Original Article

Risk characterization, stale pricing and the attributes of hedge funds performance

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ABSTRACT **The objective of this article is to evaluate the performance of hedge funds and characterize the underlying risk dynamics. Using a fairly well-known database of a set of aggregate hedge fund indices from CSFB/Tremont, we investigate whether hedge fund returns reflect the stale or managed price effect. We demonstrate that performance persistence of hedge fund is not only related to the serial correlation in hedge fund returns, but also to the correlation between hedge fund returns and lagged market portfolio returns. We find evidence of non-synchronous pricing for a significant number of hedge fund indices, and show that both stock and bond markets capture the important uncertainty components of hedge funds average returns. Our empirical results indicate that average fund alpha and risk premium should be estimated in an integrated market. Otherwise, it is difficult to identify the common sources of uncertainty. Our results imply that hedge funds that cannot get rid of the idiosyncratic component by diversification will generate lower (and in some cases below the benchmark) average returns.**

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INTRODUCTION

During the past two decades, hedge funds have become an imposing part of the global investment landscape. Not only has the amount invested in hedge funds gone up tremendously (for example, global investment in hedge fund was US$50 billion in 1990 and $2.5 trillion in 2008), enormous trades initiated by hedge funds occupy an important role in the everyday global security market, especially where ample leverage is a concern. There are various reasons behind the appeal and attractiveness of hedge fund investments and some of them go beyond its underlying features. Basically, hedge funds are supposed to provide a textbook-style diversification example that offers over-the-top returns. Despite a high price tag, as a part of an overall asset mix, hedge funds represent attractive dynamic trading strategies and can have very low or insignificant correlation with market returns (which essentially is a claim of zero betas).

The financial performance persistence of hedge funds has become a subject of extensive academic surveillance[1] recently, and this article is an attempt to deepen our understanding of that issue. The purpose of this study is to evaluate the performance of hedge fund returns and characterize the underlying risk dynamics in an integrated market. Using a fairly well-known database of a set of aggregate hedge fund indices from CSFB/Tremont, we investigate whether hedge fund returns reflect the stale or managed price effect. We show that performance persistence of hedge funds is not only related to the serial correlation in hedge fund returns, but also to the correlation between hedge fund returns and lagged market portfolio returns. Following the work of Asness *et al*[2] and Getmansky *et al*[3], we focus on the serial correlation in hedge fund returns and critically evaluate different attributes of hedge fund performance.

The focus of a sizable part of academic research has been on the covariates of hedge fund returns, in terms of proxy of various risk factors in the regression analysis. For example, Fung and Hsieh[4] employ style factors that replicate the time-series payoffs of trend-following strategies. Mitchell and Puvlino[5] suggest that return to risk arbitrage strategy is similar to those obtained from selling uncovered index put options. Agarwal and Naik[6,7] use option-like returns of dynamic trading of hedge fund manager and show that risk exposure of hedge funds can include option-based strategies. Fung *et al*[8] utilize a comprehensive data set of funds-of-funds and investigate performance, risk and capital formation in the hedge fund industry, over the decade from 1995 to 2004. Recently, Bollen and Whaley[9] employ an optimal changepoint regression that allows risk exposures to shift and illustrate the impact on performance appraisal.[10] Despite methodological differences, our approach is very much along the line of contemporary research. There are three main differences between our methodology and the existing literature. First, we discuss the economic significance of hedge fund returns and risk dynamics (beta and volatility) in an integrated market using different sets of stock and bond market factors. Second, we use a two-stage linear factor model approach to generate risk premia of hedge funds and identify their common sources of uncertainty. Third, our study incorporates a more important role of the idiosyncratic part of market risk on the average returns of hedge funds than any previous work.

The main findings of this article can be easily summarized. Our results using broad-based hedge fund indices illustrate the empirical tests of fund performance[11] and the role of common risk factors related to stock and bond market that capture systematic variation in return persistence. We show that the actual empirical estimate of hedge funds risk can be severely understated by using simple lagged beta techniques of Scholes and Williams.[12] We find the evidence of non-synchronous pricing for a significant number of hedge fund indices.[13] As the lagged beta clearly influences measures of fund performance under the assumptions of relatively integrated stock and bond markets, our results implicitly indicate that the average value of hedge funds and risk premium should not be estimated in a segmented market.

This article is organized as follows. In the next section, we describe the empirical methodology and various models of performance measurement. This is followed by a brief description of the data set. The main empirical results are presented in the subsequent section. This includes preliminary summary statistics and detailed analysis of the role of alphas, betas and an orthogonalized market factor in discovering stale or managed pricing. It also presents a discussion of estimated risk premium and the issue of beta uncertainty. The final section concludes the article.

METHODOLOGY AND MODELS OF PERFORMANCE MEASUREMENT

In this section, we briefly describe the empirical methodology used throughout the article.
A hedge fund return can be characterized by a time-varying exposure to the appropriate common risk factors. The main challenge is to uncover the simultaneous dynamic exposure of hedge fund returns with respect to stock and bond market risk factors. For the empirical analysis, we utilize a linear factor model framework usually credited to Jensen.[14] The idea is to use various combinations of underlying factors, and derive their associated risk loading that can capture hedge funds' common risk exposure.

Simple linear factor model

Jensen[14] first used a linear factor model, motivated by the capital asset pricing model (CAPM) of Sharp,[15] to evaluate the performance of mutual funds. According to the security market line, the expected excess return for an asset is proportional to the expected excess return on a portfolio of all available assets (that is, the market portfolio), and is given by

$$E\left(R_{i,t}\right) - R_{f,\,t} = \beta_i[E\left(R_{m,t}\right) - R_{f,\,t}]$$

where $E(R_{i,t})$ is the expected return of asset i at time t, $R_{f,t}$ is the risk-free rate (for example, rate of interest on short-term US Govt. debt or T-bills) at time t, $E(R_{m,t})$ is the expected return for the market portfolio (for example, S&P 500) at time t, and β_i is the index of systematic risk of asset i.

The index of systematic risk of asset i is the degree to which an asset covaries with the market portfolio and can be estimated using the following simple linear regression:

$$\begin{aligned} r_{i,t} =&\alpha_i + \beta_{i,0} r_{m,t} + u_{i,t}, E\left(u_{i,t}\right) = 0, \forall i, \\ &Cov\left(u_{i,t}, r_{m,t}\right) = 0, \forall i \\ &Cov\left(u_{i,t}, u_{j,t}\right) = 0, \forall i \neq j \end{aligned} \tag{1}$$

where $r_{i,t} = R_{i,t} - R_{f,t}$ is the excess return of asset i, $r_{m,t} = R_{m,t} - R_{f,t}$ is the excess market return, $R_{i,t}$ is the observed return of asset i at time t, $R_{f,t}$ is the observed return on the risk-free asset, $R_{m,t}$ is the observed return on the market portfolio for time t, α_i is the population intercept coefficient, and $\beta_{i,0}$ is the population slope coefficient. One can think about model (1) as nothing but a linear one-factor model with contemporaneous market portfolio return as the only common factor. The main difference is that in the CAPM version $Cov(u_{i,\,t}, u_{j,\,t}) \neq 0$, $\forall i \neq j$, whereas in a linear factor model regression residuals of different assets are all uncorrelated. Similar to CAPM, in a linear one-factor model the slope coefficient $\beta_{i,0}$ indicates asset i's exposure to a common market factor.

Linear multifactor model

Over the years, researchers have observed CAPM's inability to capture systematic variation in asset returns and, consequently, factors that have no special standing in asset pricing theory have emerged. Owing to the work of Fama and French[16] and Carhart,[17] the multifactor model has become extremely popular in empirical asset pricing. The application of the multifactor model in hedge funds research is also abundant (see, for example, Bollen and Whaley[9] for a recent treatment). In the empirical analysis, we use various alternative multifactor specifications. We start with a simple linear factor model (1), and use an extended version that includes n lags of common market factor.

$$r_{i,t} = \alpha_i + \beta_{i,0} r_{m,t} + \beta_{i,1} r_{m,t-1} + \beta_{i,2} r_{m,t-2} + \beta_{i,3} r_{m,t-3} + \cdots + \beta_{i,n} r_{m,t-n} + u_{i,t} \quad (2)$$

In both specifications (1) and (2), the estimated intercept coefficient α_i can be used to measure the performance of individual hedge funds (that is, manager's skill). Model (2) is a very simple but elegant method proposed by Scholes and Williams.[12] It incorporates not only the contemporaneous effect of market return, but also lagged market returns. As Asness *et al*[2] (p. 11) mentioned 'If hedge fund returns are not fully synchronous with market returns due to stale or managed prices, then lagged market returns should also be correlated with current hedge returns'. In other words, what we are looking for is not just one market beta but the summed beta that is, $\sum_n^{j=0} \beta_{i,j} r_{m,t-j}$. The choice of the effective lag n of course depends on the data.

Next, in order to capture the variability of hedge fund returns with respect to various common risk factors, we consider the following:

$$r_{i,t} = \alpha_i + \sum_{j=0}^{n} \beta_{i,j} r_{m,t-j} + \gamma_{i,1}[SMB_t] + \gamma_{i,2}[HML_t] + \delta_{i,1}[TERM_t] + \delta_{i,2}[DEF_t] + u_{i,t} \quad (3)$$

The idea of SMB and HML originated in Fama and French[16] and has become the workhorse of modern multifactor asset pricing analysis. In the hedge fund research, they have been widely adopted and used as well, see for example Fung and Hsieh,[4,18] Capocci and Hüebner,[19] Racicot and Théoret,[20] Bollen and Whaley,[9] Coën and Hübner,[21] and Manser and Schmid[22] and so on. Both SMB and HML represent common stock market factors. SMB (small minus big) is the difference each month between the simple average of the per cent returns on the three small-stock portfolios and the simple average of the returns on the three big-stock portfolios. HML (high minus low) is the difference each month between the simple average of the returns on the two high book-to-market (BE/ME) portfolios and the average of the returns on the two low BE/ME portfolios.[23] The intuition is if the stock and bond markets are integrated, then there should be some overlapping in the risk exposure. In order to capture this idea, we also include two additional common bond market factors. They are TERM and DEF. TERM is the difference between a 10-year government bond return and T-bill return (term spread). DEF is the difference between return on a proxy for the market portfolio of corporate bonds and long-term government bonds (default spread).

DATA SOURCES

There are many sources for the data on the returns of individual hedge funds. Some of the popular commercial database that has been used in the contemporary academic research is AltVest, CISDM, HedgeFund.net, HFR and TASS. For the empirical analysis in this article, our main source is a set of aggregate hedge fund index returns from CSFB/Tremont.[24] The CSFB/Tremont indices are asset-weighted indexes of funds with a minimum of $10 million of assets under management.[25] They also include a minimum 1-year track record and current audited financial statements. We also use data from the University of Chicago's Center for Research in Security Prices (CRSP) and Ibbotson Associates to construct two term-structure factors. The risk-free rate is the 1-month Treasury bill rate from CRSP. The returns on the market portfolio, SMB and HML are obtained from Ken French.[26] Data on government bond yields are from the FRED@ database of the Federal Reserve Bank of St. Louis. The long-term corporate bond is the composite portfolio on the corporate bond module of Ibbotson Associates. The sample period is January 1994 to December 2008.

EMPIRICAL RESULTS AND INTERPRETATIONS

Summary statistics and initial findings

Table 1 presents summary statistics for monthly CSFB/Tremont hedge fund index returns and various common risk Factors. As $r_{i,t}$ denotes the return of ith hedge fund at time t, we calculate the monthly annualized standard deviation by $\sqrt{12}std.dev\left(r_{i,t}\right)$ and quarterly annualized standard deviation by $\sqrt{4}std.dev\left(r_{i,t+2}+r_{i,t+1}+r_{i,t}\right)$. The second, third and fourth columns display monthly annualized mean, standard deviation and standard error of various hedge funds and risk factors. The highest average monthly annualized return is achieved by global macro, followed by distressed fund. Both of them posted double digit returns of 10.32 and 12.36 per cent, respectively. Funds that offer lowest average return are based on dedicated short-seller. Out of total 14 funds, nine of the hedge funds produce an average return greater than CRSP's value-weighted index on all NYSE, AMEX and NASDAQ stocks (which essentially is a proxy for the portfolio of stock market wealth). Six of them are about 2.5 standard errors from zero.

The average Sharpe ratio of the hedge funds is higher than both S&P 500 and CRSP's value-weighted index. The event-driven hedge funds specially share very high Sharpe ratios. The lowest Sharpe ratio is obtained by dedicated short-seller and fixed-income arbitrage funds. By looking closely at the higher moment features, we observe that most of our hedge fund returns are characterized by a left-skewed distribution. As a result, in small (large) probability states the average hedge fund realizes large losses (positive return). This feature is also reflected in the fact that the Jarque–Bera normality test, reported in the last column, always rejects the null hypothesis of normality.[27,28]

Comparison of summary statistics for monthly and quarterly hedge fund index returns in Table 2 suggests some important findings. Except equity market neutral, almost all the hedge funds have lower quarterly standard

Table 1: Summary statistics for monthly CSFB/Tremont hedge fund index returns and various hedge fund risk factors, January 1994–December 2008

	Monthly annualized							
	Mean	*SD*	*SE*	*SR*	*Min*	*Max*	*Median*	*JB Stat*
Aggregate hedge funds	8.64	7.93	2.05	0.62	−7.55	8.53	9.36	12.28
Convertible arbitrage	5.52	6.82	1.76	0.26	−12.59	3.57	11.52	15.36
Dedicated short-seller	0.60	16.94	4.37	−0.18	−8.69	22.71	−4.68	20.11
Emerging markets	7.68	15.83	4.09	0.25	−23.03	16.42	16.32	30.42
Equity market neutral	6.24	11.02	2.84	0.23	−40.45	3.26	8.52	21.35
Event driven	9.36	6.10	1.57	0.93	−11.77	3.68	12.00	19.25
Distressed	10.32	6.75	1.74	0.98	−12.45	4.10	13.68	17.69
Event-driven multistrategy	8.88	6.48	1.67	0.80	−11.52	4.66	10.80	24.87
Risk arbitrage	6.84	4.30	1.11	0.73	−6.15	3.81	6.84	40.45
Fixed-income arbitrage	3.48	5.99	1.55	−0.04	−14.04	2.07	8.40	32.87
Global macro	12.36	10.57	2.73	0.82	−11.55	10.60	13.68	14.53
Long/short equity	9.72	10.22	2.64	0.59	−11.43	13.01	9.72	16.43
Managed futures	7.68	11.88	3.07	0.33	−9.35	9.95	5.52	8.01
Multistrategy	6.84	5.40	1.40	0.58	−7.35	3.61	8.76	66.74
RF	3.72	0.48	0.13	0.00	0.02	0.56	4.44	57.56
S&P 500	5.55	14.97	1.15	0.12	−16.83	9.67	13.08	19.59
RM	7.32	15.59	4.02	0.23	−18.47	8.39	16.56	26.23
SMB	1.92	13.06	3.37	−0.14	−16.79	21.96	−2.04	42.04
HML	3.96	11.85	3.06	0.02	−12.4	13.85	3.96	14.19
TERM	1.44	7.27	1.88	−0.31	−1.44	4.30	1.44	18.60
DEF	3.36	7.38	1.91	0.05	−1.50	7.53	8.04	23.57

Note: SD is the standard deviation. SE is the standard error calculated as $SD/180^{1/2}$. SR is the Sharpe ratio based on annualized data, measures as excess return divided by standard deviation. JB Stat is the Jarque–Bera normality test statistic of the joint hypothesis that skewness=0 and kurtosis=3. The sample size is 180 months. RM is the return of CRSP's value-weighted index on all NYSE, AMEX and NASDAQ stocks, and RF is the 1-month T-bill rate obtained from Ibbotson and Associates. ORM is the sum of the intercept and residuals from the regression of RM–RF on SMB, HML, TERM and DEF. SMB (small minus big) is the difference each month between the simple average of the per cent returns on the three small-stock portfolios and the simple average of the returns on the three big-stock portfolios. HML (high minus low) is the difference each month between the simple average of the returns on the two high-BE/ME portfolios and the average of the returns on the two low-BE/ME portfolios. TERM is the difference between long-term government bond return and T-bill return. DEF is the difference between return on a proxy for the market portfolio of corporate bonds and long-term government bonds.

Table 2: Comparison of summary statistics for monthly and quarterly CSFB/Tremont hedge fund index returns, January 1994–December 2008

	Standard deviation		*M & Q %*	*Correlation with S&P 500*		*M & Q*	*First order autocorrelation*		*Market beta estimates*	
	M	*Q*	*Diff*	*M*	*Q*	*Diff*	*M*	*Q*	*M*	*Q*
Aggregate hedge funds	7.93	8.83	11.00	0.55	0.66	0.11	0.21	0.25	0.29*	0.34*
Convertible arbitrage	6.82	7.65	11.73	0.36	0.43	0.06	0.57	0.85	0.16*	0.25*
Dedicated short-seller	16.94	19.34	14.01	−0.73	−0.79	−0.06	0.09	0.66	−0.82*	−1.17*
Emerging markets	15.83	25.06	58.08	0.52	0.38	−0.14	0.31	0.77	0.55*	0.73*
Equity market neutral	11.02	4.62	−16.21	0.24	0.66	0.41	0.08	0.77	0.17*	0.23*
Event driven	6.10	9.21	50.86	0.61	0.66	0.05	0.39	0.79	0.25*	0.46*
Distressed	6.75	9.94	47.05	0.60	0.70	0.09	0.40	0.75	0.27*	0.53*
Event-driven multistrategy	6.48	9.79	50.74	0.54	0.56	0.02	0.33	0.81	0.23*	0.42*
Risk arbitrage	4.30	5.24	21.56	0.49	0.62	0.12	0.31	0.68	0.14*	0.24*
Fixed-income arbitrage	5.99	6.46	7.67	0.32	0.22	−0.10	0.51	0.80	0.13*	0.10
Global macro	10.57	15.84	49.87	0.26	0.28	0.01	0.09	0.72	0.18*	0.34*
Long/short equity	10.22	11.40	11.54	0.63	0.81	0.18	0.22	0.69	0.43*	0.71*
Managed futures	11.88	11.25	−5.58	−0.15	−0.14	0.00	0.07	0.62	−0.12*	−0.12
Multistrategy	5.40	5.20	−4.13	0.32	0.01	−0.31	0.35	0.67	0.11*	0.004

Note: M stands for monthly and Q stands for quarterly CSFB/Tremont hedge fund index returns. % Diff is the percentage difference between quarterly and monthly figures. First order autocorrelation is based on the regression slope coefficient from $r_{i,t+1} = \alpha + br_{i,t} + \varepsilon_{i,t+1}$ for each hedge fund returns. Market beta estimates come from the following regression $r_{i,t} = a + b_{rmt} + \varepsilon_{i,t}$ where rm_t is the S&P 500 return. (*) implies significance level at 5 per cent level.

deviation than those based on the monthly observations. Managed futures and multistrategy funds only show marginal decrease in quarterly standard deviations. This implies that an increase in quarterly volatility for 11 funds further results in a corresponding decrease in Sharpe ratios. Similarly in terms of correlation with S&P 500, the quarterly data also show substantial difference. The greatest increase in the quarterly correlation belongs to equity market neutral, followed by long/short equity and risk arbitrage fund.

The last four columns of Table 2 show the difference in first-order autocorrelation and market beta, both based on the monthly and quarterly data. Here, the first-order correlations of each hedge fund are the regression slope coefficient from

$$r_{i,t+1} = a + br_{i,t} + \varepsilon_{i,\,t+1}$$

Market beta estimates comes from the following regression $r_{i,t} = a + b\ rm_t + \varepsilon_{i,t}$, where rm_t is the S&P 500 return. Note that the main difference between monthly and quarterly annualized standard deviation is not only the scales of horizon, but also whether the returns are correlated over time. If $Corr\left(r_{i,t}, r_{i,t-1}\right) \neq 0$ and the returns are stationary, we obtain $Var\left(r_{i,t} + r_{i,t-1}\right) \neq 2Var\left(r_{i,t}\right)$, and as a result we find the presence of managed prices. It turns out that such an observation is true for all the 14 hedge fund returns we consider in Table 1. The first-order correlation of all funds using quarterly data shows substantial increase. Same is true for market beta estimates with respect to S&P 500 returns. Except fixed-income arbitrage, managed futures and multistrategy funds, the market beta is always statistically different.[29] Naturally, this trend in market beta estimates has important implications for alpha, estimate of which especially dictates the average abnormal returns. We consolidate this important issue in the next subsection.

Stale pricing and the risk premiums of individual hedge funds

A reasonable argument in favor of stale pricing is very simple. If there exists managed pricing, then the returns should be correlated over time. In addition, as mentioned by Asness *et al*,[2] the holdings of illiquid exchange-traded securities can possibly lead to non-synchronous price reactions. As a result, the hedge fund manager can smooth their returns by applying wide discretion in their month-end reporting. The intentional manager smoothing will result in low volatility and weak correlation with market index such as S&P 500, which can further lead to erroneous conclusion about the forecast ability of hedge fund returns. One can always think about the effect of non-synchronous pricing as equivalent to that of random aggregation on a time series.[30] One of the easiest ways to avoid non-synchronous pricing is to use longer horizon returns and we do so by using non-overlapping quarterly returns given in Table 2.

The preliminary evidence somewhat points to the existence of stale pricing in illiquid markets such as convertibles and event-driven funds. In comparison, the equity market has more transparent prices, and the extent of artificial smoothing is less visible. As we mentioned earlier, hedge fund managers are not only interested in beta, but also alphas that measure added value or average abnormal return that the a hedge fund yields (that is, managers' skill). We need to provide a comparative evaluation of alphas, betas and risk premium of individual funds and now we are in a position to do so.

Given that there are common grounds between stock and bonds markets, it is not surprising to visualize that hedge funds' risk premiums should depend on both markets. We calculate the risk premiums of individual hedge funds with respect to both stock and bond markets in two steps. First, we regress the excess stock returns of individual hedge funds on excess market returns using specification (1), and in the second step we take the residual from first step and regress it on the two factors related to bond market

$$u_{i,t} = \delta_{i,1}[TERM_t] + \delta_{i,2}[DEF_t] + v_{i,t} \quad (4)$$

The individual hedge funds' risk premium is given by $\beta_{0,i}E(r_m)$, where $E(r_m)$ is the stock market risk premium. The incremental risk premium of each hedge fund that is due to bond market factor is given by $\delta_{i,1}E[TERM]+\delta_{i,2}E[DEF]$, where $E[TERM]$ and $E[DEF]$ is two bond market premium associated with TERM and DEF respectively. The slope coefficient from each regression, (1) and (4), determines the magnitude and direction of the total risk premium.

The estimates of alpha, average market exposure and slope coefficients corresponding to TERM and DEF along with their respective standard errors are reported in Table 3. All the standard errors are corrected for autocorrelation with four lags and heteroskedasticity as suggested by Newey and West.[31] We observe that except dedicated short-seller and emerging markets, the reported monthly alphas for all other funds are highly statistically and economically significant. For example, after accounting for their average beta, risk arbitrage and long/short

Table 3: Alphas and risk premia of hedge fund index returns using a two-stage model

	α*(Std. error)*	β_0 *(Std. error)*	δ_1*(Std. error)*	δ_2*(Std. error)*	$E(r_1)$
Aggregate hedge funds	0.62(0.13)	0.31(0.03)	0.45(0.38)	0.44(0.03)	0.37
Convertible arbitrage	0.41(0.13)	0.17(0.03)	0.24(0.20)	0.23(0.02)	0.20
Dedicated short-seller	0.31(0.22)	−0.86(0.05)	−1.25(1.04)	−1.22(0.10)	−1.02
Emerging markets	0.45(0.27)	0.59(0.06)	0.86(0.71)	0.83(0.07)	0.70
Equity market neutral	0.47(0.23)	0.17(0.05)	0.25(0.21)	0.24(0.02)	0.20
Event driven	0.70(0.09)	0.26(0.02)	0.37(0.31)	0.36(0.03)	0.30
Distressed	0.77(0.11)	0.27(0.02)	0.40(0.33)	0.39(0.03)	0.32
Event-driven multistrategy	0.67(0.11)	0.25(0.02)	0.36(0.30)	0.35(0.02)	0.29
Risk arbitrage	0.53(0.07)	0.15(0.02)	0.22(0.18)	0.21(0.02)	0.18
Fixed-income arbitrage	0.25(0.12)	0.13(0.03)	0.19(0.16)	0.19(0.01)	0.16
Global macro	0.97(0.21)	0.19(0.04)	0.28(0.23)	0.27(0.02)	0.23
Long/short equity	0.66(0.14)	0.48(0.03)	0.70(0.58)	0.68(0.05)	0.57
Managed futures	0.67(0.25)	−0.10(0.05)	−0.15(0.12)	−0.15(0.01)	−0.12
Multistrategy	0.54(0.10)	0.13(0.02)	0.18(0.15)	0.17(0.01)	0.15
Average	0.57(0.15)	0.15(0.03)	0.22(0.35)	0.21(0.03)	0.18

Note: Estimated risk premia are obtained in two steps. In the first step, we regress the excess stock returns of individual hedge funds on excess market returns $r_{it}=\alpha_i+\beta_{0,i}r_{m,t}+u_{i,t}$. In the second step we take the residual from first step and regress it on the two factors related to bond market $u_{i,t}=\delta_{i,1}[TERM_t]+\delta_{i,2}[DEF_t]+v_{i,t}$. The total expected risk premium is calculated as $E(r_i)=\beta_{0,i}E(r_m)+\delta_{i,1}E[TERM]+\delta_{i,2}E[DEF]$ where $E(r_m)$ is the stock market risk premium and $E[TERM]$ and $E[DEF]$ are two bond market premium associated with TERM and DEF respectively. $E(r_i)$ is a monthly percentage.

equity fund generates around 6.36 and 7.92 per cent per year, respectively. The overall average annualized alpha turns out to be 6.87 per cent per year. Even though the dedicated short-seller and emerging markets average annual return is quite high (3.72 and 5.4 per cent respectively), as their return has a very high standard deviation (as observed in Table 2), the corresponding alpha becomes statistically insignificant.

The slope estimate of excess market return with respect to CRSP's value-weighted index on all NYSE, AMEX and NASDAQ stocks shows no uniform pattern. Two hedge funds, dedicated short-seller and managed futures, have negative market exposure indicating a reduction in risk. Emerging markets has the highest market beta (0.59 per cent per month), and fixed-income arbitrage shares the lowest beta (0.13 per cent per month) with multistrategy fund. The average risk exposures with respect to bond market factors are non-trivial. The estimated average annualized slope of TERM is 2.67 per cent per year and for DEF it is 2.56 per cent per year. Fixed-income arbitrage captures the highest bond market beta, whereas multistrategy has the lowest corresponding figure. Overall, in addition to dedicated short-seller and managed futures, the bond market positively affects all the individual hedge fund returns. The last column of Table 3 reports the estimated hedge fund risk premium. The emerging markets fund has the highest risk premium (which is 13 basis points higher than its nearest competitor long/short equity fund) because of its high market exposure or beta. Not surprisingly, funds with below the average market exposure, such as risk arbitrage, fixed-income arbitrage and multistrategy, have the lowest risk premiums.

Joint role of stock market and bond market factors

The central message we have so far is that, when used alone, dominant role of market premium and non-synchronous pricing of hedge funds are interlinked. It is noticeable that we have not demonstrated yet the extent of overlapping roles of common stock and bond market factors. In this subsection, we clear that muddy issue by reemphasizing the role of market risk factors through a series of tests in the time series regression framework. For this we not only consider the average return of CRSP's value-weighted index but also two Fama–French factors: SMB and HML. We want to determine whether common stock market factors, when used alone or together with term-structure factors, have any incremental effect on the lagged values of market risk exposure.

First we summarize the correlations structure and autocorrelation trend of the explanatory returns in Table 4. Consistent with the findings in the literature, the excess market return is negatively correlated with the distress factor HML and positively correlated with other three factors. For SMB, HML, TERM and DEF, we do not observe any significant pairwise correlations. This indicates the absence of multicollenarity and bolsters any attempt to use them simultaneously in a multiple regression framework. However, as the excess market return is highly correlated with the other four factors, one may always raise question about its effectiveness as an instrument in a multifactor model. We avoid this sensitive issue by creating an orthogonalized market factor, and call it ORM. ORM is the sum of the intercept and residuals from the regression of RM-RF on SMB, HML, TERM and DEF. As we will see later, variable ORM, by construction, shares

Table 4: Pearson correlations and autocorrelation of stock market and bond market risk factors, January 1994–December 2008

	Correlations						*Autocorrelation*			
	RM-RF	*ORM*	*SMB*	*HML*	*TERM*	*DEF*	*Lag 1*	*Lag 2*	*Lag 12*	*Lag 20*
RM-RF	1.00	—	—	—	—	—	0.14	−0.03	−0.01	−0.02
ORM	0.76	1.00	—	—	—	—	0.03	−0.02	−0.02	0.03
SMB	0.21	−0.00	1.00	—	—	—	−0.06	0.01	−0.02	−0.02
HML	−0.43	0.00	−0.05	1.00	—	—	0.07	0.04	−0.08	0.03
TERM	0.13	0.00	0.10	0.07	1.00	—	0.06	0.03	−0.02	−0.03
DEF	0.17	−0.00	0.20	−0.09	0.10	1.00	0.25	−0.11	0.07	0.00

Note: RM is the return of CRSP's value-weighted index on all NYSE, AMEX and NASDAQ stocks, and RF is the 1-month T-bill rate obtained from Ibbotson and Associates. ORM is the sum of the intercept and residuals from the regression of RM-RF on SMB, HML, TERM and DEF.

very high correlation with excess market return but zero correlation with the other four factors. Overall, autocorrelations in lags among all the factors shows a uniform trend – they are high at first lag but then slowly decrease.

In Table 5, we report the estimate of our simple linear regression of monthly aggregate hedge fund index returns on various combinations of common risk factors. Here M1 to M7 indicates alternative model specifications. For example, M1 is the simplest one-factor linear model and M6 is a multifactor linear model, which not only uses the contemporaneous value of R_m-R_f, SMB, HML, TERM and DEF, but also includes their three period lags as potential explanatory variables. When used alone or used with other stock market factors such as SMB and HML, the slope of excess market return remains statistically significant at 0.31 per cent per month. If we introduce common bond market factors, the market exposure of aggregate hedge fund goes down to 0.27 per cent per month. Adding only lagged values of R_m-R_f in the model (that is, equation (2) with $n=3$) has no meaningful implications in addition to an increase in adjusted R^2. However, when we include the lags of other stock market factors (that is, SMB and HML) and bond-market factors (that is, TERM and DEF) at the same time, the estimated market beta goes down by 10 basis points per month. On the flip side, we end up with a situation where a lagged value of R_m-R_f captures some non-synchronous effect of aggregate hedge fund index returns and adjusted R^2 shows large improvement. The lower value of AIC and BIC indicates that both M6 and M7 are way better model than any other specifications.

Table 6 replicates the same exercise but utilizes ORM as the explanatory variable related to overall market. As mentioned before, we derive the orthogonalized market factor by running the following regression using monthly returns between January 1994 and December 2008:

$$R_{m,t} - R_{f,t} = 0.25 + 0.16 SMB_t - 0.57 HML_t + 0.23 TERM_t + 0.14 DEF_t + e_t \quad (5)$$

t-statistics (2.61) (2.45) (−8.33) (2.31) (3.53).

Table 5: Simple linear regression of monthly aggregate hedge fund index returns on various risk factors, January 1994–December 2008

	M1	*M2*	*M3*	*M4*	*M5*	*M6*	*M7*
ALPHA	0.63⋆	0.62⋆	0.60⋆	0.57⋆	0.57⋆	0.68⋆	0.67⋆
$R_{m,t}-R_{f,t}$	0.32⋆	0.31⋆	0.31⋆	0.27⋆	0.27⋆	0.22⋆	0.23⋆
$R_{m,t-1}-R_{f,-1}$	0.06⋆	—	—	—	—	0.03⋆	—
$R_{m,t-2}-R_{f,-2}$	0.11⋆	—	—	—	—	0.08	—
$R_{m,t-3}-R_{f,-3}$	−0.00	—	—	—	—	0.07	—
SMB_t	—	—	0.13⋆	—	0.12⋆	0.11⋆	0.11⋆
SMB_{t-1}	—	—	—	—	—	0.06	0.06
SMB_{t-2}	—	—	—	—	—	−0.06	−0.07
SMB_{t-3}	—	—	—	—	—	0.04	0.04
HML_t	—	—	0.04	—	0.02	−0.03	−0.04
HML_{t-1}	—	—	—	—	—	0.04	0.04
HML_{t-2}	—	—	—	—	—	−0.10⋆	−0.07
HML_{t-3}	—	—	—	—	—	0.05	0.09⋆
$TERM_t$	—	—	—	0.31	0.12	−0.95⋆	−0.55
$TERM_{t-1}$	—	—	—	—	0.83	—	1.08⋆
$TERM_{t-2}$	—	—	—	—	0.95⋆	—	0.87⋆
$TERM_{t-3}$	—	—	—	—	—	−1.96⋆	−2.47⋆
DEF_t	—	—	—	0.14⋆	0.11	0.18⋆	0.17⋆
DEF_{t-1}	—	—	—	—	—	0.14⋆	0.10
DEF_{t-2}	—	—	—	—	—	0.19⋆	0.06
DEF_{t-3}	—	—	—	—	—	0.05	−0.05
N	180	177	180	180	180	177	177
Adj R^2	0.38	0.44	0.41	0.38	0.41	0.47	0.48
AIC	726.43	723.96	718.66	727.66	721.17	695.25	696.10
AIC	732.82	709.84	731.43	740.13	740.32	708.26	709.01

Note: M1 to M7 indicates alternative model specification. For all models the dependent variable is monthly aggregate Hedge Fund index returns. (⋆) implies significance level at 5 per cent level.

Table 6: Simple linear regression of monthly aggregate hedge fund index returns on various risk factors (with orthogonalized market factor), January 1994–December 2008

	M1	*M2*	*M3*	*M4*	*M5*	*M6*	*M7*
ALPHA	0.77★	0.82★	0.79★	0.53★	0.57★	0.68★	0.67★
ORM_t	0.27★	0.26★	0.27★	0.27★	0.27★	0.22★	0.23★
ORM_{t-1}	—	0.03	—	—	—	0.03	—
ORM_{t-2}	—	0.03	—	—	—	0.07	—
ORM_{t-3}	—	−0.01	—	—	—	0.07	—
SMB_t	—	—	0.14★	—	0.08★	0.08★	0.07★
SMB_{t-1}	—	—	—	—	—	0.06	0.05
SMB_{t-2}	—	—	—	—	—	−0.06	−0.08★
SMB_{t-3}	—	—	—	—	—	0.04	0.03
HML_t	—	—	−0.13★	—	−0.14★	−0.16★	−0.17★
HML_{t-1}	—	—	—	—	—	0.04	0.02
HML_{t-2}	—	—	—	—	—	−0.10★	−0.12★
HML_{t-3}	—	—	—	—	—	0.05	0.05
$TERM_t$	—	—	—	0.70★	0.75★	−0.42	−0.50
$TERM_{t-1}$	—	—	—	—	—	0.83★	1.14★
$TERM_{t-2}$	—	—	—	—	—	0.95★	1.05★
$TERM_{t-3}$	—	—	—	—	—	−1.96★	−2.31★
DEF_t	—	—	—	0.52★	0.47★	0.48★	0.49★
DEF_{t-1}	—	—	—	—	—	0.14★	0.13★
DEF_{t-2}	—	—	—	—	—	0.19★	0.16★
DEF_{t-3}	—	—	—	—	—	0.05	0.04
N	180	177	180	180	180	177	177
Adj R^2	0.20	0.29	0.32	0.34	0.41	0.47	0.48
AIC	793.61	780.81	769.48	740.63	731.74	701.23	702.15
AIC	799.99	796.69	782.26	753.40	744.51	714.24	715.11

Note: M1 to M7 indicates alternative model specification. For all models, the dependent variable is monthly aggregate Hedge Fund index returns. ORM is the sum of the intercept and residuals from the regression of RM-RF on SMB, HML, TERM and DEF. (★) implies significance level at 5 per cent level.

As regression (5) produces a value of adjusted R^2 of 0.45 and all the slope coefficients are significant, it clearly demonstrates that in addition to SMB and HML, two term-structure factors do not fail to capture the common variation in excess market return. Following Fama and French,[16] we can call ORM as a zero-investment portfolio return that is uncorrelated with all four explanatory variables in (5). As by construction the orthogonalized market factor is uncorrelated with the stock market factors and term-structure factors, using ORM jointly with the four other explanatory variables provide a filtered image. The estimation results of various models for aggregate hedge fund index returns in Table 6 suggest separate but strong roles of stock and bond market factors. The slope coefficient of the contemporaneous market factor is very similar to those reported in Table 5. So are the slope coefficients of two stock market factors when they used alone or in the presence of contemporaneous bond market factors (that is, models M3 and M5).

The main surprising outcome of Table 6 is the slope coefficients of TERM and DEF. With ORM as a proxy for the excess return on a portfolio of stock market wealth, model M4 produces slopes on TERM and DEF close to 0.75 and 0.52, respectively. The same slope corresponding to model M4 is 0.31 and 0.14 respectively. Even when we add two stock market factors, both term-structure factors continue to load heavily; for example, compare the slopes of TERM and DEF coming from model M5 in Tables 5 and 6. Naturally, the question is why do we see this discrepancy? One possible explanation is that in reality common variation in aggregate hedge funds return is intrinsically related to both bond and stock market factors. But when we use unorthogonalized excess return of CRSP's value-weighted index, it somehow takes away some of the role played by TERM and DEF. The only way to recover the buried role of bond market factors is to use orthogonalized version of the market portfolio returns.[32] In terms of the effect of lagged values of stock and bond market factors, Table 6 provides a better picture of their separate decisive role as well. Just like in Table 5, both the model selection criterion (that is, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC)) and adjusted R^2 supports multifactor specification M7 in Table 6.

Next we perform similar time series tests with respect to 13 other hedge fund index returns. For brevity, we report only the estimation of model specification (3) (that is, M7 from Tables 5 and 6 that is supported by superior AIC and BIC figures). Table 7 reports the results. As with the aggregate hedge fund, for individual hedge fund index returns, by reporting market risk exposure using both regular excess market return and orthogonalized market return we see some noticeable differences. The greatest change in the estimated market beta as a result of using an orthogonalized market factor belongs to risk arbitrage fund. For managed futures, the first two lags of the market factor increases sharply in absolute value. Overall, the intercept and slope coefficient corresponding to the stock market factors do not show much variation. Spread in SMB and HML factor reveals that the sensitivity of fund returns varies widely by sector. As mentioned by Capocci and Hüebner,[19] a positive sign of the SMB slope parameter Y_1 indicates that the corresponding fund prefers small firms over large firms, and it is the case for all but dedicated short-seller and equity market neutral funds. Similarly, a positive sign of the

Table 7: Simple linear regression of 13 monthly hedge fund index returns on various risk factors (with and without orthogonalized market factor), January 1994–December 2008

	α	β_0	β_1	β_2	β_3	γ_1	γ_2	δ_1	δ_2	$Adj\ R^2$
Convertible arbitrage										
Market	0.29★	0.00	0.06★	0.09★	0.06★	0.02	0.03	–0.62	0.55★	0.41
Orthogonal market	0.28★	0.02	0.01	0.04	0.05	0.03	0.04	0.22	0.56★	0.33
Dedicated short-seller										
Market	0.24	−0.87★	−0.03	0.09★	0.04	−0.27★	0.11	−0.56★	0.32★	0.69
Orthogonal market	0.27	−0.86★	−0.12	0.14	0.01	−0.13★	0.61★	−2.45★	−0.89★	0.70
Emerging markets										
Market	0.45	0.52★	0.11★	0.06	−0.05	0.20★	−0.02	−0.59	0.04	0.36
Orthogonal market	0.38	0.53★	0.11	0.02	−0.02	0.13	−0.30★	1.56★	0.80★	0.35
Equity market neutral										
Market	−0.48★	0.01	0.10★	0.06	0.00	−0.02	0.05	2.93★	0.43	0.38
Orthogonal market	−0.53★	0.02	0.06	0.02	0.02	−0.01	0.06	2.80★	0.47★	0.35
Event driven										
Market	0.59★	0.21★	0.09★	0.06★	0.02	0.09★	0.05	−0.02	0.12★	0.58
Orthogonal market	0.55★	0.23★	0.11★	0.06★	0.03	0.05★	−0.07★	1.44★	0.44★	0.53
Distressed										
Market	0.56★	0.20★	0.08★	0.07★	0.02	0.07★	0.04	0.86★	0.19★	0.55
Orthogonal market	0.52★	0.22★	0.11★	0.04	0.04	0.03	−0.08★	2.30★	0.49★	0.51
Event−driven multistrategy										
Market	0.62★	0.22★	0.10★	0.07★	0.02	0.11★	0.06	−0.60	0.07	0.49
Orthogonal market	0.59★	0.24★	0.11★	0.08★	0.02	0.07★	−0.07★	0.92★	0.40★	0.44
Risk arbitrage										
Market	0.63★	0.16★	0.04★	0.01	−0.01	0.09★	0.09★	−1.44★	0.02	0.43
Orthogonal market	0.61★	1.17★	0.04	0.01	−0.01	0.07★	0.00	−0.79★	0.26★	0.41
Fixed-income arbitrage										
Market	0.01	−0.04	0.03	0.10★	0.06★	0.00	0.04	0.55	0.56★	0.49
Orthogonal market	0.01	−0.02	−0.01	0.07★	0.03	0.01	0.06★	1.21★	0.50★	0.39
Global macro										
Market	1.13★	0.19★	−0.02	0.15	−0.01	0.07	0.09	−1.68★	0.10	0.09
Orthogonal market	1.12★	0.20★	−0.01	0.16★	0.03	0.03	−0.04	−0.46★	0.34★	0.27
Long/short equity										
Market	0.84★	0.41★	0.05★	0.11★	0.01	0.22★	−0.12★	−1.43★	0.00	0.69
Orthogonal market	0.81★	0.42★	0.01	0.08★	0.06	0.16★	−0.35★	0.47★	0.57★	0.66

Table 7 *Continued*

	α	β_0	β_1	β_2	β_3	γ_1	γ_2	δ_1	δ_2	*Adj* R^2
Managed futures										
Market	0.66★	0.02	−0.12★	0.00	−0.08	0.06	0.13	0.50	−0.24	0.08
Orthogonal market	0.66★	−0.01	−0.21★	−0.12	0.03	0.08	0.14	−0.40★	−0.26★	0.20
Multistrategy										
Market	0.34★	0.00	0.04	0.09★	0.05★	0.02	0.01	0.57	0.37★	0.36
Orthogonal market	0.33★	0.02	−0.01	0.05	0.08★	0.02	0.01	1.32★	0.38	0.30

Note: Market models are estimated using the specification1 $r_{i,t} = \alpha_i + \beta_{i,0} r_{m,t} + \beta_{i,1} r_{m,t-1} + \beta_{i,2rm,t-2} + \beta_{i,3} r_{m,t-3} + \gamma_{i,1}[SMB_t] + \gamma_{i,2}[HML_t] + \alpha_{i,1}[TERM_t] + \alpha_{i,2}[DEF_t] + u_{i,t}$ Orthogonal market models are estimated using the specification1 $r_{i,t} = \alpha_i + \beta_{i,0} r_{m,t} + \beta_{i,1} r_{m,t-1} + \beta_{i,2rm,t-2} + \beta_{i,3} r_{m,t-3} + \gamma_{i,1}[SMB_t] + \gamma_{i,2}[HML_t] + \alpha_{i,1}[TERM_t] + \alpha_{i,2}[DEF_t] + u_{i,t}$ where $r_{m,t}$ is the sum of the intercept and residuals from the regression of RM-RF on SMB, HML, TERM and DEF. (★) implies significance level at 5 per cent level.

HML slope parameter Y_2 suggests that the corresponding fund prefers firms with high BE/ME ratio over firms with low BE/ME ratio. For example, dedicated short-seller fund prefers firms with high BE/ME ratio. In contrast, funds such as emerging markets, even driven, and long/short equity have a strong preference for low BE/ME ratio firms.

Just as with the aggregate hedge fund index, the pattern in the slope coefficient of TERM and DEF factor in Table 7 displays some interesting behavior. Using orthogonalized market factor changes the sign of the TERM slope parameters for six funds. Except equity market neutral, the estimated value of the TERM slope estimate changes significantly for all the funds. For DEF slope parameter, the change is more pronounced in all but three; they are – convertible arbitrage, managed futures and multistrategy funds. In other words, for these hedge funds indices, the orthogonalized market factors do not add much to the shared variation in returns already captured by stock and bond market factors.

CONCLUSION

Unlike traditional stock and bond investments, hedge fund investments are synonymous with diversification benefits. It is a common investor's perception that hedge funds are an 'absolute return' vehicle and have no close benchmark such as a common stock market index. Therefore, even when equity markets perform badly, hedge fund investments would generate positive returns. There are plenty of empirical studies that both support and question this common wisdom. In this article, we made an attempt to understand the underperformance and overachievement of some of the hedge fund indices. Our contributions are as follows. First, similar to the work of Asness *et al*,[2] we look at the issue of stale pricing through longer horizon returns. We demonstrate evidence of non-synchronous pricing for a significant number of hedge fund indices. Second, we show that both stock and bond markets capture the important uncertainty components of hedge funds average returns. Our empirical results demonstrate that average fund alpha and risk premium should be estimated in an integrated market. Otherwise, it is difficult to identify the common sources of uncertainty. Third, we show the importance of not only the market component of the common variation, but also of the idiosyncratic component through market residual volatility. Our results suggest that hedge funds that cannot get rid of the idiosyncratic component by diversification will generate lower (and in some cases below the benchmark) average returns.

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27 This observations is also reported in Malkiel and Saha[28].
28 Malkiel, B.G. and Saha, A. (2005) Hedge funds: Risk and return. *Financial Analysts Journal* 61(6): 80–88.
29 This observation is true irrespective of the fact whether we use S&P 500 returns or CRSP's value weighted index as a representative benchmark market factor. Also the use of particular benchmark does not result in large differences in our alpha calculation. Typically if one uses T-bill return as a benchmark, measures of alpha (or average annual return) becomes highest.
30 Tsay, R.S. (2001) *Analysis of Financial Time Series*, 1st edn. New York: Wiley-Interscience.
31 Newey, W. and West, K. (1987) A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55(3): 703–708.
32 This observation is true even if we use contemporaneous and lagged market returns (that is, model M6 and M7) in up and down markets. As expected, we find that the lagged betas of market returns are more economically and statistically significant in negative markets than in positive markets. Details are available upon request.
33 Schneeweis, T. (1998) Evidence of superior performance persistence in hedge funds: An empirical comment. *Journal of Alternative Investments* (Fall): 76–80.