably used. The analysis of adding hedge funds to traditional portfolios as explained by Dopfel (2005) would also be more accurate should hedge funds adopt a more static exposure to market risk factors. For example, it is easier for an institutional investor to have a 60 per cent exposure to global equities when they know the average equity β of their hedge fund managers is 0.40 rather than when the equity β fluctuates unexpectedly between 0.20 and 0.60. Static β exposures would also make it easier to determine the α, or skill, of hedge fund managers and could give an explicit incentive, or penalty, for market timing should a manager's incentive fee be based on an explicit β exposure. An example of this fee structure would be a 1 per cent management fee and a 20 per cent incentive fee on returns in excess of a 0.40 β exposure to the S&P 500 Index.

CONCLUSION

While some investors may include traditional market β exposures in their returns-based style analysis of hedge fund index returns, we find that traditional market exposures tell only part of the story. Because hedge fund managers take substantial exposures to leverage, alternative βs and illiquidity risks, it is inappropriate to measure the complete risk of hedge funds simply by using traditional factors such as stock and bond market returns. Through the addition of leverage and slope terms, lagged returns to market sectors and hedge fund indices, and alternative βs, such as currencies or credit default swaps, the average adjusted R^2 of returns-based style analysis regressions across hedge fund styles increases by 0.124–0.145. Adding these additional factors to the regressions not only increases the explanatory power of the regressions, but also allows hedge fund investors to more accurately model the true risk exposures found in their hedge fund portfolios. Once these true risk exposures are known, it can be easier to integrate hedge fund allocations into the larger portfolio, where investors can see the equity risk of the entire portfolio. Institutional investors, then, may be better served by aggregating all βs at the portfolio level. Rather than assuming that the portfolio is 50 per cent equity, 40 per cent fixed income and 10 per cent hedge funds, it is more accurate to state that the portfolio is 54 per cent equity, 43 per cent fixed income and 3 per cent alternative βs. The logical conclusion, then, is that equity hedge funds may someday be included in the equity portion of investor portfolios, while fixed income hedge funds may become a part of the fixed income portfolio.

There are two important implications of determining the underlying factor risks borne by their underlying hedge fund. First, investors can better determine the value added by hedge fund managers, and may wish to compensate their managers on α net of all factor exposures than on the total return of the fund. Second, investors who understand the factor risks of their hedge fund portfolio will better equipped to calculate the factor exposure at the total portfolio level, including both hedge funds as well as traditional stock and bond investments.

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