Beta Uncertainty, Risk, and the Performance Characteristics of Hedge Funds

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This study examines the empirical performance of aggregate hedge fund indices in the presence of beta uncertainty. We use a two-stage multifactor approach to generate risk premia of hedge funds returns and disentangle the common sources of beta uncertainty. We show that the actual estimate of hedge funds risk are severely understated and is related to the issue of non-synchronous pricing. Our finding directly indicates the existence of stale pricing in illiquid markets. We demonstrate a concise relationship between time-varying idiosyncratic volatility (IVOL) emanating from market portfolio and expected returns of individual hedge funds. Our results reveal that the hedge funds with high IVOL prefers growth firms characterized by low book-to-market ratios, and the hedge funds with low IVOL singles out small size firms. Overall, our key findings that the exposure to common risk factors and idiosyncratic component of market risk display strong predictive power for performance characterization of hedge funds significantly adds to the literature.

JEL classification: G20; G23
Keywords: Hedge funds, Systematic risks, Beta uncertainty, Stale pricing, Risk characterization

1. Introduction

The purpose of this study is to provide new empirical evidence on the performance of aggregate hedge funds returns. We reexamine the issue of hedge funds performance persistence and characterize the underlying risk dynamics in the presence of beta uncertainty. We use a fairly well known database of a set of aggregate hedge fund index returns from CSFB/Tremont and investigate whether hedge fund returns reflect the stale effect in the context of a two-stage multifactor approach. We focus on the shift in cross-correlations of hedge funds returns with common risk factors, and critically evaluate different attributes of hedge funds performance. We demonstrate that the performance persistence of hedge funds is not only related to the correlation between hedge fund returns and lagged market portfolio returns, but also to other common risk factors pioneered by Fama and French (1993). We discuss the economic significance of hedge fund returns risk dynamics through time-varying beta and idiosyncratic volatility in an integrated market.

We employ a simple lagged beta technique of Scholes and Williams (1977) in a multifactor methodological framework to present new empirical evidence on the performance persistence of aggregate hedge funds. We extend prior studies by testing for the presence of risk and highlight the important role of Fama-French (1993) common risk factors related to stock and bond market that captures systematic variation in return persistence. We use a two-stage multifactor model approach to generate risk premia of hedge funds and characterize the common sources of beta uncertainty. We find that that actual estimate of hedge funds risk are severely understated and is related to the issue of non-synchronous pricing. We also demonstrate a concise relationship between time-varying idiosyncratic volatility (IVOL) emanating from market portfolio and expected returns of individual hedge funds indices. We find that hedge funds with high IVOL prefers firms with low book-to-market ratios (BE/ME) and hedge funds with low IVOL singles out small size (ME) firms. Our study suggests more important role of the idiosyncratic component of market risk in the average return variability of hedge funds than any previous works.

The paper is organized as follows. In the next section we briefly review the related literature. In section 3 we describe empirical methodology and our main data set. All the empirical results are presented in the following section. It includes preliminary discussion of summary statistics, and a detail analysis of the role of alphas, betas, and common risk factors in discovering stale or managed pricing. Section 4 also presents a comparative discussion of the estimated risk premium, the issue of beta uncertainty, and the pervasive role of idiosyncratic volatility. The final section concludes the paper.

2. Literature Review

Hedge funds are relatively unregulated and unconstrained investment pools. The recent literature in hedge funds research is ripe with stylized facts about its increasing role in the global investment landscape[1]. For example, Brown, Goetzmann, and Ibbotson (1999) consider 399 funds from the U.S. Offshore Funds Directory between 1989 and 1995, and find no performance persistence at a yearly horizon[2]. Agarwal and Naik (2000) examine 746 funds from the hedge funds research database between 1982 and 1998, and report persistence in hedge fund performance at quarterly horizons. Asness, Krail, and Liew (2001) show that hedge funds price their securities at a lag which can cause a downward bias of simple risk estimates based on monthly returns. Capocci and Hüebner (2004) examine hedge fund performance levels and persistence using various asset pricing models and find limited evidence of persistence in performance but not for extreme performers. Getmansky, Lo and Makarov (2004) argue that serial correlation in hedge fund returns is not due to unexploited profit opportunities, but is more likely the result of illiquid securities that contained in the fund.

However, despite the fact that it has become a subject of extensive academic surveillance, the empirical evidence on the evaluation of fund performance is mixed. It is not clear to what extent time-varying systematic risk affects the performance persistence and stale pricing issue of aggregate hedge funds. Relation between sensitivity to market volatility innovations and hedge funds returns may not yet be fully understood. Our paper develops a simple explanation for this relationship.

There exist a number of studies that is closely related to our paper. For example, our paper is related to the evidence presented in Racicot and Théoret (2007) who investigate the link between beta and market risk premium (e.g., a negative such link known as the beta puzzle) of a sample of HFR hedge fund indices and a sample of HFR individual funds pooled by strategy. Our paper differs from Racicot and Théoret (2007) as they show that there is generally no beta puzzle in the hedge fund industry. In other related studies, Harri and Brorsen (2004) report performance persistence in hedge funds and a strong negative relation between hedge fund capitalization and returns. Bollen and Pool (2008) argue that a fund manager may artificially smoothes reported returns that can reduce the measured volatility of the fund. Manser and Schmid (2009) investigate the performance persistence of long/short equity hedge funds. They find that fund returns show very little persistence at the annual horizon irrespective of the length of the formation period. Recently, Eling (2009) and Jordan and Simlai (2011) provide an updated overview and new empirical evidence on hedge fund performance persistence[3].

It is important to note that despite methodological differences, the focus of a sizable part of academic research (i.e., most of the papers cited above) has been on the covariates of hedge fund returns in terms of proxy of various risk factors in the regression analysis. In this paper we differ in terms of an alternative empirical methodology and it is built in an integrated framework. Our work extends the existing literature on the financial performance persistence of aggregate hedge fund indices and relates it to the issue of stale pricing and idiosyncratic risks. We build on the findings of Asness, Krail, and Liew (2001), and directly examine the idea that the hedge funds performance

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[1] Lo (2008) provides a comprehensive summary.

[2] They observe that, even though hedge funds with similar investment styles generate similar returns, there is no clear evidence of superior individual manager skill within a particular style group.

[3] It has also been argued that volatility of hedge fund returns is more persistent than their return level (Schneeweis 1998). Using daily data from the S&P hedge fund index series (SPHG), Füss, Kaiser, and Adams (2007) examine the conditional volatility of daily management style and composite returns and show differences concerning persistence, mean reversion and asymmetry between September 2002 and May 2006.

persistence is a reflection of the deficiency of the underlying asset pricing models used in the literature. Our analysis can also be directly related to the risk-based hypotheses of Bollen and Whaley (2009) that employ an optimal change-point regression and allows risk exposures to shift and illustrate the impact on performance appraisal.

3. Empirical Methodology and Data

By denoting a hedge fund index i at period t $(t = 1,\ldots,T)$ as $y_{i,t}$, we can define its corresponding rate of return $r_{i,t}$ as

$$r_{i,t} = 100\left[log\ \ y_{i,t}\ \ - log\ \ y_{i,t-1}\ \right]$$

where the index t denotes the observations for each month. Note that, intuitively whether we find the presence of managed prices (or not) intricately depends on whether $Corr\ \ r_{i,t}, r_{i,t-1}\ \ \neq 0$. For example, if $Corr\ \ r_{i,t}, r_{i,t-j}\ \ = \rho(j), j = 1,2$, the ratio of $Var\ \ r_{i,t} + r_{i,t-1}$ and $2Var\ \ r_{i,t}$ is not equal to 1 but $1 + \rho(1)$. Similarly, the ratio of $Var\ \ r_{i,t} + r_{i,t-1} + r_{i,t-2}$ and $3Var\ \ r_{i,t}$ is $[1 + 2\left(\frac{2}{3}\rho\ \ 1\ \ + \frac{1}{3}\rho\ \ 2\ \right)]$. The general expression is that for a stationary process

$$Var\ \ r_{i,t}\ \ = Var\ \ r_{i,t-k} \quad \text{and} \quad Cov\ \ r_{i,t-k}, r_{i,t-l}\ \ = Cov\ \ r_{i,t}, r_{i,t-l+k}\ \ .$$

As a result

$$Var\ \ r_{i,t} + r_{i,t-1} + \ldots. + r_{i,t-(q-1)}\ \ = \sum_{k=0}^{q-1} Var\ \ r_{i,t-k}\ \ + 2\sum_{k=1}^{q-1}\ q - k\ \ \rho_k$$

where $\rho_k = \dfrac{Cov\ \ r_{i,t}, r_{i,t-k}}{Var\ \ r_{i,t}}$. Interestingly, a hedge fund can always claim its low correlation to the market but we know that correlation not necessarily conveys the same statistical information as beta. It is possible that with large residual variance, we may end up with low adjusted coefficient of determination and a large beta, but not necessarily high correlation. The implication is severe in terms of individual funds performance measurement as low $\bar{R}^2$ and a relatively small sample period can results in large standard errors coupled with small and statistically insignificant t-statistics[4]. It also may reflect that grouping by fund style doesn't do much.

The above discussion motivates us to consider a general form of a risk-based model specification given by

$$r_{i,t} = \alpha_i + \sum_{j=0}^{L} \beta_{i,j} r_{m,t-j} + \sum_{j=1}^{M} \gamma_{i,j} F_j + u_{i,t} \tag{1}$$

where $r_{i,t}$ is the return of hedge fund index i at time t, α_i is the expected return on hedge fund index i conditional on the information set at time t, $r_{m,t-j}$ is the return of the market portfolio with j $(j = 0,\ldots L)$ lag, $F_j (j = 1,\ldots M)$ is the set of factors, $\gamma_{i,j}$ is the factor loading of hedge fund i on factor j, and $u_{i,t}$ is the hedge-fund specific component of return. As we mentioned before,

[4] Residual variance will be even higher for individual hedge funds compare to aggregate indices that represents portfolio of funds.

the presence of large residual variance $\sigma^2(u)$ can lead to large β's, low $\bar{R}^2$, and small $Corr(r_{i,t}, r_{m,t-k})$.

In our empirical evaluation, we implement various parsimonious versions of model (1). They include a market factor model and common risk factor model by Fama and French (1993):

$$r_{i,t} = \alpha_i + \sum_{j=0}^{L} \beta_{i,j} r_{m,t-j} + \gamma_{i,1}\left[SMB_t\right] + \gamma_{i,2}\left[HML_t\right] + \gamma_{i,3}\left[TERM_t\right] + \gamma_{i,4}\left[DEF_t\right] + u_{i,t} \qquad (2)$$

In specification (2) r_m is the excess return of CRSP's value-weighted index on all NYSE, AMEX, and NASDAQ stocks over 1-month T-bill rate obtained from Ibbotson and Associates, SMB (small minus big) is the difference each month between the simple average of the percent returns on the three small-stock portfolios and the simple average of the returns on the three bog-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, and DEF is the difference between return on a proxy for the market portfolio of corporate bonds and long-term government bonds.

The primary data source of our set of aggregate hedge fund index returns is CSFB/Tremont[5]. The CSFB/Tremont indices are asset-weighted indices of funds with a minimum of $10 million of assets under management[6]. They also include a minimum one-year track record and current audited financial statements. The returns on the market portfolio, SMB, and HML are obtained from Ken French[7]. We also use data from the University of Chicago's Center for Research in Security Prices, government agencies (such as FRED@ database of the Federal Reserve Bank of St. Louis), and Ibbotson Associates to construct various risk factors. The risk free rate is the one-month Treasury bill rate. For our sample we employ monthly data for the period January 1994 to December 2009.

4. Empirical results and interpretations

4.1. Summary statistics and initial findings

We start with the summary statistics for monthly CSFB/Tremont hedge fund index returns and various common risk factors in Table 1. Note that our sample period is influenced by four major economic and financial crises: (i) the Asian financial crisis (1997); (ii) the Russian/LTCM crisis (1998); (iii) the high-tech stock market bubble burst (2000-01); and (iv) US economic recession (2007-08) fueled by subprime mortgage crisis and related events. To our surprise, even after acknowledging the market correction, the hedge fund indices performed reasonable well[8]. The highest average monthly annualized return is achieved by global macro, followed by distressed fund. Both of them posted double digit returns of 11.06% and 10.19%, respectively. The high performers (in terms of above average) were the event driven, the long/short equity, and the emerging markets. The fund that offers lowest monthly annualized return is the dedicated short–seller. Other low performers over this period include the fixed-income arbitrage.

The above fact can indirectly be supported if we compare the cumulative returns for a principal hedge fund strategy with major indices returns. In Figure 1 we do so by comparing the cumulative

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[5] For further information about these data see www.hedgeindex.com.

[6] Some example of recent studies that uses CSFB/Tremont indices are Asness et al. (2001), Amenc et al. (2003), Jordan and Simlai (2011).

[7] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[8] Before we get into the empirical results, it is important to note that there exist three potential biases which may affect the performance of published indices of hedge fund returns (Fung and Hsieh (2002)). They are survivorship bias, backfill bias and self-selection bias. Despite the best effort of the data vendor it is difficult to eliminate all three biases entirely. Therefore, our empirical results should be evaluated in the light of these biases.

return of aggregate hedge funds with 3 major indices: S&P 500, NASDAQ, and DJIA. We see that, despite considerable heterogeneity over the entire sample period, at the end of the year 2009, the cumulative returns of aggregate hedge fund returns is higher than all 3 major indices.

Table 1
Summary Statistics for Monthly CSFB/Tremont Hedge Fund Index Returns and Various Hedge Fund Risk Factors, January 1994–December 2009

	Mean	SE	SR	Min	Max	Median
Aggregate Hedge funds	7.32	3.11	0.59	-8.69	8.53	8.24
Convertible arbitrage	6.34	1.52	0.31	-13.70	3.57	10.90
Dedicated short-seller	1.60	7629.00	0.22	-9.38	22.71	-4.05
Emerging markets	7.59	3.78	0.28	-24.50	16.42	15.30
Equity market neutral	6.69	1.96	0.31	-44.30	3.26	7.49
Event driven	9.20	2.39	0.88	-14.10	3.68	11.20
Distressed	10.19	1.99	0.92	-13.10	4.10	12.70
Event-driven multistrategy	9.01	1.21	0.77	-11.60	4.66	11.40
Risk arbitrage	6.84	1.38	0.80	-7.39	3.81	7.87
Fixed-income arbitrage	2.69	1.78	-0.12	-18.60	2.07	8.06
Global macro	11.06	3.01	0.86	-16.10	10.60	14.10
Long/short equity	8.23	3.67	0.62	-12.70	13.01	9.07
Managed futures	6.97	2.98	0.37	-11.80	9.95	6.19
Multistrategy	5.27	2.01	0.55	-9.37	3.61	7.81
RF	3.72	0.13	0.00	0.00	0.57	3.68
S&P 500	6.12	1.15	0.31	-29.40	9.59	12.10
RM	7.32	4.02	0.21	-31.00	8.37	15.70
SMB	1.92	3.37	-0.13	-19.20	21.80	-3.32
HML	3.96	3.06	0.03	-16.10	13.85	4.05
SC-LC	0.72	0.93	-0.23	-16.36	18.43	0.05
10Y	0.89	0.07	-2.97	-0.94	1.44	0.09
CredSpr	1.44	0.05	-3.19	-1.44	0.43	0.12
BdOpt	-0.10	0.04	-7.43	-0.25	0.69	-0.04
FXOpt	0.10	0.05	-5.27	-0.30	0.90	-0.03
ComOpt	0.02	0.04	-7.64	-0.23	0.65	-0.03
TERM	1.44	1.88	-0.08	-1.57	4.30	1.42
DEF	3.36	1.91	0.12	-1.92	7.53	8.06

Notes: SE is the standard error calculated as $Std.Dev / 192^{1/2}$. SR is the Sharp ratio based on annualized data, measures as excess return divided by standard deviation. 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. SMB (small minus big) is the difference each month between the simple average of the percent 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. . SC-LC is the difference between Wilshire Small Cap 1750 and Wilshire Large Cap 750 return, 10Y is the month-end to month-end change in the U.S Federal Reserve 10-year constant-maturity yield; CredSpr is the month-end to month-end change in the difference between Moody's Baa yield and the Federal Reserve's 10-year constant-maturity yield; BdOp is the return of a portfolio of lookback straddles on bond futures; FXOp is the return of lookback straddles on currency futures, ComOp is the return of a portfolio of lookback straddles on commodity futures.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.

Figure 1
Cumulative returns of aggregate hedge funds (R_t) and three major indices

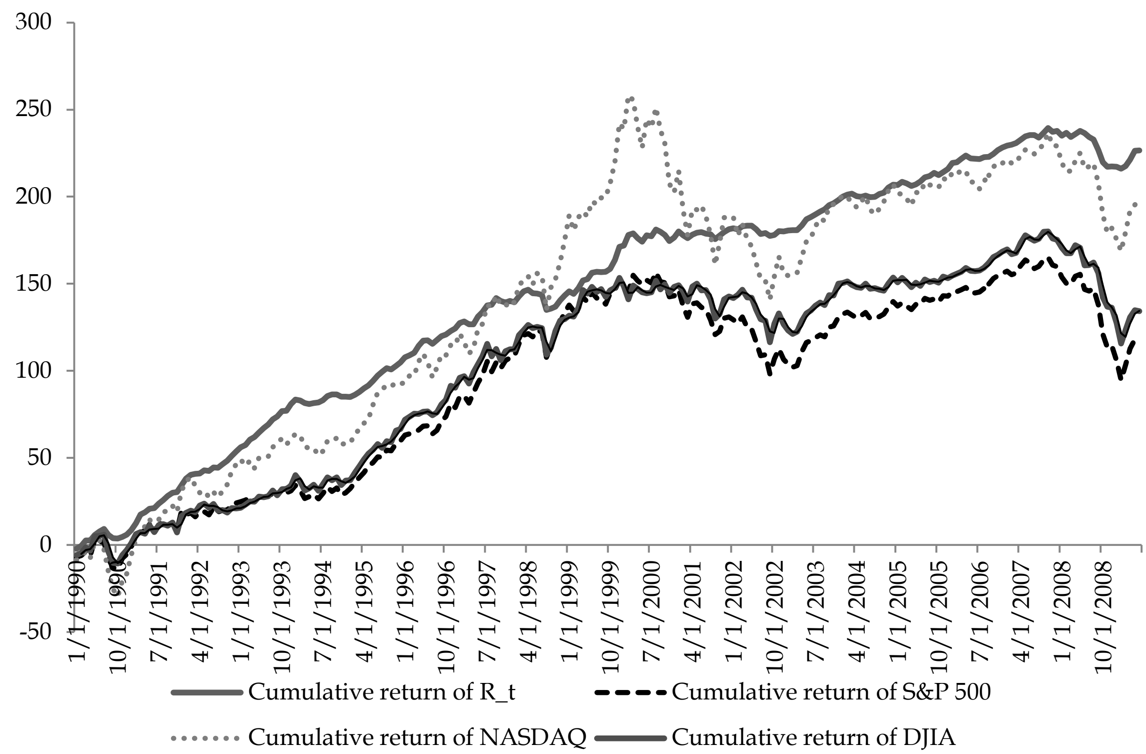
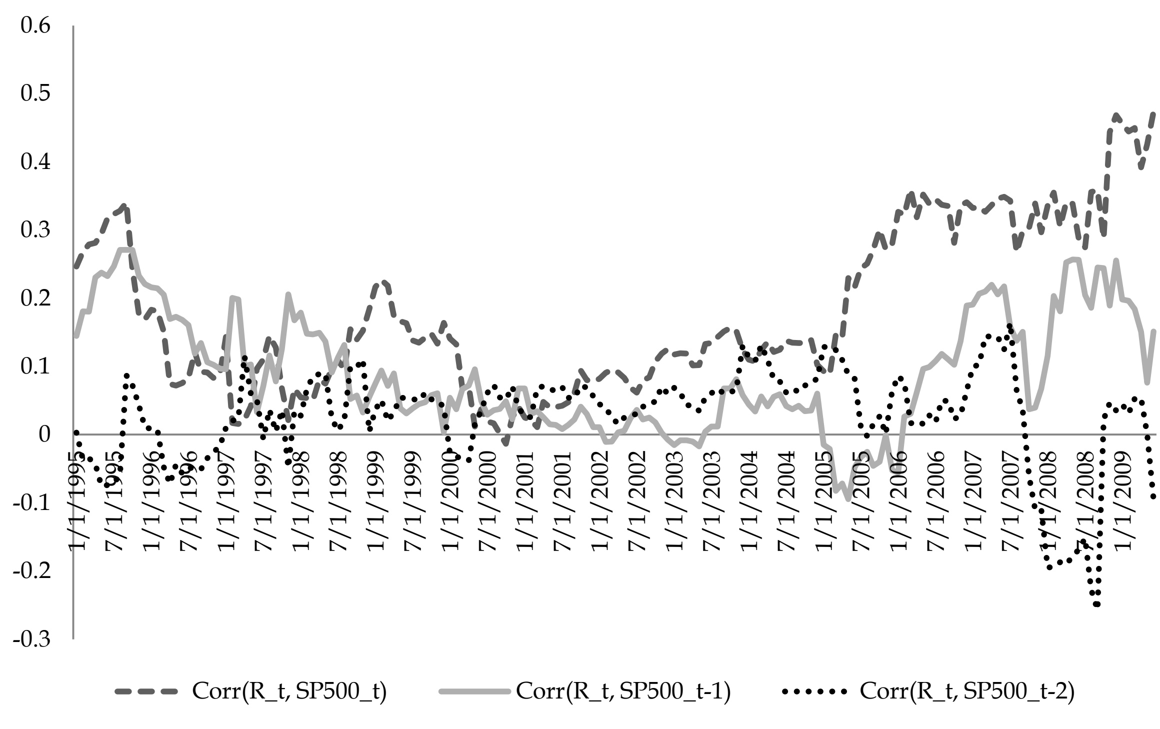


Figure 2
Time-varying correlations between aggregate hedge funds (R_t) and S&P 500 returns



From Table 1 results we also see that out of our 14 total funds, 9 produce an average return greater than the CRSP's value-weighted index on all NYSE, AMEX, and NASDAQ stocks. Five of them are about 2.2 standard errors from zero. Some hedge funds display lower monthly standard deviation (which we calculate by $\sqrt{12}\ \text{std.dev}\ r_{i,t}$), and better Sharpe ratios than equity market representative S&P 500. The average Sharp ratio of the hedge funds is higher than the CRSP's value-weighted index. As reported in the literature, the event driven hedge funds specially share very high Sharp ratios. The lowest Sharp ratio is obtained by dedicated short–seller and fixed-income arbitrage funds.

We complement the above discussion by looking at the rolling correlations for a principal hedge fund strategy (aggregate hedge funds in our case) with a tested market factor (such as S&P 500 returns). Figure 2 display the relationship. It is imperative that the contemporaneous correlation between aggregate hedge fund and S&P 500 returns remains fairly constant between 1996 and 2005. The same correlation during other time period drastically changes over time. In contrast, one and two period lagged correlations between aggregate hedge fund and S&P 500 index returns exhibit a wide variability throughout the entire sample period. Figure 2 also shows that aggregate hedge fund has very low (i.e., closed to zero), or, in some cases, negative lagged correlation with S&P 500 returns, and display some form of heterogeneity. In summary, the fact that lagged hedge fund correlations are not stable over time justifies their incorporation in a multifactor risk model.

4.2. Stale pricing and average abnormal returns using alternative risk model

As we mentioned before, the trend in market beta estimates has important implications for alpha - the estimate of which dictates the average abnormal returns[9]. We investigate this important issue in the next set of results. An examination of the beta coefficient also provides some interesting implications. In order to compare the monthly regression betas with and without lagged market factor we put them together side by side in Table 2. Column 1 reports the market beta estimate without any lagged market exposure. Column 2 and 3 reports the contemporaneous and sum of lagged beta estimates (from equation (2)) respectively. For all but five of the funds, the estimated beta changes significantly from model 1 to model 2. Five funds - dedicated short-seller, event driven, event-driven multistrategy, risk arbitrage, and global macro, exhibit very similar or insignificantly different beta coefficients. The effects of the lagged market factor on these five funds are not noteworthy. The result also shows that the beta coefficients for contemporaneous and lagged market factors have the same signs for all funds.

It is evident that the lagged betas play an economically meaningful role to explain the variability for at least 10 hedge funds returns even in the presence of common stock and bond market factors. The effect is dramatic for convertible arbitrage style since total beta estimates increases from 0.02 (column 1) to 0.21 (column 4). Funds such as managed futures and multistrategy also clearly have strong lagged market exposures (which is also supported by highly significant test statistics). Except risk arbitrage style, the difference in contemporaneous beta from a single factor model and the sum of all the betas from a lagged model is 10 basis points. This re-establishes the idea of Asness et al. (2001) that even under a multifactor risk set up, if we account for non-synchronous pricing, hedge funds do a lot less hedging. The preliminary evidence therefore 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.

Next, in order to see the sensitivity of our results with respect to alternative model specification, we also implement the asset-based styles factor model of Fung and Hsieh (2004) given by (3).

In specification (3), SP = Standard and Poor's 500 stock return, SCLC = Wilshire Small Cap 1750 minus Wilshire Large Cap 750 return; CMY = month-end to month-end change in the U.S Federal

[9] Alphas can also be influenced by bias such as survivorship etc., whereas betas may be much less sensitive.

Reserve 10-year constant-maturity yield; CredSpr = month-end to month-end change in the difference between Moody's Baa yield and the Federal Reserve's 10-year constant-maturity yield; BdOp = return of a portfolio of lookback straddles on bond futures; FXOp = return of lookback straddles on currency futures, and ComOp = return of a portfolio of lookback straddles on commodity futures.

$$r_{i,t} = \alpha_i + \sum_{j=0}^{L}\beta_{i,j}\left[SP_{t-j}\right] + \gamma_{i,1}\left[SCLC_t\right] + \gamma_{i,2}\left[CMY_t\right] + \gamma_{i,3}\left[CredSpr_t\right] + \gamma_{i,4}\left[BdOp_t\right] + \gamma_{i,5}\left[FXOp_t\right] + \gamma_{i,6}\left[ComOp_t\right] + \varepsilon_{i,t} \quad (3)$$

Table 2
Beta comparisons of 14 Monthly Hedge Fund Index Returns, January 1994–December 2009

	(1)	(2)	(3)	(4)	
	Model 1	Model 1	Model 2	Model 2	(4)-(1)
	β_0	β_0	$\sum_1^3 \beta_i$	$\sum_0^4 \beta_i$	*Diff*
Aggregate Hedge funds	0.27*	0.24*	0.19*	0.43*	0.16*
Convertible arbitrage	0.02	0.00	0.21*	0.21*	0.19*
Dedicated short-seller	-0.86*	-0.87*	0.10*	-0.77*	0.09*
Emerging markets	0.54*	0.52*	0.12*	0.64*	0.10*
Equity market neutral	0.02	0.01	0.16*	0.17*	0.15*
Event driven	0.23*	0.21*	0.17*	0.38*	0.15*
Distressed	0.22*	0.20*	0.17*	0.37*	0.15*
Event-driven multistrategy	0.24*	0.22*	0.19*	0.41*	0.17*
Risk arbitrage	0.17*	0.16*	0.04	0.20*	0.03
Fixed-income arbitrage	-0.02	-0.04	0.19*	0.15*	0.17*
Global macro	0.20*	0.19*	0.12*	0.31*	0.11*
Long/short equity	0.42*	0.41*	0.17*	0.58*	0.16*
Managed futures	-0.01	0.02	-0.20*	-0.18*	-0.17*
Multistrategy	0.02	0.00	0.18*	0.18*	0.16*

Notes: For each hedge fund we use two alternative model specifications. For FF specification, model 1 is $r_{i,t} = \alpha_i + \beta_{i,0} r_{m,t} + \gamma_{i,1}\left[SMB_t\right] + \gamma_{i,2}\left[HML_t\right] + \delta_{i,1}\left[TERM_t\right] + \delta_{i,2}\left[DEF_t\right] + u_{i,t}$ and model 2 is $r_{i,t} = \alpha_i + \beta_{i,0} r_{m,t} + \beta_{i,1} r_{m,t-1} + \beta_{i,2} r_{m,t-2} + \beta_{i,3} r_{m,t-3} + \gamma_{i,1}\left[SMB_t\right] + \gamma_{i,2}\left[HML_t\right] + \delta_{i,1}\left[TERM_t\right] + \delta_{i,2}\left[DEF_t\right] + u_{i,t}$. (*) implies significance level at 5% level.

Note that, one can always argue about the incorporation of many other potential trend-following factors which may capture general macroeconomic or financial market conditions (e.g., size, value, momentum, reversal, liquidity, market volatility, exchange rate risk, etc.)[10]. Our idea is not to come up with the best possible multifactor model for hedge fund returns. Instead, our goal is to employ various alternative parsimonious specifications involving a small number of common factors, and uncover the risk and return dynamics of hedge fund returns[11]. We intend to see whether the stale pricing and the persistence of hedge funds performance is consistent under the joint presence of common stock and bond market factors.

[10] For example, Agarwal and Naik (2000, 2004) and Agarwal (2001) use factors such as the MSCI Emerging markets, the Salomon Brothers Government and Corporate Bond Index, and the Lehman High Yield Bond Index. Fung and Hsieh (1997) use a Gold Index. Capocci, Corhay, and Hübner (2005) use Goldman Sachs Commodity Index as an additional factor.

[11] A careful review of the literature suggests that there is no unanimously accepted multifactor model. As Capocci and Hübner (2004) suggest it is preferable to use several specifications in order to compare the obtained results.

Table 3
Simple Linear Regression of 13 Monthly Hedge Fund Index Returns on Various Risk Factors

	α	β_0	γ_1	γ_2	γ_3	γ_4	γ_5	γ_6	$Adj\,R^2$
Convertible arbitrage									
Market	0.28	0.15*	0.08*	0.75	0.52	-1.18	-1.38	0.72	0.20
Orthogonal Market	0.30	0.26*	0.09*	0.41	0.08	-1.22	-1.08	-0.78	0.27
Dedicated short-seller									
Market	0.53	-0.87	-3.49	0.05	-0.27	-0.13	-1.38	-2.76	0.68
Orthogonal Market	0.31	-0.88	-0.49	1.46	0.76	1.15	-1.37	-1.63	0.45
Emerging markets									
Market	0.23	0.53*	0.32*	0.78	0.61	-4.60	-1.77	1.53	0.37
Orthogonal Market	0.35	0.58*	0.32*	-0.12	-0.11	-5.32	-1.67	0.88	0.29
Equity market neutral									
Market	-0.31	0.15*	0.02	-1.42	6.88	-2.34	1.70*	2.07	0.36
Orthogonal Market	-0.28	0.25	0.02	-1.76	6.45	-2.38	1.99	2.01	0.38
Event driven									
Market	0.54*	0.24*	0.13*	0.14	0.80	-2.78	0.02	0.33	0.52
Orthogonal Market	0.59*	0.26*	0.13*	-0.26	0.48	-3.10	0.07	0.04	0.43
Distressed									
Market	0.47	0.26*	0.12*	0.36	1.78*	-2.75	0.01	0.86	0.51
Orthogonal Market	0.53*	0.30*	0.12*	-0.09	1.39	-3.08	0.10	0.56	0.43
Event-driven multistrategy									
Market	0.59*	0.22*	0.14*	-0.02	0.21	-2.85	-0.01	-0.18	0.43
Orthogonal Market	0.65*	0.24*	0.14*	-0.39	-0.08	-3.16	0.02	-0.46	0.35
Risk arbitrage									
Market	0.62*	0.14*	0.12*	-0.01	-1.05	-1.67	0.14	-0.15	0.42
Orthogonal Market	0.65*	0.14*	0.12*	-0.24	-1.20	-1.89	0.11	-0.35	0.31
Fixed-income arbitrage									
Market	-0.01	0.11	0.05	0.93	1.65*	-1.38	-1.99	0.35	0.22
Orthogonal Market	0.00	0.21*	0.06	0.66	1.26*	-1.36	-1.69	0.34	0.31
Global macro									
Market	0.62*	0.20*	0.08	2.93*	0.50	-2.94	1.04	1.81	0.16
Orthogonal Market	0.67*	0.20*	0.08	2.61*	0.29	-3.27	1.01	1.53	0.12
Long/short equity									
Market	0.23*	0.44*	0.08*	0.53*	0.73	1.16	0.62	1.16	0.61
Orthogonal Market	0.62*	0.51*	0.37*	0.40	-0.96	-2.50	0.55	0.70	0.50
Managed futures									
Market	0.19	-0.04	0.03*	2.54	2.21	3.71	4.28*	3.72*	0.22
Orthogonal Market	0.19	-0.11	0.03*	2.66*	2.43	3.64*	4.08*	3.68	0.22
Multistrategy									
Market	0.36	0.11*	0.06*	0.12	1.26*	-0.49	0.06	0.03	0.16
Orthogonal Market	0.38	0.19*	0.06*	-0.14	0.93	-0.52	0.28	-0.02	0.22

Notes: Market models are estimated using the specification

$$r_{i,t} = \alpha_i + \beta_{i,0} r_{m,t} + \gamma_{i,1}\left[SCLC_t\right] + \gamma_{i,2}\left[CMY_t\right] + \gamma_{i,3}\left[CredSpr_t\right] + \gamma_{i,4}\left[BdOp_t\right] + \gamma_{i,5}\left[FXOp_t\right] + \gamma_{i,6}\left[ComOp_t\right] + \varepsilon_{i,t}$$

.Orthogonal Market models are estimated using the specification

$$r_{i,t} = \alpha_i + \beta_{i,0} r^*_{m,t} + \gamma_{i,1}\left[SCLC_t\right] + \gamma_{i,2}\left[CMY_t\right] + \gamma_{i,3}\left[CredSpr_t\right] + \gamma_{i,4}\left[BdOp_t\right] + \gamma_{i,5}\left[FXOp_t\right] + \gamma_{i,6}\left[ComOp_t\right] + \varepsilon_{i,t}$$

where $r^*_{m,t}$ is the sum of the intercept and residuals from the regression of RM-RF on SMB, HML, TERM, and DEF. All the independent variables are as defined in the main text. (*) implies significance level at 5% level.

The estimated results are reported in Table 3 and an examination of which provides some interesting insights. It is important to note that the excess market return is highly correlated with the four other factors, so one may always raise the question about its effectiveness as an instrument in a multifactor model. We avoid this sensitive issue by creating an orthogonalized market factor which is the sum of the intercept and residuals from the regression of RM-RF on SMB, HML, TERM, and DEF. Intuitively, by construction the orthogonalized market factor shares a very high correlation with excess market return but it has zero correlation with the other four factors.

Regression (3) produces a modest average adjusted R^2 but it is less than what we observe for model (2). It's a bit surprising that adjusted R^2 are low given that our test assets are indices not individual funds. Since, on average, not all the slope coefficients are significant, it clearly demonstrates that in addition to SMB, HML and two term-structure factors, Fung and Hsieh (2004) model do not add anything substantial to capture the common variation in hedge fund returns. The slope coefficient of the contemporaneous market factor is very similar to those reported in Table 2. For all but five of the funds, the beta changes significantly from the market model to the orthogonalized counterpart. Five funds - dedicated short-seller, event driven, event-driven multistrategy, risk arbitrage, and global macro, continue to exhibit uniform beta coefficient or insignificantly different betas. Therefore, the effects of the orthogonalized market factor on these five funds are not noteworthy. Table 3 also shows that the beta coefficients for market and orthogonalized market factor have the same signs for all funds. Our results also suggest that a careful analysis of the hedge fund world requires a lot of style comparison and traditional peer comparison is not informative enough.

4.3. Estimating the beta uncertainty

Most of our analysis so far assumes that the market exposure or betas are constant over the entire sample period. As we know, for many reasons the actual beta estimate can be time varying and that can complicate the risk premium estimates of individual hedge funds. Hedge funds β's may not be stable over time and for a particular hedge fund whose style is market timing this can be a potential problem. In order to capture the beta uncertainty, in this section we implement a 36-month rolling regression procedure. This gives us an estimate of expected beta $(i.e., E\ \beta_0\ )$ and its time-varying variability $(i.e., Var\ \beta_0\ )$ for all hedge funds.

We use three different parsimonious specifications. They are based on equation (1) and equation (2) with $n=0$ and $n=3$ lag[12]. Briefly, the three specifications are:

$r_{i,t} = \alpha_i + \beta_{i,0} r_{m,t} + u_{i,t}$ (Model 1),

$r_{i,t} = \alpha_i + \beta_{i,0} r_{m,t} + \gamma_{i,1}\left[SMB_t\right] + \gamma_{i,2}\left[HML_t\right] + \delta_{i,1}\left[TERM_t\right] + \delta_{i,2}\left[DEF_t\right] + u_{i,t}$ (Model 2), and

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

In the first stage we obtain $E\ \beta_0$, the time-series average of the rolling estimates of $\beta_{i,0}$. In the second stage, following Fama and French (1997), we calculate the implied variance of the beta estimates using the following approximation

$$Var\ \beta_0 = Var\ \beta_{0,t} - Var(Sampling\,Error) \quad (4)$$

[12] We also compute time-varying betas and implied volatility estimates using various Fung and Hsieh (2004) type model specifications (3). The results are qualitatively similar to the ones presented for the Fama-French (1993) model and are omitted for the sake of brevity; they are readily available upon request.

where $Var\ \beta_{0,t}$ is the time series variance of the rolling regression beta. The second part on the right hand side is the time series average of the sampling error variance of the rolling beta estimates. Therefore, $Var\ \beta_0$ in (4) is calculated as the difference between the variance of the rolling β_0's and the time-series average of the squared standard errors of the rolling β_0's.

Table 4
Time-varying Betas and Implied Variance Estimates

	Model 1		Model 2		Model 3	
	$E(\beta_0)$	$V(\beta_0)$	$E(\beta_0)$	$V(\beta_0)$	$E(\beta_0)$	$V(\beta_0)$
Aggregate Hedge funds	0.32	0.07	0.33	0.15	0.34	0.15
Convertible arbitrage	0.09	0.07	0.01	0.03	0.01	0.18
Dedicated short-seller	-1.03	0.16	-0.78	0.34	-0.8	0.29
Emerging markets	0.57	0.09	0.61	0.18	0.61	0.21
Equity market neutral	0.07	0.02	0.06	0.06	0.06	0.05
Event driven	0.26	0.06	0.23	0.11	0.23	0.1
Distressed	0.25	0.09	0.19	0.15	0.18	0.14
Event-driven multistrategy	0.26	0.08	0.27	0.09	0.26	0.09
Risk arbitrage	0.16	0.04	0.17	0.15	0.17	0.14
Fixed-income arbitrage	0.04	0.09	0.01	0.18	0.01	0.19
Global macro	0.21	0.13	0.31	0.05	0.33	0.05
Long/short equity	0.5	0.13	0.47	0.12	0.47	0.15
Managed futures	0.14	0.41	0.22	0.02	0.23	0.03
Multistrategy	0.09	0.07	0.05	0.08	0.05	0.10
Average	0.14	0.11	0.15	0.12	0.15	0.14

Notes: For each individual hedge fund returns the estimated time varying betas are calculated using rolling window regressions of 36 months. For FF, the three specifications are: $r_{i,t} = \alpha_i + \beta_{0,i} r_{m,t} + u_{i,t}$ (model 1), $r_{i,t} = \alpha_i + \beta_{i,0} r_{m,t} + \gamma_{i,1}[SMB_t] + \gamma_{i,2}[HML_t] + \delta_{i,1}[TERM_t] + \delta_{i,2}[DEF_t] + u_{i,t}$ (model 2), $r_{i,t} = \alpha_i + \sum_{j=0}^{3} \beta_{i,j} r_{m,t-j} + \gamma_{i,1}[SMB_t] + \gamma_{i,2}[HML_t] + \delta_{i,1}[TERM_t] + \delta_{i,2}[DEF_t] + u_{i,t}$ (model 3). $E(\beta_0)$ is the time-series average of the rolling estimate of $\beta_{i,0}$. $V(\beta_0)$ is calculated as the difference between the variance of the rolling β_0's and the time-series average of the squared standard errors of the rolling β_0's.

Table 4 reports the estimated value of $E\ \beta_0$ and $Var\ \beta_0$ for each hedge funds corresponding to the three model specifications described earlier. The expected beta premium shows some variation even though for majority of the funds the value stays close to the mean estimate observed earlier. Introducing more explanatory variables in the data generating process brings more variability but the overall trend stays the same. Emerging markets fund captures the highest market exposure and fixed income arbitrage fund always display the lowest value of $E\ \beta_0$. Interestingly, the rolling window estimates correct for the negative market exposure of managed futures fund. The average value in the last row of Table 8 indicates that adding lagged value of market factor introduces more uncertainty in the estimates of beta. Even though the average value of $E\ \beta_0$ do not show any changes, the implied variance of beta increases slightly. As we know hedge funds consciously change styles to chase different opportunities. Therefore, the incorporation of lagged market returns may capture a more precise measure of hedge funds market risk exposure. This also implicitly indicates the non-synchronous behavior of hedge fund returns with respect to monthly market returns.

4.4. The spillover effects of market idiosyncratic volatility

One final issue that we want to clarify is the spillover effects of idiosyncratic volatility of the market factor on hedge funds returns. It will instruct us if the best forecast of future hedge fund returns is not only intrinsically related to prior market returns but also to prior market volatility. In order to capture the time-varying property of idiosyncratic market risk we use exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model proposed by Nelson (1991)[13]. We investigate the impact of contemporaneous volatility in two steps. First we estimate the time-varying conditional volatility from the following EGARCH regression.

$$r_{m,t} = c_0 + c_1 r_{m,t-1} + c_2 r_{m,t-2} + c_3 r_{m,t-3} + e_{m,t}, e_{m,t} \sim N(0, \sigma^2_{m,t})$$

$$\ln \sigma^2_{m,t} = d_0 + g\left(Z_{m,t-1}\right) + d_3 \sigma^2_{m,t-1},$$

$$g\left(Z_{m,t}\right) = d_1 Z_{m,t} + d_2 \left[\left|Z_{m,t}\right| - E\left|Z_{m,t}\right|\right], \quad Z_{m,t} = \frac{e_{m,t}}{\sqrt{\sigma_{m,t}}} \tag{5}$$

In the above specification monthly return process of market portfolio is regressed on its three period lags, and the conditional (on the information set at time $t-1$) distribution of the regression residual has mean zero and variance $\sigma^2_{m,t}$. In (5) the estimate of the conditional variance is obtained by an EGARCH(1,1) process[14]. In the second step, we estimate the idiosyncratic volatility spillovers using the following regression

$$r_{i,t} = \alpha_i + \beta_{i,0} r_{m,t} + \gamma_{i,1}\left[SMB_t\right] + \gamma_{i,2}\left[HML_t\right] + \delta_{i,1}\left[TERM_t\right] + \delta_{i,2}\left[DEF_t\right]$$
$$+\theta_i E_{t-1}\left[IVOL_t\right] + u_{i,t}, \; u_{i,t} \sim N(0, \sigma^2_{i,t}) \tag{6}$$

where conditional idiosyncratic volatility is the standard deviation of the predicted residual from EGARCH regression obtained from (5). The estimated EGARCH parameters from step 1 are used to forecast expected conditional idiosyncratic volatility at each month t.

In Table 5 we report the summary statistics of idiosyncratic volatility in lags and square lags. $IVOL_{t-1}$ is the expected conditional idiosyncratic volatility $E_{t-1}\left[IVOL_t\right]$ used in the second step of regression model (6). The mean $E_{t-1}\left[IVOL_t\right]$ is almost 50% with a standard deviation of 32%. This indicates that the idiosyncratic volatility corresponding to CRSP's value-weighted index vary substantially over time. The correlations between $IVOL_t$ and $E_{t-1}\left[IVOL_t\right]$ is statistically significant. The estimated conditional idiosyncratic volatility is also very highly correlated with its recent squared counterpart. Panel A and B also show that autocorrelations in lags and squared lags of $IVOL_t$ is high at first lag but then slowly decreases. The last column of Panel C reports the random walk test following augmented Dicky-Fuller and Phillips-Perron unit root tests. For all the cases we reject the null hypothesis of a random walk. This suggests that it is not appropriate to use random walk process to capture the time-varying property of idiosyncratic volatility.

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[13] In order to capture asymmetric property of conditional volatility (also known as leverage effects), EGARCH is one of the most popular variant among the ARCH-GARCH class of models pioneered by Engle (1982) and Bollerslev (1988). The original study that shows the superior overall performance of EGARCH in compare to other GARCH specifications is by Pagan and Schwert (1990).

[14] The choice of EGARCH(1,1) against any other higher order specifications is based on the value of the lowest Akaike Information Criterion (AIC). We also use maximum log-likelihood value and Schwartz Information Criterion (SIC) of model selection. Our final results are not sensitive to alternative specification (i.e., Fama and French (1993) or Fung and Hsieh (2004)) and conditional variance. Details are available upon request.

Table 5
Time Series property of Idiosyncratic Volatility

Panel A: Autocorrelation in Lags

	1	2	3	4	5	6	7	8	10	15	20
$IVOL_t$	0.15	0.04	0.02	-0.01	0.02	0.07	0.09	0.09	0.1	-0.04	-0.02
$IVOL_{t-1}$	0.10	0.01	0.02	-0.01	0.00	0.08	0.1	0.08	0.08	-0.05	-0.02

Panel B: Autocorrelation in Squared Lags

	1	2	3	4	5	6	7	8	10	15	20
$IVOL_t^2$	0.04	0.10	-0.10	-0.08	0.00	0.18	0.03	0.17	-0.02	-0.01	-0.08
$IVOL_{t-1}^2$	0.04	0.10	-0.10	-0.09	0.00	0.18	0.03	0.17	-0.02	-0.01	-0.08

Panel C: Summary Statistics

	Mean	Med	StdDev	Skew	Kurt	ADF (p-value)	PP (p-value)
$IVOL_t$	0.49	0.57	0.32	-1.01	4.81	-3.98 (0.009)	-11.43 (0.000)
$IVOL_{t-1}$	0.49	0.58	0.32	-1.03	4.96	-4.21 (0.004)	-11.34 (0.000)
$IVOL_t^2$	0.52	0.39	0.32	1.49	5.68	-4.55 (0.001)	-12.83 (0.000)
$IVOL_{t-1}^2$	0.52	0.37	0.32	1.49	5.64	-4.44 (0.001)	-11.80 (0.000)

Notes: IVOL is calculated from the predicted conditional standard deviation from the following regression $r_{m,t} = c_0 + c_1 r_{m,t-1} + c_2 r_{m,t-2} + c_3 r_{m,t-3} + e_{m,t}, e_{m,t} \sim N\left(0, \sigma_{m,t}^2\right)$ and $\ln \sigma_{m,t}^2 = d_0 + g\left(Z_{m,t-1}\right) + d_3 \sigma_{m,t-1}^2$, $g\left(Z_{m,t}\right) = d_1 Z_{m,t} + d_2 \left[\left|Z_{m,t}\right| - E\left|Z_{m,t}\right|\right]$, $Z_{m,t} = \frac{e_{m,t}}{\sqrt{\sigma_{m,t}}}$. ADF is the augmented Dickey-Fuller test statistic for unit root. PP is the Phillips-Perron test statistic for unit root. Under the null hypothesis the variable contains a unit root and under the alternative the variable is generated by a stationary process.

Table 6 presents our final scoreboard on the performance of all hedge fund indices that includes idiosyncratic market risk as an additional explanatory variable. For the aggregate hedge fund index, the addition of idiosyncratic market risk reduces the average return or alpha values. The slope parameter of idiosyncratic market risk has statistically significant value of 0.55. This observation is true irrespective of whether we include the lagged value of market factor in the mean specification. The risk loadings of stock and bond market factors are not affected by the inclusion of $IVOL$. For other types of individual hedge fund indices the effect of the inclusion of idiosyncratic market risk is quite visible as well. Convertible arbitrage and emerging markets yield a statistically and economically insignificant alpha. Global macro has the highest drop in the average return estimate.

The estimated slope of market beta do not changes much from our earlier reported results. Even after controlling for $IVOL$, dedicated short-seller and equity market neutral funds continue to prefer larger firms over small size firms. Event driven funds prefers to load more on stocks with small size and high BE/ME ratios. Managed future funds has the highest preference for high BE/ME ratio firms, and both global macro and long/short equity has the highest preference for small size firms. The individual role of the term-structure factors remains relevant for more than half of the hedge fund indices. The slope parameter of $IVOL$ suggests that hedge funds with high conditional idiosyncratic volatility prefers firms with low BE/ME ratios whereas funds with low conditional idiosyncratic volatility is symptomatic for a preference of smaller firms.

Table 6
Regressions With Idiosyncratic Volatility, January 1994–December 2008

	α	β_0	γ_1	γ_2	δ_1	δ_2	θ	$Adj\ R^2$
Aggregate Hedge funds	0.35*	0.26*	0.11*	-0.01	-0.13	0.09	0.55*	0.61
Convertible arbitrage	0.00	0.01	0.02	0.03	-0.24	0.49*	0.68*	0.56
Dedicated short-seller	0.35	-0.86*	-0.28*	0.11	-0.09	0.24*	-0.16	0.69
Emerging markets	-0.01	0.53*	0.20*	-0.01	-0.24	0.06	0.98*	0.56
Equity market neutral	-0.92*	0.01	-0.02	0.05	1.09*	0.39*	0.94*	0.57
Event driven	0.23*	0.22*	0.09*	0.06*	0.26	0.09	0.81*	0.56
Distressed	0.20*	0.21*	0.07*	0.05	1.13*	0.16*	0.78*	0.53
Event-driven multistrategy	0.23*	0.23*	0.11*	0.07	-0.29	0.04	0.89*	0.47
Risk arbitrage	0.47	0.17*	0.09*	0.09*	-1.35*	0.01	0.34*	0.41
Fixed-income arbitrage	-0.17	-0.02	-0.01	0.04	0.92*	0.50*	0.44*	0.6
Global macro	0.33*	0.41*	0.22*	-0.10*	-1.38*	0.02	1.02*	0.68
Long/short equity	0.54*	0.42*	0.22*	-0.12*	-1.11*	-0.04	0.60*	0.66
Managed futures	0.45*	0.09	0.12*	0.19*	-0.58*	0.33*	0.40*	0.51
Multistrategy	0.16	0.01	0.02	0.01	0.91*	0.31*	0.44*	0.49

Notes: For each hedge funds the model specification is $r_{i,t} = \alpha_i + \beta_{i,0} r_{m,t} + \gamma_{i,1}\left[SMB_t\right] + \gamma_{i,2}\left[HML_t\right] + \delta_{i,1}\left[TERM_t\right] + \delta_{i,2}\left[DEF_t\right] + \theta[IVOL_{t-1}] + u_{i,t}$. (*) implies significance level at 5% level.

Overall, controlling for idiosyncratic market risk provides us a better measure of average hedge funds returns under the presence of common stock and bond market factors. Without any doubt, hedge funds are exposed to lots of risks beyond the market. Our analysis therefore suggests that for a significant number of aggregate hedge funds we don't contemplate any exploitation of information not reflected in observed prices. Rather the hedge funds are taking dynamic exposure to common risk factors that the hedge fund managers understand better.

5. Conclusion

In this study we examine a comprehensive sample of aggregate hedge funds indices and explore how their common risk exposures are related to the performance persistence. Our finding indicates a concise non-synchronous behavior of hedge funds and supports the existence of stale pricing in illiquid markets. We demonstrate that the idiosyncratic component of market risk can disentangle hedge funds with high preferences for low book-to-market and small size firms. Our evidence leads us to conclude that high value of the idiosyncratic market volatility has more downside weakness effect (and very little upside strength) on the hedge funds returns. Our work can be extended to many directions. One immediate puzzle that needs to be resolved is what causes the dynamic exposure to common risk factors to change over time. What role macroeconomic factors play in uncovering the stale pricing effect is another interesting issue.

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