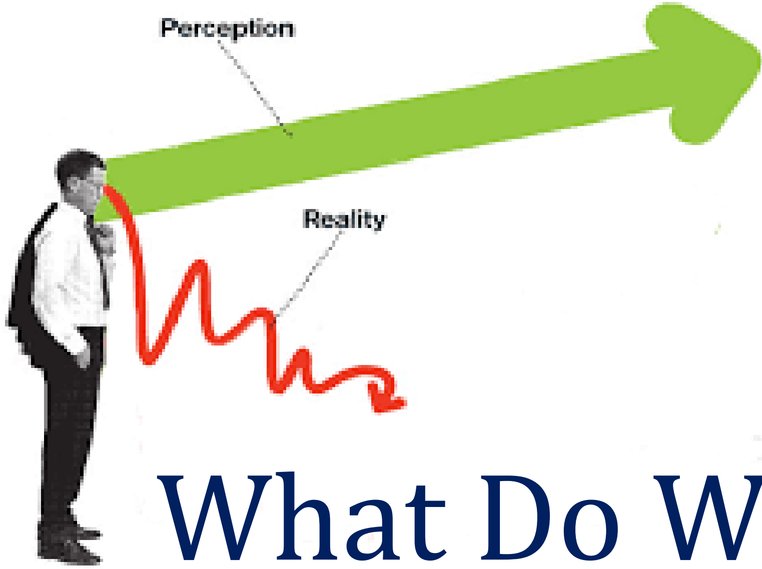

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What Do We Know About Hedge Funds?

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Fall 2018

Mean-Variance Allocations for Hedge Funds?

- Agarwal and Naik (2004, RFS) stress that HFs exhibit non-normal payoffs for reasons as their use of options, or option-like strategies
- They recommend a mean-conditional Value at-Risk (M-CVaR) framework for portfolio construction involving HFs
- The traditional mean-variance framework underestimates the tail risk of hedge funds by as much as 54% compared to M-CVaR ptfs.
- Fung and Hsieh (1999, EL) suggest that MV interpreted as a 2nd order Taylor expansion of power utility works less for HFs vs MFs

Rank correlation between actual and second order approximations for power utilities

	Second order approx			Log			Sharpe		
	Sim. portf	Mut. funds	Hedge funds	Sim. portf	Mut. funds	Hedge funds	Sim. portf	Mut. funds	Hedge funds
Power utility:									
0.5	1.00	1.00	1.00	1.00	1.00	0.99	1.00	−0.10	0.55
1.0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	−0.07	0.62
1.5	1.00	1.00	1.00	1.00	1.00	0.99	1.00	−0.04	0.68
2.0	1.00	1.00	1.00	1.00	1.00	0.98	1.00	−0.01	0.73
γ 5.0	1.00	1.00	0.99	1.00	0.95	0.75	1.00	0.16	0.89
10.0	1.00	1.00	0.99	1.00	0.71	0.48	1.00	0.49	0.89
15.0	1.00	0.99	0.98	1.00	0.37	0.37	1.00	0.75	0.87
20.0	1.00	0.98	0.97	1.00	0.07	0.29	1.00	0.89	0.85
25.0	1.00	0.97	0.96	1.00	−0.15	0.24	1.00	0.92	0.83
30.0	1.00	0.98	0.95	1.00	−0.26	0.20	1.00	0.91	0.81

Idetical by constructrion

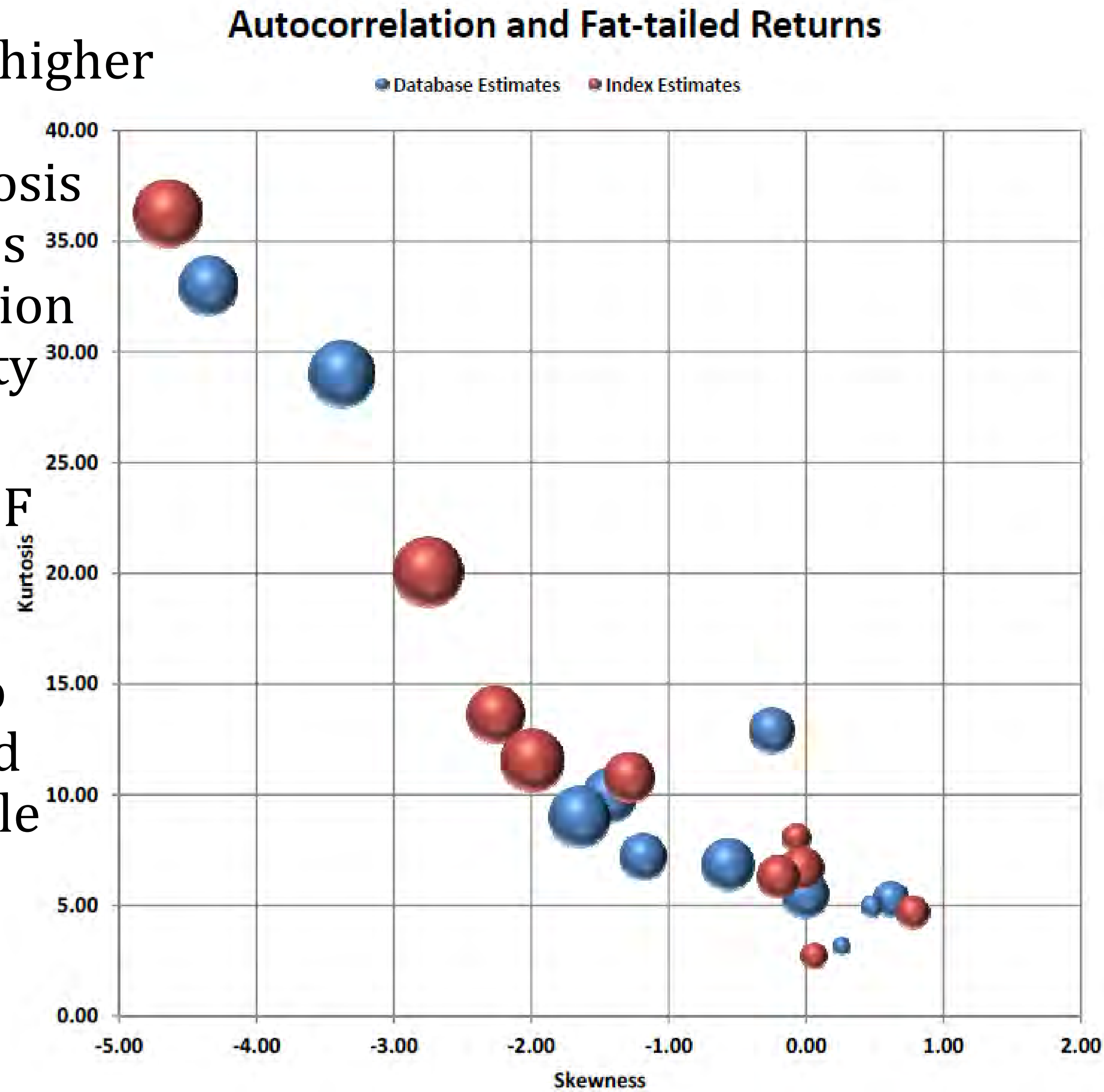
Mean-Variance Allocations for Hedge Funds?

- Amin and Kat (2003, JPM) find evidence that low volatility is generally obtained at the cost of lower skewness and higher kurtosis
- Hitaj, Martellini, and Zambruno (2010) adopt Martellini and Ziemann's (2010, RFS) improved estimates of co-skew and co-kurtosis
  - The factor-based and the constant correlation approaches + statistical shrinkage
- They find that the use of these enhanced estimates generates significant improvement for investors in HFs out-of-sample gains
- The use of improved estimators leads to substantial increases in the investor's utility as compared to using sample estimators, that instead may actually lead to negative economic values

Hedge Fund Strategy	Mean Return	Volatility	Skew	Kurt	JBTest	PValue
'Convertible Arbitrage'	7.967	6.944	-2.684	19.178	1840.10	0.000
'CTA Global'	8.071	8.706	0.134	2.887	0.539	0.764
'Distressed Securities'	9.973	6.356	-1.675	9.439	333.630	0.000
'Emerging Markets'	10.357	13.361	-1.258	8.103	204.960	0.000
'Equity Market Neutral'	7.446	3.120	-2.748	20.407	2110.300	0.000
'Event Driven'	9.540	6.357	-1.718	9.113	311.480	0.000
'Fixed Income Arbitrage'	5.197	4.909	-3.707	22.510	2758.900	0.000
'Global Macro'	9.606	5.896	0.815	4.766	36.586	0.000
'Long/Short Equity'	9.720	7.681	-0.382	4.247	13.533	0.001
'Merger Arbitrage'	8.453	3.869	-1.647	8.793	281.310	0.000
'Relative Value'	8.345	4.571	-2.102	12.165	643.860	0.000
'Short Selling'	5.109	19.087	0.578	5.249	40.479	0.000
'Funds of Funds'	7.338	6.309	-0.459	6.299	74.287	0.000

Mean-Variance Allocations for Hedge Funds?

- HF styles that exhibit higher autocorrelation generally also exhibit kurtosis and negative skewness (positive autocorrelation is a proxy for illiquidity risk)
- When investing in a HF with positively auto-correlated returns, investors may want to consider the increased likelihood that a simple analysis based on the returns' volatility will understate the actual downside risk



Are HFs Just Glorified Mutual Funds?

- Allowing for macro predictability is important in ex ante identify-ing subgroups of funds that deliver significant outperformance
- Yet, the major source of investment profitability is predictability in managerial skills: long-only strategies that incorporate predictability in managerial skills outperform their Fung and Hsieh (2004) benchmarks by over 17% per year

Investor type	Description
ND	No predictability, dogmatic about no managerial skills
PD-1	Predictable betas, dogmatic about no managerial skills
PD-2	Predictable betas and factors, dogmatic about no managerial skills
NS	No predictability, skeptical about no managerial skills
PS-1	Predictable betas, skeptical about no managerial skills
PS-2	Predictable betas and factors, skeptical about no managerial skills
PS-3	Predictable alphas, skeptical about no managerial skills
PS-4	Predictable alphas, betas, and factors, skeptical about no managerial skills
NA	No predictability, agnostic about no managerial skills
PA-1	Predictable betas, agnostic about no managerial skills
PA-2	Predictable betas and factors, agnostic about no managerial skills
PA-3	Predictable alphas, agnostic about no managerial skills
PA-4	Predictable alphas, betas, and factors, agnostic about no managerial skills

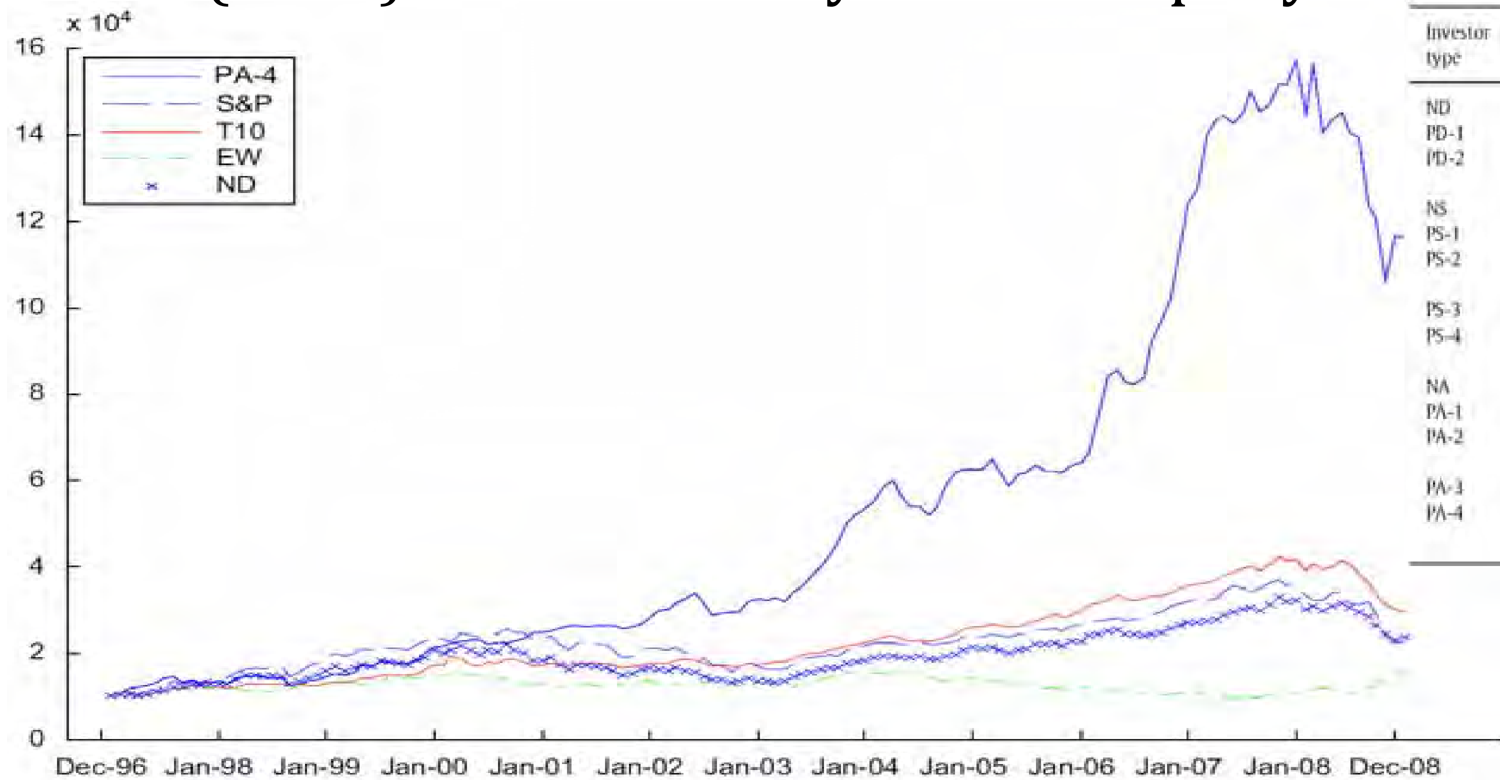


Fig. 1. Cumulative wealth for different portfolio strategies. This figure plots the cumulative wealth of an investor that invests $10,000 in five different strategies starting in January 1997. The strategies include PA-4 (dotted line) and ND (asterisked line) described in Table 1, the strategy T10 that invests in the top 10% of funds each year (dashed line), the strategy S&P that invests in the S&P 500 (solid line), and the strategy EW that is an equal-weighted investment in the seven Fung and Hsieh (2004) risk factors (dashed-dotted line).

Are HFs Just Glorified Mutual Funds?

- This is over 10% per annum higher than that earned by an investor who does not allow for predictability and over 13% per annum higher than that earned by an investor who completely excludes all predictability and the possibility of managerial skills
- Some of the impressive returns generated in 2003, 2006, and 2007 are traced to positions in HFs operating in emerging markets

- How do HFs generate returns, given that their performances may be appealing even after fees and in risk-adjusted terms?
- Many studies employ linear multifactor models
  - Betas correspond to the component of the fund's return related to its exposure to different systematic risk factors
  - Alpha is the portion of the HF return not explained by the risk factors

$$(R_h - R_f) = \alpha + \beta (R_i - R_f) + e_h$$

  - A fund is said to be market neutral if its returns are uncorrelated with those of market indices or a collection of other systematic risk factors

How Do HFs Generate Performance? Do They Hedge?

- Early studies concluded that HFs had low risk exposure to the U.S. equity market (see Fung and Hsieh, 1997, RFS; Liang, 1999, FAJ)
  - Some papers using classical, statistical principal components

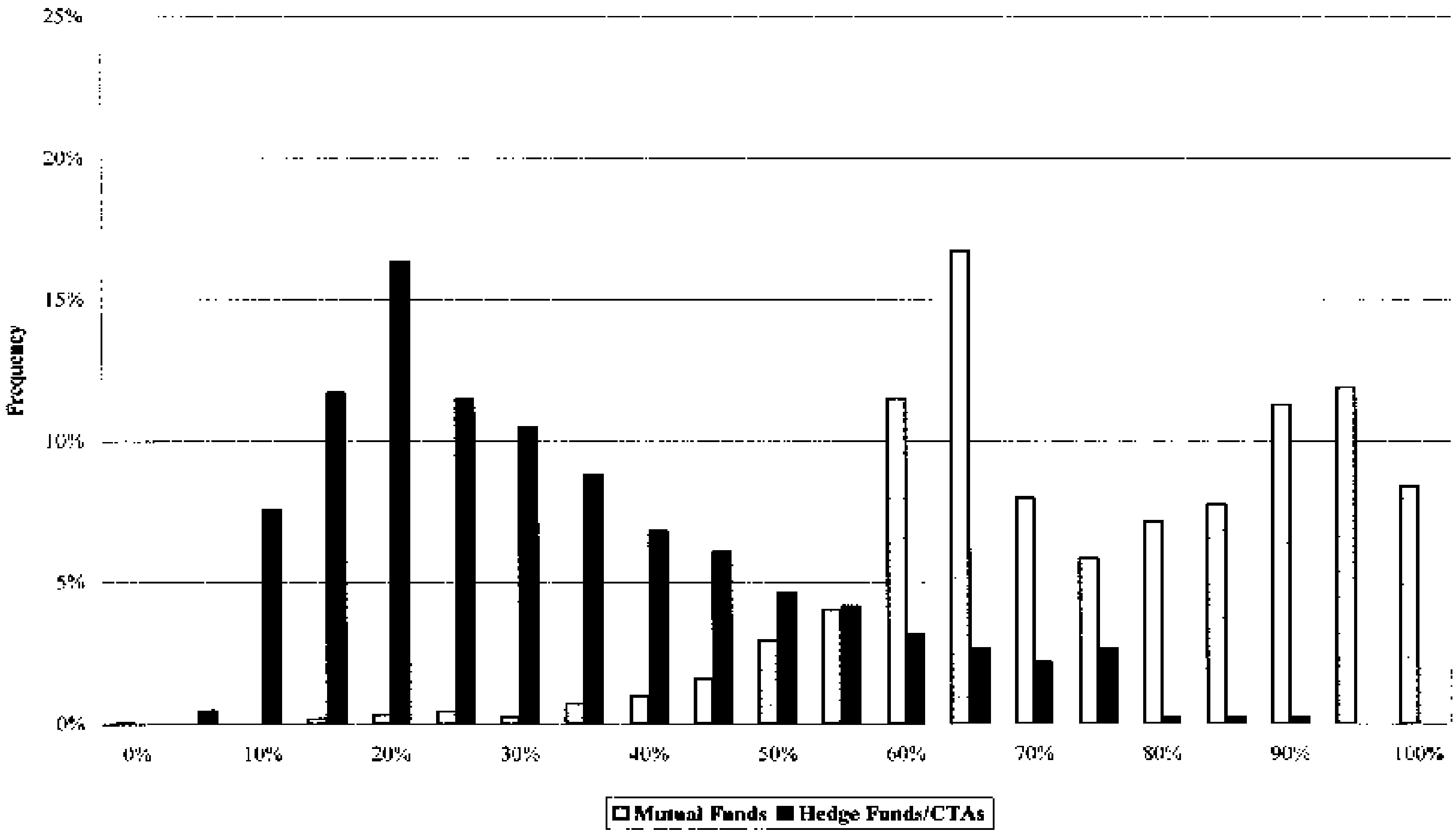


Figure 1
Distribution of R^2 versus asset classes

Fung, W., & Hsieh, D.A. (1997). Empirical characteristics of dynamic trading strategies: The case of hedge funds. *The Review of Financial Studies, 10*(2), 275-302.

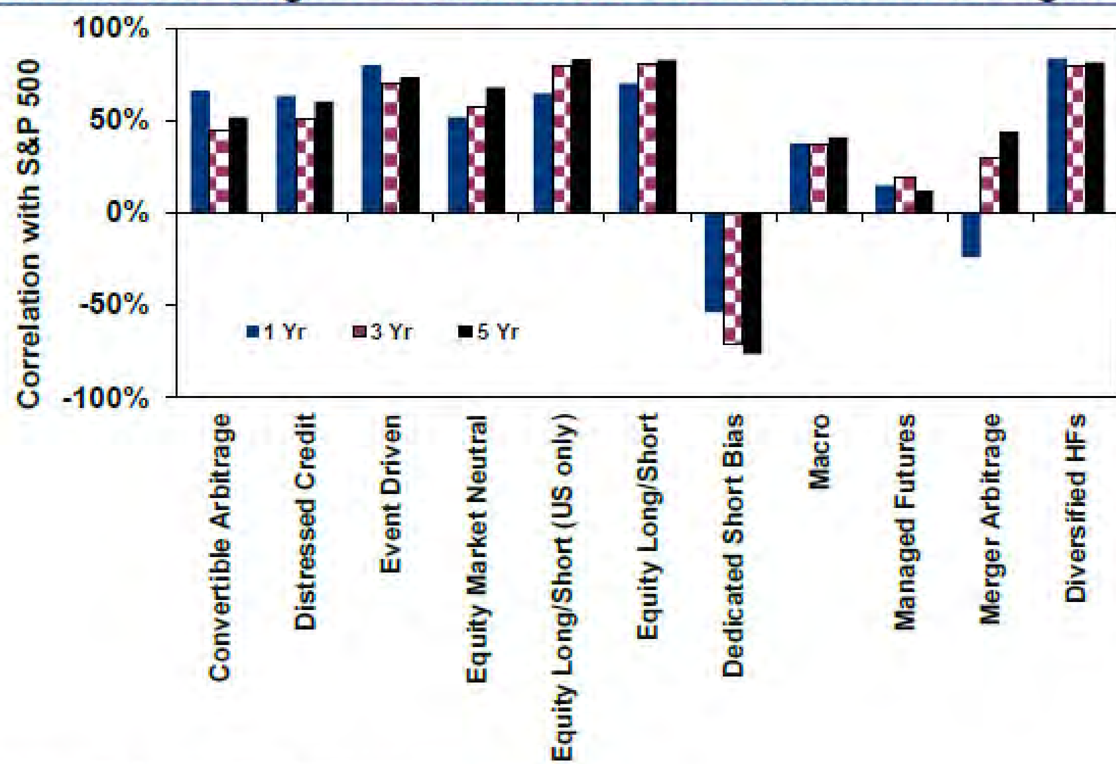
How Do HFs Generate Performance? Do They Hedge?

- It is well accepted that the world of financial securities is a multifactor world consisting of different risk factors, each associated with its own factor risk premium
- No single investment strategy can span entire "risk factor space"
- Therefore investors wishing to earn risk premia associated with different risk factors need to employ different kinds of strategies
- Sophisticated investors, like endowments, seem to have recognized this fact as their portfolios consist of MFs as well as HFs
- Mutual funds typically employ a long-only buy-and-hold-type strategy on standard asset classes, and help capture risk premia associated with equity risk, interest rate risk, default risk, etc.
- However, MFs are not helpful in capturing risk premia associated with dynamic strategies: this is where HFs come into the picture
  - Investors can create exposure like HFs by trading on their own, but in practice they encounter frictions due to incompleteness of markets
  - Same is true of the financing market as well, where investors encounter difficulties shorting securities and obtaining leverage

How Do HFs Generate Performance? Do They Hedge?

- Recent studies have revisited HFs' claims of market neutrality: Patton (2009, RFS) extends the linear notion of correlation to more broadly define neutrality
  - He uses 5 measures of neutrality: mean neutrality, variance neutrality, VaR neutrality, tail neutrality, and complete neutrality
- Only about 25% of so-called market neutral funds are truly neutral
  - However, the percentage of funds that are truly neutral is the highest for the group of funds claiming to follow a market neutral strategy

Chart 2: A wide range of correlation with S&P 500 across HF strategies

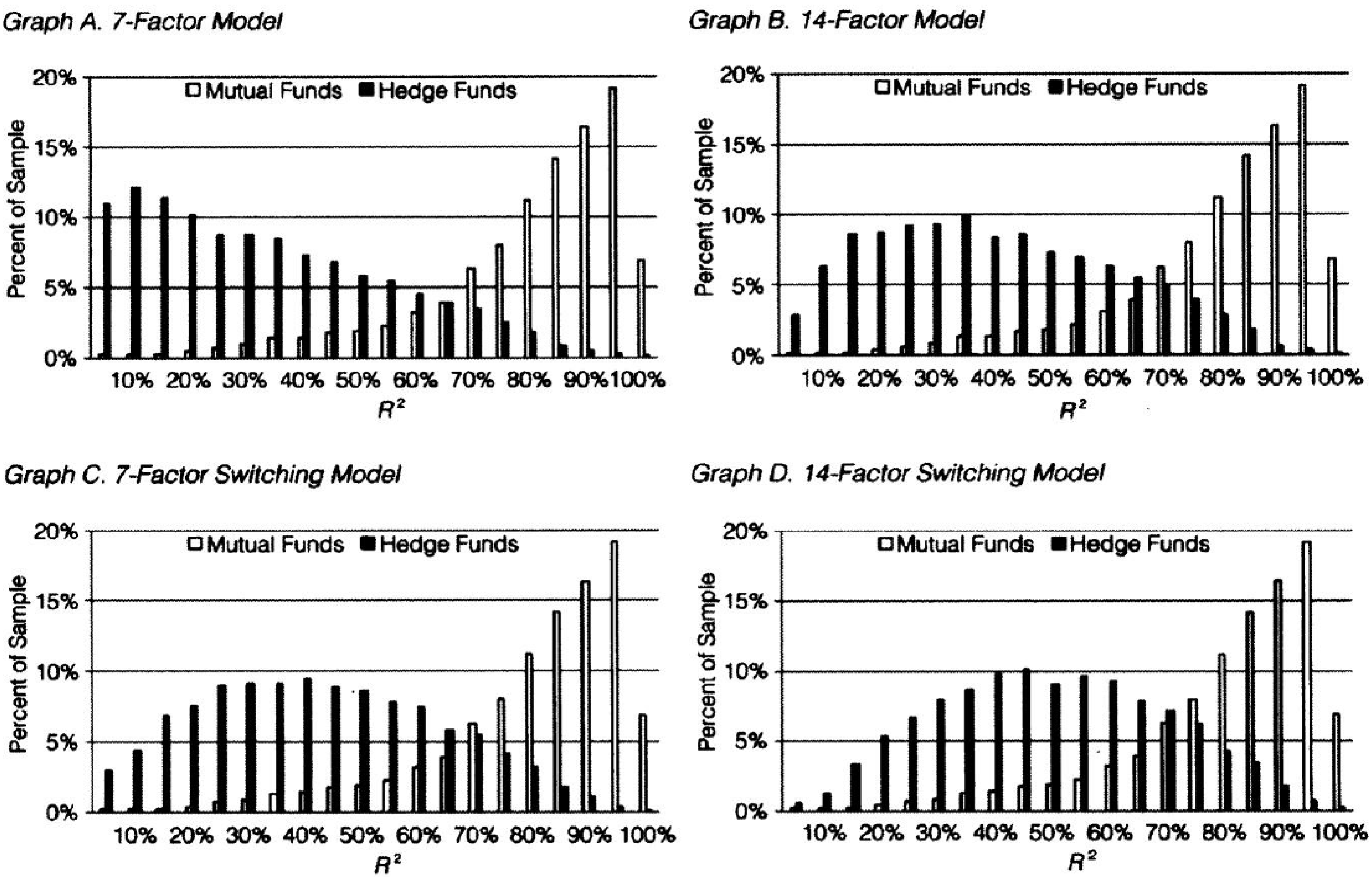


Source: BofA Merrill Lynch Global Research, Bloomberg

Exhibit 2: Low dispersion environments present challenges for hedge fund performance
As of November 14, 2014

Source: HFR and Goldman Sachs Global Investment Research.

How Do HFs Generate Performance? Do They Hedge?



Nicolas P. Bollen *The Journal of Financial and Quantitative Analysis* Vol. 48, No. 2 (APRIL 2013), pp. 519-547

How Do HFs Generate Performance? Do They Hedge?

Listed for each style are the number of funds, average R^2, and the percent of funds for which the R^2 is insignificantly different from 0. Data are from the 1994–2008 period. Results are displayed for 2 sets of factors: a 7-factor model and a 14-factor model. For each fund, the optimal subset of up to 3 factors is selected to maximize the R^2. The significance of each fund's R^2 is assessed by simulated critical values.

		7-Factor Model		14-Factor Model	
Style	No. of Funds	Avg. R^2	% Zero-R^2	Avg. R^2	% Zero-R^2
Equity	2,890	33.2%	31.7%	41.6%	25.3%
Multistrategy	708	31.2%	37.0%	39.4%	31.1%
Event driven	550	31.7%	29.3%	37.2%	28.9%
Emerging markets	533	33.3%	25.0%	39.0%	25.5%
Equity market neutral	479	18.6%	62.8%	29.7%	45.5%
Fixed income	411	25.7%	48.7%	31.5%	46.5%
Macro	428	22.5%	50.5%	29.4%	47.2%
Convertible arbitrage	253	25.4%	45.8%	30.1%	46.6%
Sector	178	32.0%	31.5%	41.5%	28.7%
Other	80	24.2%	51.3%	32.0%	46.3%
Distressed securities	74	36.9%	23.0%	41.4%	18.9%
Short bias	55	33.6%	36.4%	40.1%	32.7%
Single strategy	48	47.3%	10.4%	53.5%	10.4%
Total	6,687	30.4%	36.6%	38.1%	31.4%

Nicolas P. Bollen *The Journal of Financial and Quantitative Analysis* Vol. 48, No. 2 (APRIL 2013), pp. 519-547

How Do HFs Generate Performance? Do They Hedge?

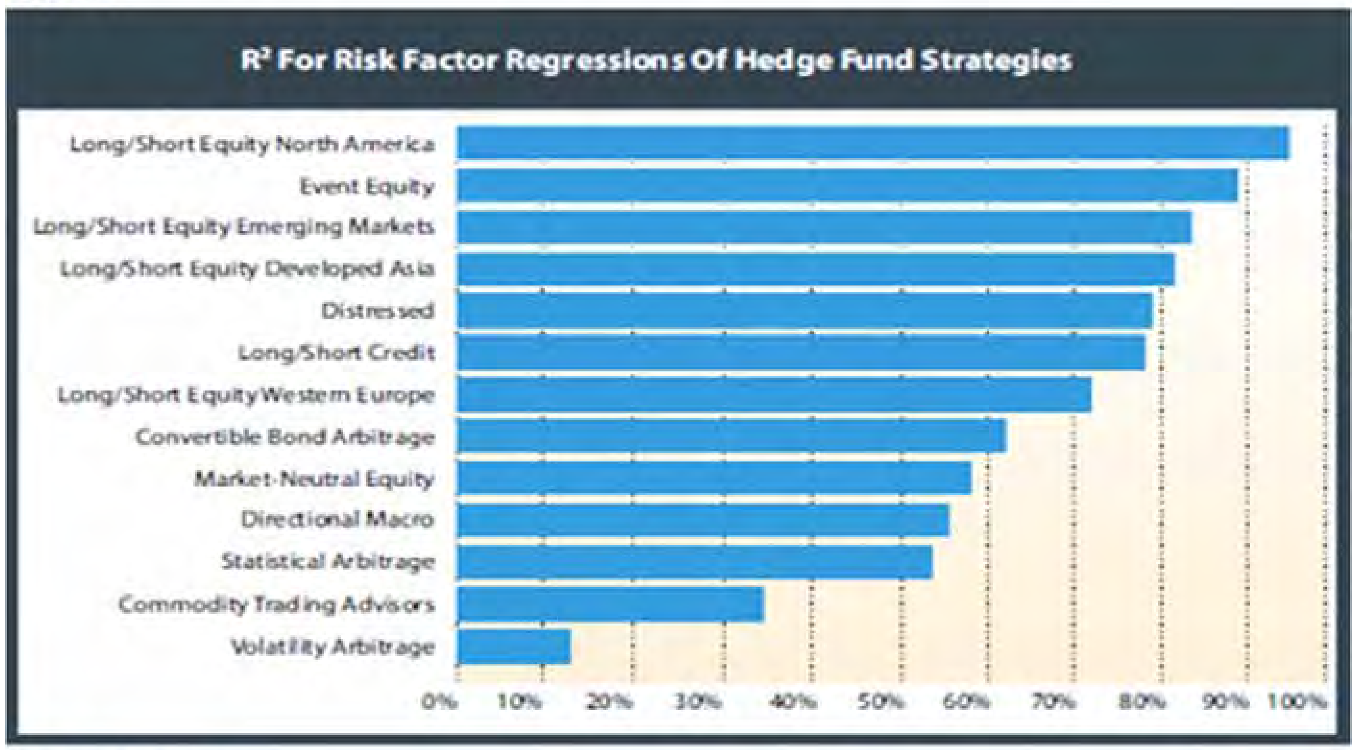
- Bali, Brown, and Caglayan (2011, JFE) investigates HFs' exposures to various financial and macroeconomic risk factors through alternative measures of factor betas
- They examine their performance in predicting the cross-sectional variation in hedge fund returns
- Both parametric and non-parametric tests indicate a significantly positive (negative) link between default premium beta (inflation beta) and future hedge fund returns
- Results are robust across subsample periods and states of the economy, and after controlling for mkt, size, book-to-market, and momentum as well as trend-following factors in stocks, interest rates, currencies, and commodities

Quintiles	Average β^{DEF} in each Quintile	Next Month Average Raw Returns	Next Month 4-Factor Alphas	Next Month 9-Factor Alphas
Low β^{DEF}	–8.404	0.061 (0.26)	–0.213 (–1.93)	–0.057 (–0.42)
2	–1.491	0.182 (1.20)	–0.006 (–0.06)	0.109 (1.18)
3	0.792	0.247 (1.81)	0.081 (0.89)	0.200 (2.50)
4	3.295	0.357 (2.75)	0.205 (2.88)	0.353 (5.33)
High β^{DEF}	11.292	0.530 (2.25)	0.267 (2.18)	0.388 (2.15)
High β^{DEF} – Low β^{DEF} Return/Alpha Diff.		**0.469** **(2.16)**	**0.480** **(2.23)**	**0.445** **(2.56)**
High β^{DEF} – Rest of Quintiles Return/Alpha Diff.		**0.319** **(2.02)**	**0.250** **(1.99)**	**0.237** **(2.02)**
Rest of Quintiles – Low β^{DEF} Return/Alpha Diff.		**0.268** **(1.97)**	**0.350** **(2.99)**	**0.320** **(3.18)**

How Do HFs Generate Performance? Do They Hedge?

- Bali, Brown and Caglayan (2012, JFE) stress if HFs are not neutral, they are exposed to systematic risk (default premium and inflation shocks) that predicts performance
- Funds in the highest SR quintile generate 6% more average annual returns compared with funds in the lowest SR quintile
- Systematic risk is able to predict future fund returns
- Given the evidence that HFs are exposed to significant systematic risk, the literature has used 2 different approaches to attribute HFs' performance to risk:

❶ Identify pre-specified factors explaining HF perfor-mance in a "top-down" way, from returns to generating process



Source: eVestment

How Do HFs Generate Performance? Do They Hedge?

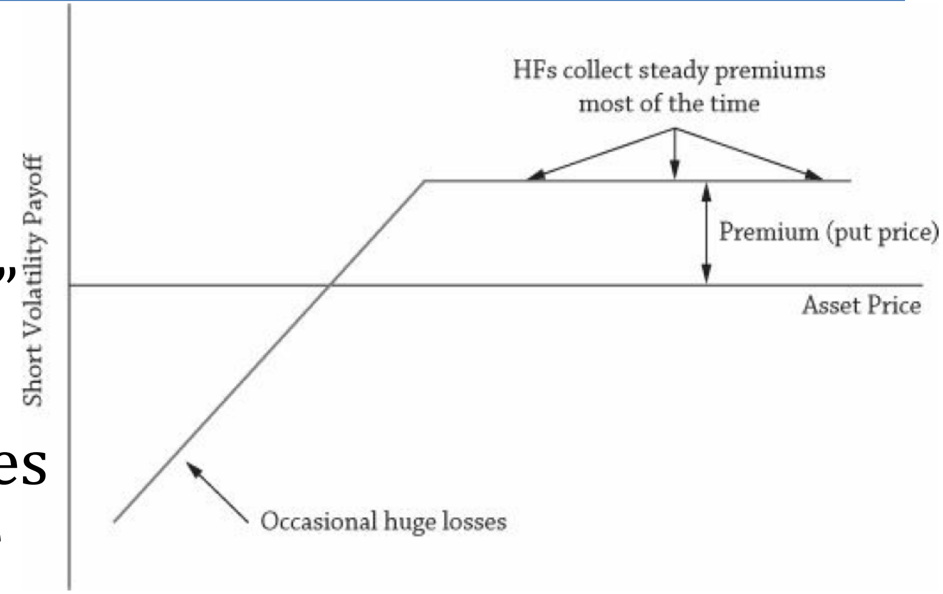
- Ang (2014) claims that HF are just ptfs. of exposures to equity and volatility risk, that they would simply «re-package»
- The HF index is the key HFR index and the volatility factor is compiled by Merrill Lynch and is a return series from a short volatility strategy (selling VIX insurance)
- Partial correlations are estimated from monthly data from Jan. 2000 to Sept. 2012 and they control for the effect of other vars
- Only for the long-short HFs, of which a large number are quant funds, is the partial correlation with equity market risk low at 0.11 and statistically insignificant
- The partial correlations of HF returns with the volatility risk factor are somewhat smaller but still quite large

Hedge Fund Partial Correlations

	Equity	Volatility
HF Index	0.664	0.262
p-value	0.00	0.00
Distress	0.411	0.440
p-value	0.00	0.00
Merger Arbitrage	0.453	0.195
p-value	0.00	0.02
Equity Long/Short	0.106	0.175
p-value	0.19	0.03
Emerging Markets	0.616	0.297
p-value	0.00	0.00
Event Driven	0.624	0.384
p-value	0.00	0.00
Macro	0.399	−0.340
p-value	0.00	0.00
Relative Value	0.330	0.646
p-value	0.00	0.00
Convertible Arbitrage	0.180	0.657
p-value	0.03	0.00

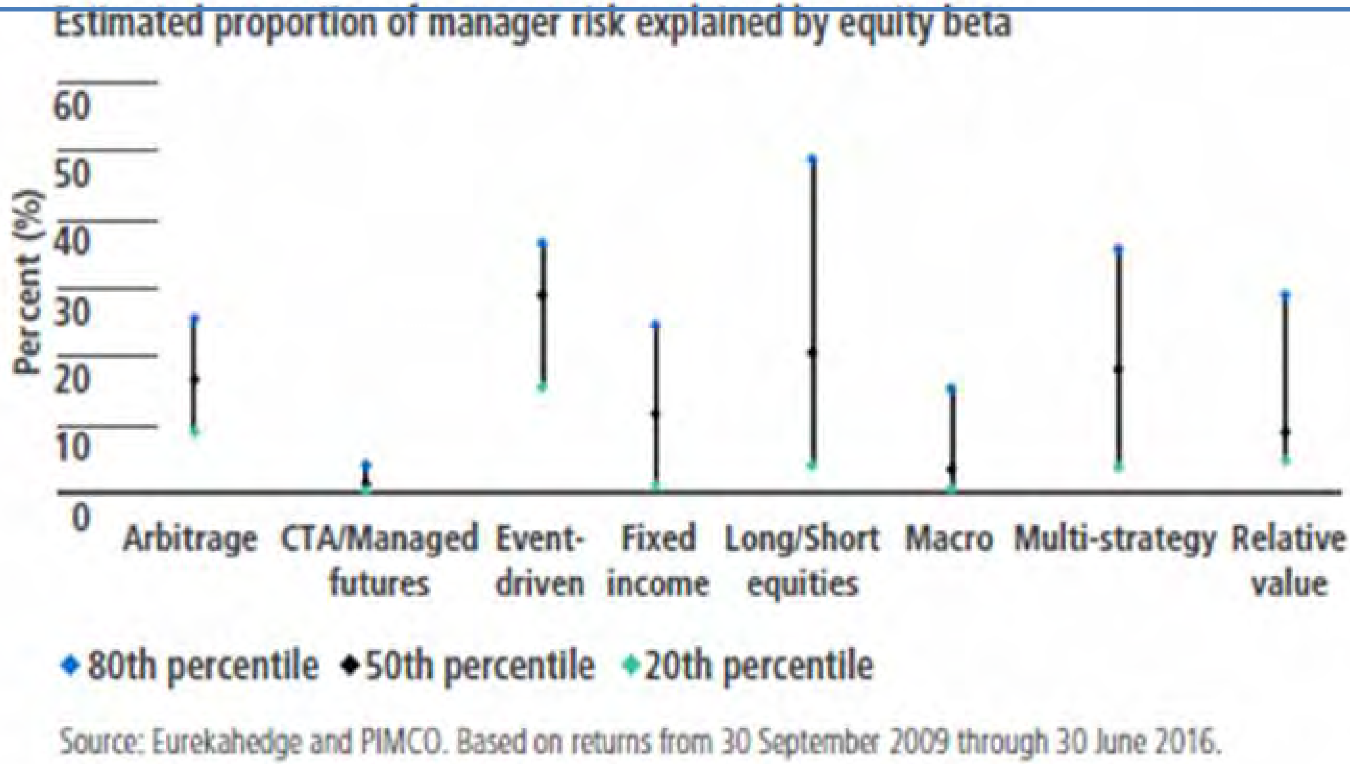
How Do HFs Generate Performance? Do They Hedge?

- We picture a short volatility payoff
- Most of the time, HFs collect small and steady premiums equal to the put price; these profits seem "alpha"
- This premium does not come for free: there are occasional large losses when the assets fall sharply in price



- The losses are higher vs. just put-selling because HFs use leverage
- As losses are rare, for long periods it may be confused with alpha from long-only positions in plain-vanilla fixed income and equities
  - This is actually the payoff of a rebalancing strategy, see Appendix A
  - Some HFs are put buyers, generating small losses most of the time but making a killing when markets tank: these funds (e.g., http://www.universa.net/home.html) lose money in the long run because they need to short volatility to earn the volatility risk premium
- If most individual HF styles are short volatility, then the entire HF industry is just a short put, see Jurek and Stafford (2015, JF)

How Do HFs Generate Performance? Do They Hedge?



❷ Replicate ptfs. by trading in the underlying securities obtaining the asset-based style factors, see Fung and Hsieh (2002, FAJ), in a "bottom-up" fashion, from the characteristics of securities to styles

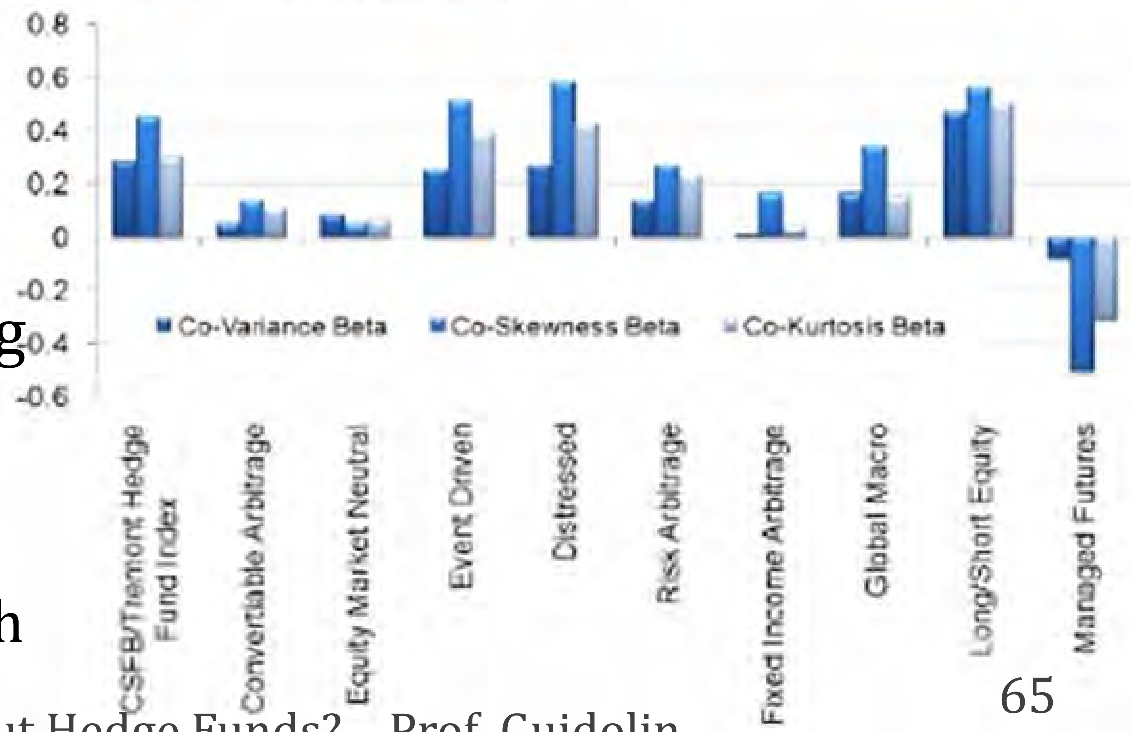
- While the strategies analyzed and the securities used to construct factors differ, the finding is that HFs have nonlinear risk exposure
  - E.g., Duarte, Longstaff, and Yu (2007, RFS) apply ABS approach to fixed income strategies to find that a range of them generate positive alpha, after accounting for bond and equity market risks and fees

How Do HFs Generate Performance? Do They Hedge?

  - They suggest that alpha comes from need of “intellectual capital”
- However, HF alpha is often significantly lower after accounting for the risks spanned by the benchmarks, transaction costs, and fees
- Researchers have typically augmented the multifactor models used for MFs with risk factors constructed from options to capture the significant nonlinearities in HF returns

$$r_t^i = \alpha^i + \beta^{1,i}\,\mathrm{SNPMRF}_t + \beta^{2,i}\,\mathrm{SCMLC}_t + \beta^{3,i}\,\mathrm{BD10RET}_t + \beta^{4,i}\,\mathrm{BAAMTSY}_t$$
$$+ \beta^{5,i}\,\mathrm{PTFSBD}_t + \beta^{6,i}\,\mathrm{PTFSFX}_t + \beta^{7,i}\,\mathrm{PTFSCOM}_t + \varepsilon_t^i,$$

- Agarwal, Bakshi, and Huij (2010) construct investable factors for higher-moments (volatility, skewness, and kurtosis) of equity risk using traded put and call options
  - HFs following equity-oriented strategies exhibit significant loadings on high moment factors



The Most Typical 7-Factor Model for Hedge Fund Returns

$$\begin{aligned} r_t^i &= \alpha^i + \beta^{1,i}\,\mathrm{SNPMRF}_t + \beta^{2,i}\,\mathrm{SCMLC}_t + \beta^{3,i}\,\mathrm{BD10RET}_t + \beta^{4,i}\,\mathrm{BAAMTSY}_t \\ &\quad + \beta^{5,i}\,\mathrm{PTFSBD}_t + \beta^{6,i}\,\mathrm{PTFSFX}_t + \beta^{7,i}\,\mathrm{PTFSCOM}_t + \varepsilon_t^i, \end{aligned}$$

- SNPMRF_t is S&P 500 index return minus the riskfree rate in month t;
- SCMLC_t is the Frank Russell 2000 index return minus the S&P 500 index return in month t;
- $\mathrm{BD10RET}_t$ reflects the return difference between the 10-year Treasury bond and the riskfree rate;
- $\mathrm{BAAMTSY}_t$ measures the credit spread defined as Moody's Baa bond return minus the 10-year Treasury bond return;

See https://www.financialencyclopedia.net/derivatives/l/lookback-straddle.html

- PTFSBD_t, PTFSFX_t, and $\mathrm{PTFSCOM}_t$ are returns of lookback straddles on bonds, currencies, and commodities respectively in month t.

Capture the idea that trend-following HFs find profit opportunities in large market moves in several asset classes

Fung, W., & Hsieh, D. A. (2004). Hedge fund benchmarks: A risk-based approach. *Financial Analysts Journal*, *60*(5), 65-80.

The Most Typical 7-Factor Model for Hedge Fund Returns

	Annualized Category Volatility	R Squared	Monthly Alpha	Bond Trend Following Factor	Currency Trend Following Factor	Commodity Trend Following Factor	Equity Market Factor	Size Spread Factor	Bond Market Factor	Credit Spread Factor
Annualized Factor Volatility	N/A	N/A	N/A	*51.4%*	*63.4%*	*50.1%*	*15.4%*	*11.8%*	*92.6%*	*76.9%*
Convertible Arbitrage	*7.3%*	0.58	0.332%*	-0.014*	-0.003	-0.010	0.114*	0.055	-0.020*	-0.061*
Dedicated Short Bias	*15.6%*	0.62	0.557%*	-0.022	0.000	-0.006	-0.722*	-0.410*	-0.013	-0.009
Emerging Markets	*14.2%*	0.52	0.181%	-0.041*	0.015	-0.006	0.468*	0.210*	-0.010	-0.047*
Equity Market Neutral	*3.3%*	0.24	0.333%*	-0.012*	0.002	-0.002	0.037*	0.054*	-0.001	-0.010*
Event Driven	*5.9%*	0.67	0.391%*	-0.020*	0.003	-0.008	0.167*	0.120*	-0.004	-0.029*
Fixed Income Arbitrage	*4.4%*	0.43	0.374%*	-0.010*	-0.007	0.000	0.009	0.019	-0.018*	-0.039*
Global Macro	*5.2%*	0.24	0.310%*	-0.008	0.024*	0.015*	0.100*	0.009	-0.015*	-0.017*
Long/Short Equity Hedge	*9.0%*	0.72	0.322%*	-0.003	0.009	0.003	0.388*	0.300*	-0.002	-0.014*
Managed Futures	*9.4%*	0.23	0.389%*	0.016	0.033*	0.048*	0.051	0.070	-0.019*	-0.003
Multi-Strategy	*5.2%*	0.43	0.339%*	-0.003	-0.003	0.006	0.156*	0.100*	-0.006	-0.016*
Fund of Funds	*6.0%*	0.46	0.147%	-0.011	0.010	0.007	0.185*	0.113*	-0.008*	-0.022*
All Single Manager Funds	*6.3%*	0.66	0.304%*	-0.008	0.010*	0.007	0.246*	0.161*	-0.008*	-0.022*
Correl. w/ Equity Factor	N/A	N/A	N/A	-0.23	-0.21	-0.17	1.00	0.08	0.22	-0.44

Conditional exposures of average hedge fund category returns to the seven Fung and Hsieh (2001) factors. The exposures for the 10 main Lipper TASS hedge fund categories, Funds of Funds, and All Single Manager Funds found in the Lipper TASS database are based on a multivariate regression with a constant term. Regression outputs that are significant with 95% confidence are indicated by "*" and shown in color (orange for negative and blue for positive). Monthly correlations between hedge fund returns and all seven factors are presented. This analysis spans January 1996 through December 2014.

How Do HFs Generate Performance: Higher Moments

- Proxies of tradable high order moments from S&P 500 options

$$\mathbb{M}_{2,t} \equiv e^{-r^f \tau}\, \mathbb{E}^{\mathbb{Q}}\left((R_{t,t+\tau} - \mathbb{M}_{1,t})^2 \right), \quad \text{Value of Second Central Return Moment Payoff} \; (1)$$

$$\mathbb{M}_{3,t} \equiv e^{-r^f \tau}\, \mathbb{E}^{\mathbb{Q}}\left((R_{t,t+\tau} - \mathbb{M}_{1,t})^3 \right), \quad \text{Value of Third Central Return Moment Payoff} \; (2)$$

$$\mathbb{M}_{4,t} \equiv e^{-r^f \tau}\, \mathbb{E}^{\mathbb{Q}}\left((R_{t,t+\tau} - \mathbb{M}_{1,t})^4 \right), \quad \text{Value of Fourth Central Return Moment Payoff} \; (3)$$

- $\mathbb{M}_{2,t}$, $\frac{\mathbb{M}_{3,t}}{(\mathbb{M}_{2,t})^{3/2}}$, and $\frac{\mathbb{M}_{4,t}}{(\mathbb{M}_{2,t})^{2}}$ are the arbitrage- free values of the claims to market variance, skewness, and kurtosis
- This can be derived from options, for instance:

$$\mathbb{M}_{2,t} = \int_{K>S_t} \omega^{vo}[K]\, C[K]\, dK + \int_{K<S_t} \omega^{vo}[K]\, P[K]\, dK, \quad \text{with} \quad \omega^{vo}[K] \equiv \frac{2\left(1 - \ln\left(\frac{K}{S_t}\right)\right)}{K^2}$$

- Five of ten styles – Long/Short Equity, Emerging Markets, Managed Futures, Global Macro, and Dedicated Short – exhibit extreme positive/negative higher-moment exposures
  - Consistent with higher moment risks more important to those fund styles that tend to apply their strategies to the equity markets
  - The alphas from multi-factor models that do not include these factors show significant spreads when funds are sorted

How Do HFs Generate Performance: Higher Moments

Higher-moment factors and individual Managed Futures

For each of the *329 hedge funds* in the Managed Futures category with at least 36 monthly observations, we perform the following regression and report the results in Panel D ($r_t^{mf,i}$ is excess returns of hedge fund i in the Managed Futures category):

$$
\begin{aligned}
r_t^{mf,i} &= \alpha^i + \beta^{1,i}\,\mathrm{SNPMRF}_t + \beta^{2,i}\,\mathrm{SCMLC}_t + \beta^{3,i}_{FH7}\,\mathrm{BD10RET}_t + \beta^{4,i}\,\mathrm{BAAMTSY}_t \\
&+ \beta^{5,i}\,\mathrm{PTFSBD}_t + \beta^{6,i}\,\mathrm{PTFSFX}_t + \beta^{7,i}\,\mathrm{PTFSCOM}_t + \underbrace{\beta^{8,i}F_t^{vo} + \beta^{9,i}F_t^{sk} + \beta^{10,i}F_t^{ku}}_{\text{higher}-\text{moment factors}} + \varepsilon_t^i
\end{aligned}
$$

where F_t^{vo}, F_t^{sk} and F_t^{ku} are volatility, skewness, and kurtosis factors

	Panel A: volatility factor						Panel B: skewness factor					
	coef. avg.	coef. > 0 # funds	coef. > 0 and $p<0.10$ # funds	avg.	coef. < 0 and $p<0.10$ # funds	avg.	coef. avg.	coef. > 0 # funds	coef. > 0 and $p<0.10$ # funds	avg.	coef. < 0 and $p<0.10$ # funds	avg.
Constant	0.001	170	45	0.018	46	-0.014	0.003	171	35	0.028	47	-0.016
snpmrf	0.040	164	61	0.574	40	-0.572	0.087	195	51	0.770	21	-0.581
scmlc	0.037	194	19	0.479	9	-0.590	0.029	183	18	0.464	12	-0.505
bd10ret	0.360	249	138	0.800	16	-0.896	0.400	248	148	0.842	14	-0.894
baamtsy	0.319	223	38	2.041	7	-3.403	0.275	210	33	1.892	7	-2.001
ptfsbd	0.030	224	95	0.098	17	-0.119	0.036	239	103	0.096	13	-0.107
ptfsfx	0.035	229	110	0.088	11	-0.070	0.038	239	114	0.092	10	-0.066
ptfscom	0.049	237	81	0.161	13	-0.106	0.047	234	78	0.160	10	-0.115
F^{vo}	0.006	229	81	0.020	14	-0.021						
F^{sk}							0.004	192	44	0.022	25	-0.016
$\bar{R}^2$	21.8%						21.3%					

	Panel C: kurtosis factor						Panel D: all three higher-moment factors together					
	coef. avg.	coef. > 0 # funds	coef. > 0 and $p<0.10$ # funds	avg.	coef. < 0 and $p<0.10$ # funds	avg.	coef. avg.	coef. > 0 # funds	coef. > 0 and $p<0.10$ # funds	avg.	coef. < 0 and $p<0.10$ # funds	avg.
Constant	0.010	201	74	0.050	44	-0.053	-0.023	129	15	0.106	51	-0.088
snpmrf	0.061	175	62	0.631	36	-0.581	0.050	176	46	0.809	28	-0.663
scmlc	0.035	192	19	0.479	8	-0.657	0.039	194	23	0.519	12	-0.527
bd10ret	0.359	250	139	0.799	17	-0.907	0.358	249	137	0.803	15	-0.894
baamtsy	0.315	213	38	1.970	6	-1.877	0.298	218	38	1.943	9	-1.838
ptfsbd	0.030	227	98	0.094	14	-0.124	0.030	229	97	0.094	14	-0.124
ptfsfx	0.037	237	117	0.089	8	-0.067	0.033	232	102	0.088	9	-0.068
ptfscom	0.046	234	80	0.156	12	-0.113	0.051	237	87	0.160	11	-0.107
F^{vo}							0.013	244	47	0.045	4	-0.027
F^{sk}							0.000	175	28	0.029	24	-0.036
F^{ku}	0.012	204	79	0.052	31	-0.063	-0.030	122	11	0.097	42	-0.112
$\bar{R}^2$	21.7%						22.2%					

How Do HFs Generate Performance? Do They Hedge?

- Bali, Brown, and Caglayan (2014, JFE) include measures of macroeconomic uncertainty
  - Conditional volatilities of default spread, short-term interest rate changes, aggregate dividend yield, equity market index, inflation rate
- Avramov, Barras and Kosowski (2013, JFQA) find individual HF predictability from VIX, default spread, and aggregate fund flows
  - They link that to business cycle conditions: HFs can trade in different markets and at different frequencies and this allows them to engage in dynamic strategies that depend on the states of the economy
  - They rely heavily on leverage, which might be curtailed in bad times

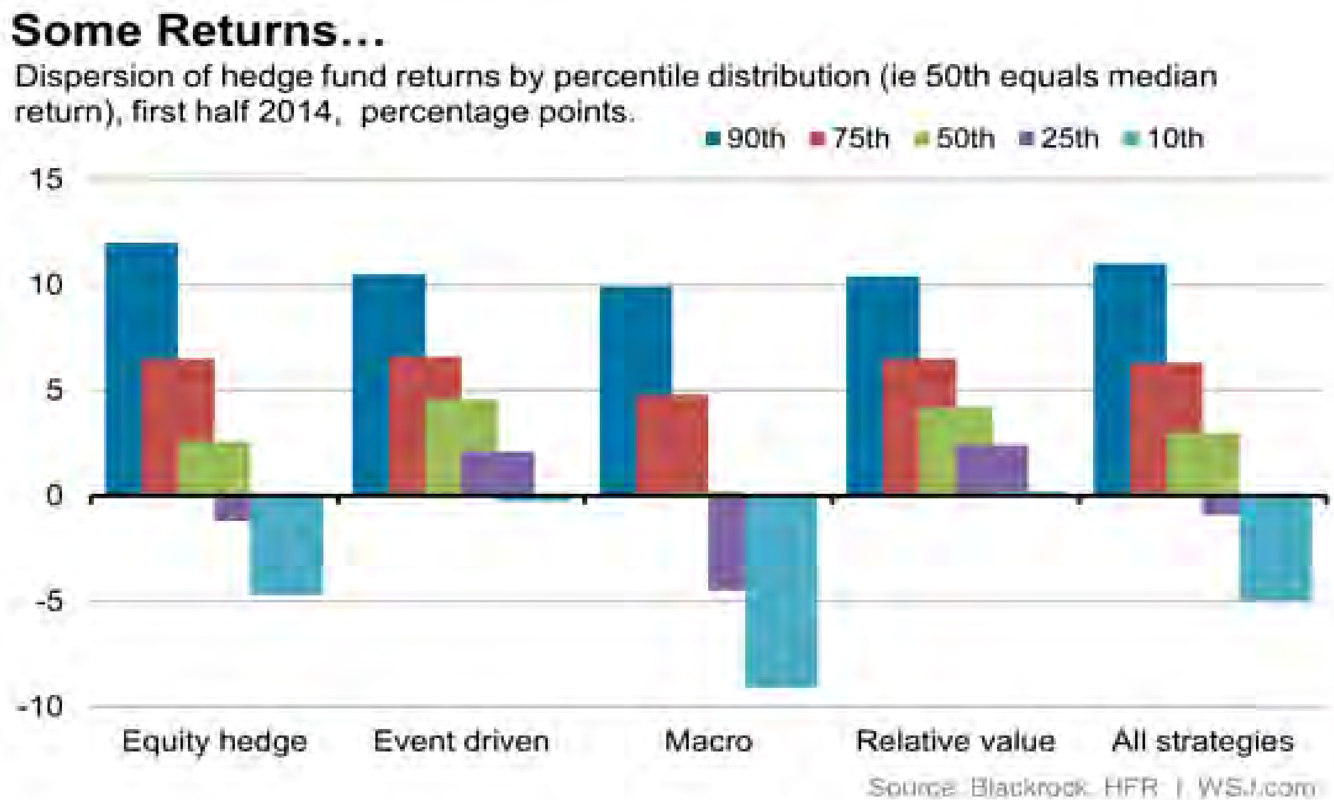
	Fung-Hsieh Alpha (Ann.)			Excess Return (Ann.)			Without 2008	
	$\hat{\alpha}$	$\hat{\sigma}_{\text{RES}}$	$\text{IR} = \hat{\alpha}/\hat{\sigma}_{\text{RES}}$	$\hat{\mu}$	$\hat{\sigma}_{\text{TOT}}$	$\text{SR} = \hat{\mu}/\hat{\sigma}_{\text{TOT}}$	IR	SR
Unconditional	3.8%	3.4%	1.1	4.9%	4.8%	1.0	2.4	1.7
Single-Predictor								
Default spread	5.3% (0.05)	3.9%	1.4 (0.19)	6.2% (0.10)	6.0%	1.0 (0.41)	2.1 (0.85)	1.6 (0.81)
Dividend yield	6.4% (0.00)	4.0%	1.6 (0.04)	7.2% (0.00)	6.1%	1.2 (0.12)	2.2 (0.81)	1.5 (0.89)
VIX	6.1% (0.00)	3.7%	1.6 (0.04)	7.1% (0.01)	5.0%	1.4 (0.03)	1.8 (0.95)	1.6 (0.85)
Aggregate flows	3.7% (0.63)	3.3%	1.1 (0.57)	5.0% (0.48)	5.2%	1.0 (0.68)	2.1 (0.88)	1.6 (0.80)
Multi-Predictor	4.4% (0.27)	3.9%	1.1 (0.48)	5.1% (0.41)	4.9%	1.0 (0.40)	1.4 (0.99)	1.3 (0.97)
Combination	5.5% (0.00)	3.0%	1.8 (0.00)	6.6% (0.00)	5.1%	1.3 (0.02)	2.7 (0.06)	1.9 (0.09)
Index (VW)	2.8% (0.86)	4.3%	0.6 (0.94)	3.8% (0.88)	5.5%	0.7 (0.91)	1.0 (1.00)	1.0 (1.00)
Index (EW)	3.2% (0.78)	3.7%	0.8 (0.86)	4.0% (0.83)	5.6%	0.7 (0.91)	1.3 (1.00)	1.0 (1.00)

How Do HFs Generate Performance? Do They Hedge?

- They examine whether conditional strategies based on very simple trading rules can successfully exploit predictability out of sample
- 63.3% of the funds have expected returns that vary across changing business conditions.
- The predictive patterns are strongly "asymmetric" because changes in the predictor value tend to drive individual fund returns in the same direction
- Another hypothesis is that HFs generate high returns because they are exposed to the volatility of volatility (VOV)
- Agarwal, Arisoy, and Naik (2018, JFE) show that HFs take state dependent bets and pursue dynamic strategies related to unexpected changes in economic conditions
  - They capture this uncertainty through a lookback straddle written on the VIX and refer to it as the VOV factor
  - Using HF returns at the index and fund levels, they find that most strategies have significantly negative exposures to VOV after controlling for the seven factors, including liquidity and correlation risk

How Do HFs Generate Performance? Do They Hedge?

- HF stratey returns are also nonlinear because unstable over time



- Meligkotsidou, Vrontos, and Vrontos (2009 JEF) point out that a OLS regression cannot consider the possibility that risk exposure may not be the same for all regions of HFs' return distributions
- They use quantile regressions and find that the variation of returns in the extreme quantiles is explained by a larger number of risk factors as compared to the middle quantiles

How Do HFs Generate Performance? Do They Hedge?

- Meligkotsidou and Vrontos (2008, BJF) use a Bayesian approach to detect the number and timing of structural breaks in HF returns

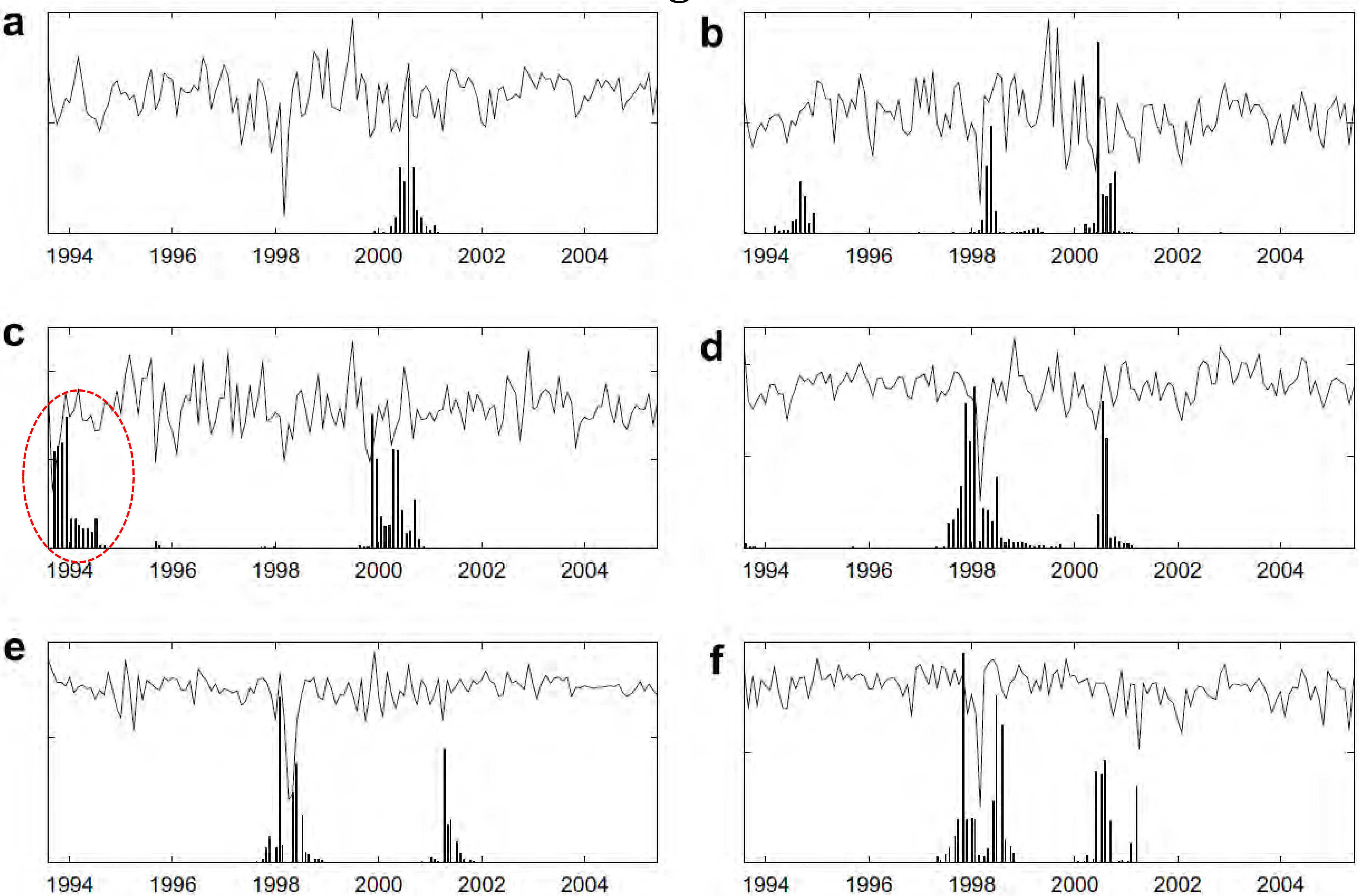
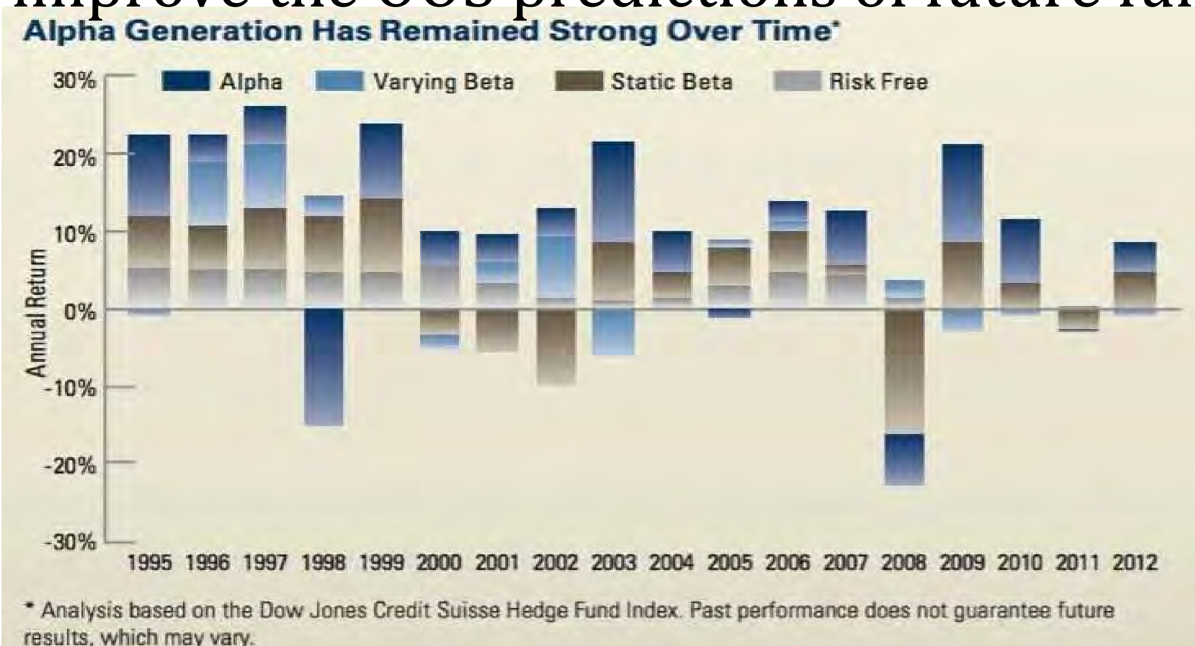


Fig. 3. Posterior distribution of the break-date(s) for the HFR indices: (a) emerging markets, (b) equity hedge, (c) macro, (d) distressed securities, (e) fixed income arbitrage and (f) merger arbitrage.

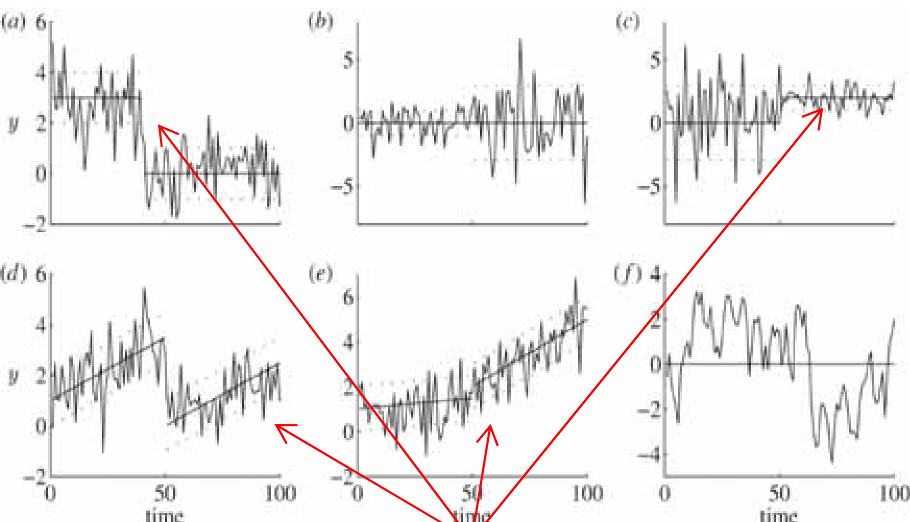
How Do HFs Generate Performance? Do They Hedge?

- Bollen and Whaley (2009, JF) compare several techniques for modeling time-varying risk exposures
  - They consider a constant-parameter rolling window, a stochastic autoregressive beta, and an optimal changepoint regression model
  - The optimal changepoint method is the most effective: under this method, betas are allowed to vary a discrete number of times and the points of change are selected concurrently with the other parameters
- They show that accounting for time-varying risk exposures has a substantial impact on the estimates of HFs' alphas and the new estimates improve the OOS predictions of future fund success.



How Do HFs Generate Performance? Do They Hedge?

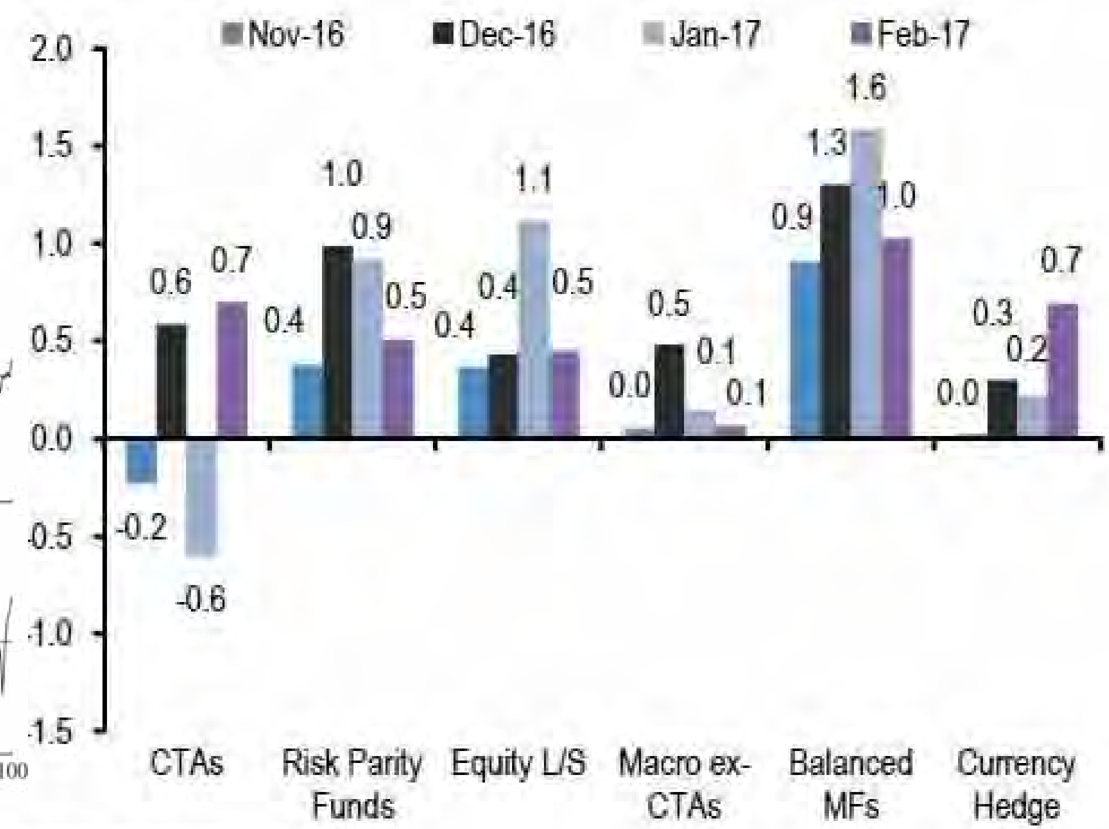
- Patton and Ramadorai (2013, JF) show that the use of high-frequency information in change-point regressions results in greater explanatory power and better identification



Change-point regressions

Figure 3: Betas of various types of investors

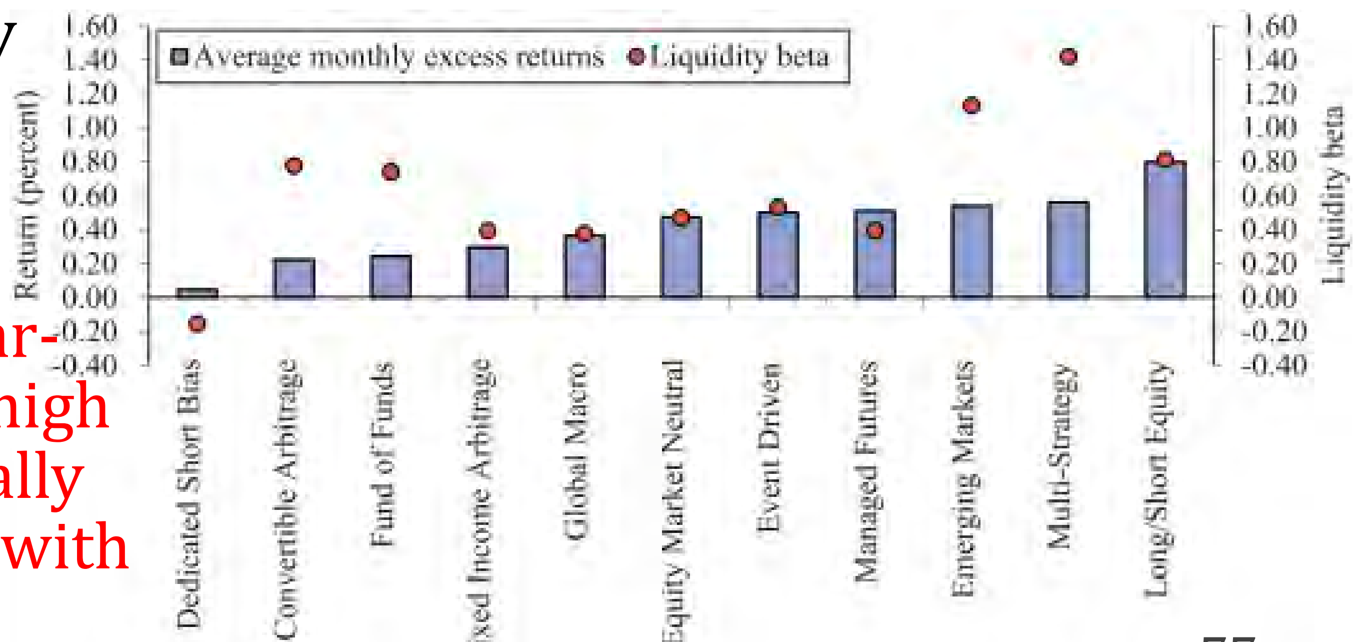
CTAs, Macro ex CTAs and Equity Long/Short hedge funds depict the ratio of their return vs. the return of the S&P500 index for each month. Currency Hedge funds depict the ratio of their return vs. the DXY Index return. Balanced Mutual funds depict the ratio of their return vs. the return of a 60:40 S&P500:Barclays US Agg Bond Index portfolio. Risk Parity funds depict the ratio of their return vs. the return of a 25:75 S&P500:Barclays US Agg Bond Index portfolio.



Source: Bloomberg, J.P. Morgan.

Liquidity Risk Exposure

- Several studies examine hedge funds' exposure to aggregate market-wide liquidity as an undiversifiable risk factor
- Sadka (2010, JFE) focus on this issue after noting that many funds with supposedly low exposure to market risk performed poorly during the quant crisis of August 2007
- He investigates whether liquidity risk is priced in HF returns by using the liquidity risk factors of Sadka (2006, JFE), Pastor and Stambaugh (2003, JPE), and Acharya and Pedersen (2005, JFE)
- HF with high exposure to aggregate liquidity risk outperform those with low exposure by 6% annually during normal months
- Yet, during periods where liquidity is scarce, these funds with high liquidity risk drastically underperform those with low exposure



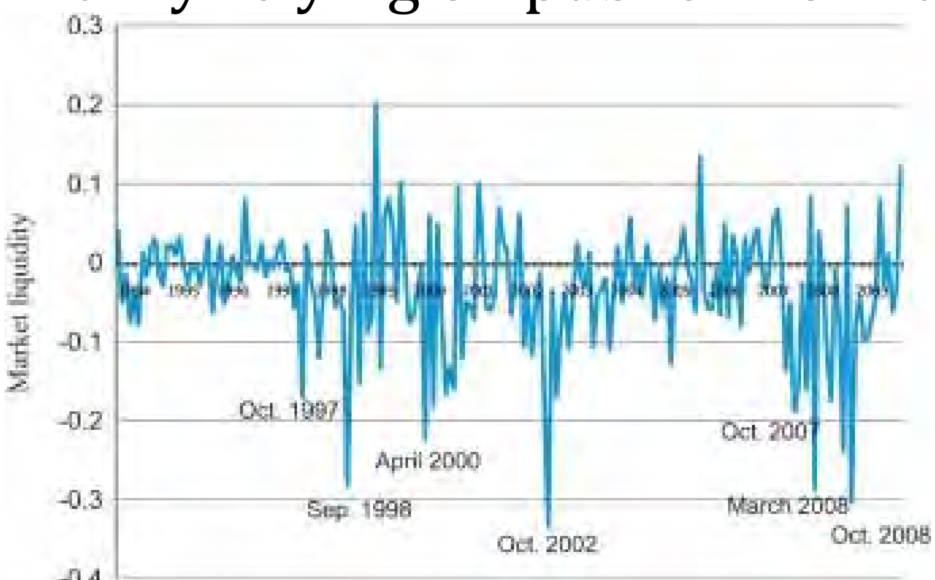
Liquidity Risk Exposure

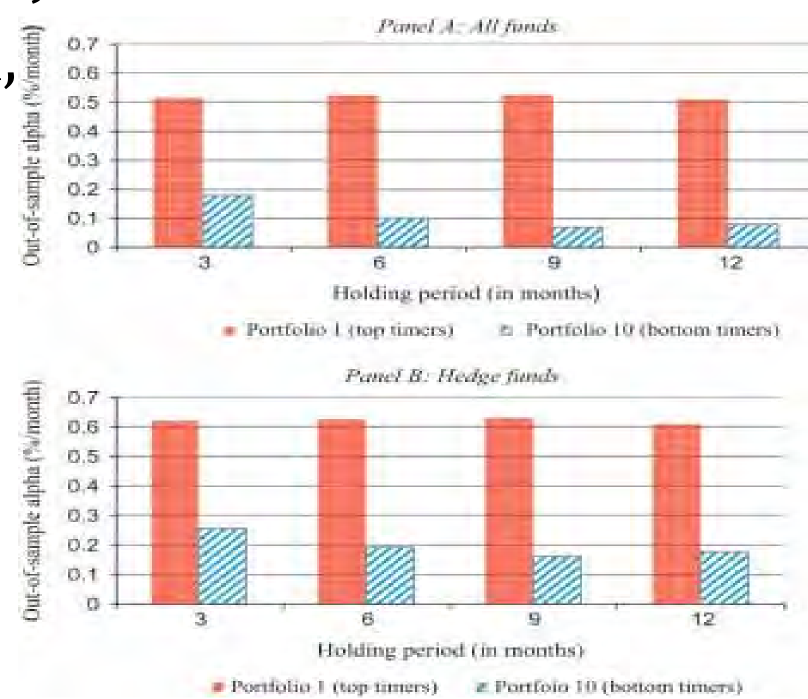
- The returns are independent of the liquidity a fund provides to its investors as measured by lockup and redemption notice periods
- Gibson and Wang (2013, JFQA) find that abnormal performance disappears after accounting for systematic liquidity risk
- Franzoni and Plazzi (2013) analyze both the time-series and cross-sectional determinants of HFs' liquidity provision to the market
- They find that liquidity provision decreases when funding and mkt conditions deteriorate
- A decline in HF fund trading predicts a decline in liquidity at the individual stock level
- Nagel (2012, RFS) argues that short-term reversal strategies are a form of liquidity provision and this is a short put

- Prices decline because other mkt participants wish to sell, and quant HFs provide liquidity by picking up the slack

Liquidity Risk Exposure

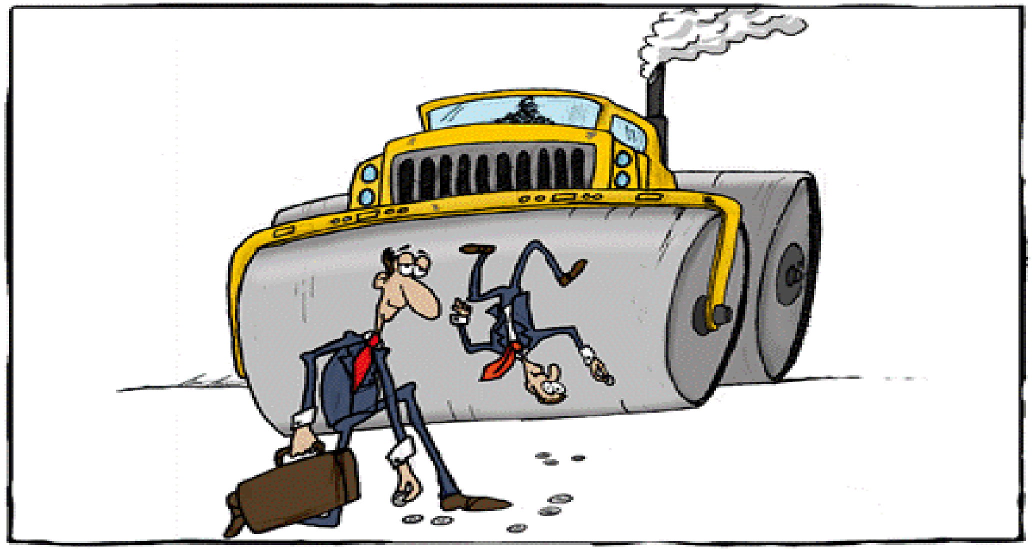
- Cao, Chen, Liang, and Lo (2013, JFE) test whether HFs can time market liquidity through adjusting their portfolios' market exposure as aggregate liquidity conditions change
- Using a large sample of hedge funds, they strong evidence of liquidity timing, while a bootstrap analysis suggests that top-ranked liquidity timers cannot be attributed to pure luck
- In out-of-sample tests, top liquidity timers outperform bottom timers by 4.0–5.5% annually on a risk-adjusted basis
- Liquidity timing is not liquidity reaction, primarily relying on public information





Tail Risk Exposure

- HFs are often described as pursuing trading strategies that generate small positive returns most of the time before incurring a big loss akin to “picking up pennies in front of a steam roller” or “selling earthquake insurance”

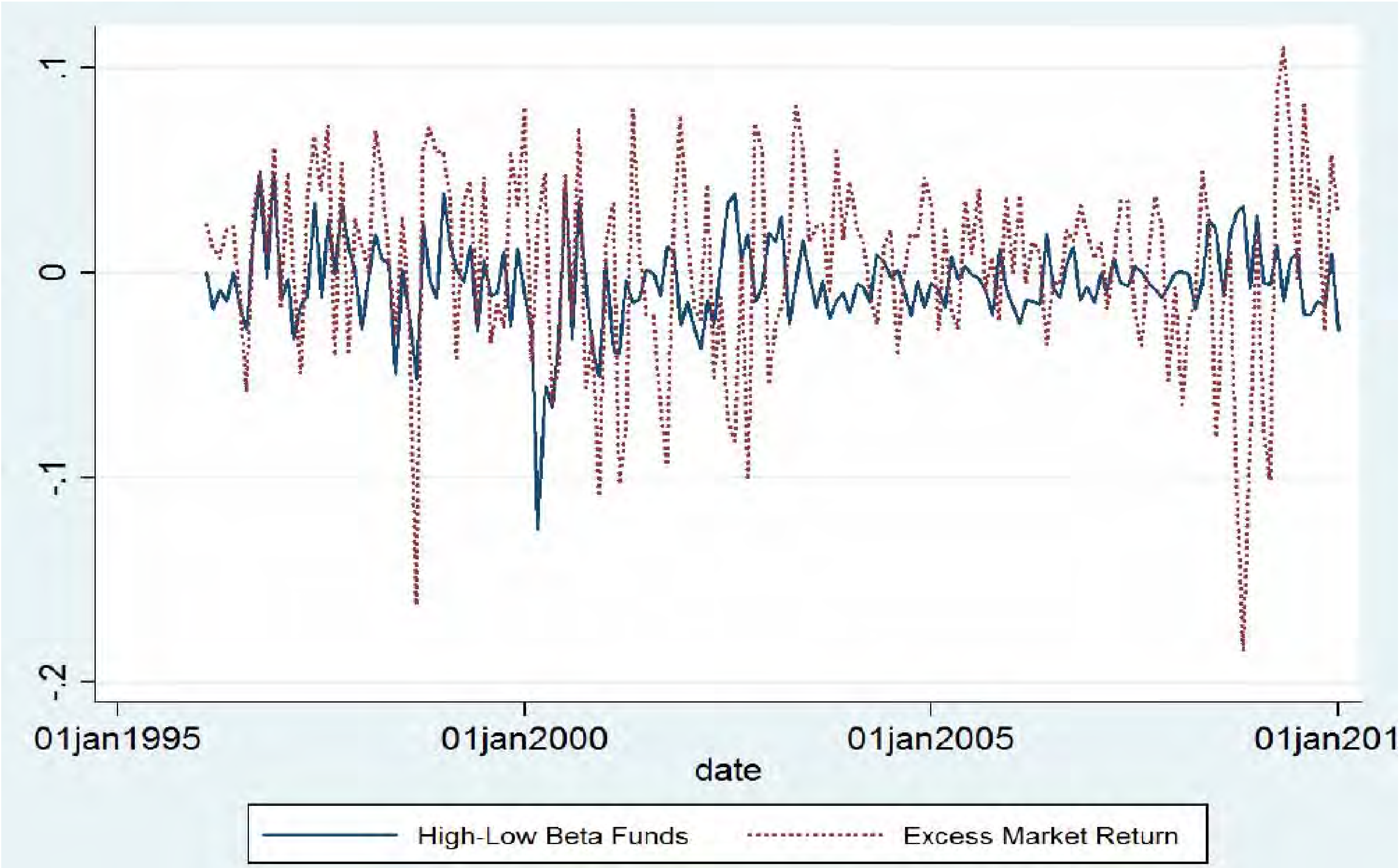


- HFs are therefore likely to be exposed to substantial tail risk, i.e., they can incur substantial losses in times when investors’ marginal utility is very high
- If HFs provide crash insurance, they earn premia in normal times but severe losses in tail events
- Adding leverage to this kind of strategy can further enhance a fund's performance, as long as the hazard does not materialize
- When a large disaster strikes, payouts on the crash insurance that it has written can quickly drive a fund's capital to zero
- Studies capture tail risk using measures such as Expected Shortfall (ES) and Tail Risk (TR) i.e., a HF’s st. dev. conditional return below VaR

Tail Risk Exposure

- Several papers examine whether the downside risk in HFs is priced, i.e., if the funds with higher down-side risk ⇒ higher returns
- Bali, Gokcan, and Liang (2007, JBF) examine the relation between HFs' returns and VaR and find that HFs with high exposure to VaR outperform other live funds with lower VaR by approximately 9%
  - However, they find that the relation between VaR and returns is negative within the sample of dead funds consistent with fund's extremely poor returns upon realization of the tail event
- Jiang and Kelly (2012) develop a tail measure based on the mean and variation of the lowest 5% of all returns each month, shocks to the tail risk factor result in lower contemporaneous returns
- A one st. dev. increase in aggregate tail risk ⇒ decline of 2.88% in the value of HF ptf, after controlling for the loadings of HF returns on Fung and Hsieh's (2004, FAJ) seven-factor model

Tail Risk Exposure



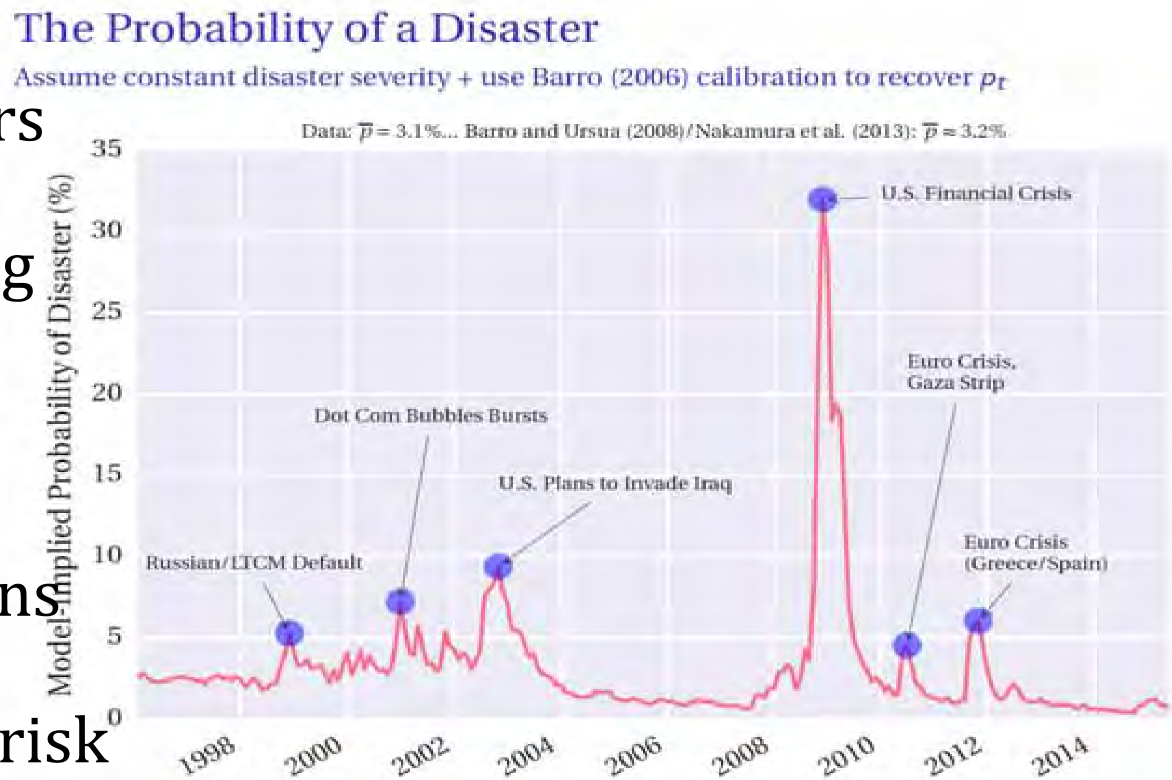
Return Spread between Hedge Funds with High and Low Tail Risk Beta. This figure plots the return time series (solid blue) for a hedge fund portfolio that is long funds in the highest tail risk beta quintile and short funds in the lowest quintile. In each month, we form five tail risk beta portfolios where betas are estimated in a regression of the funds' excess return on the market excess return and tail risk shocks in the past 24 months. Funds with high (low) tail risk betas tend to hedge against (load on) tail risk. We also plot the contemporaneous aggregate stock market return in excess of the risk-free rate (dotted red).

Tail Risk Exposure

- This negative exposure emerges across 9 out of 10 investment styles, and is statistically significant for 6 of the 10
- In normal times, funds exposed to the tail factor are compensated with approximately 6% higher annual returns, so that exposure to this tail risk factor is akin to selling disaster insurance
  - This large spread is unattenuated by adjusting for Fung-Hsieh factors
  - These results imply a need to account for tail risk exposure in evaluating managers' performance: alpha may not represent skill, but merely the willingness to sell "earthquake insurance"
- The funds that are most susceptible to tail risk are those that are young, have a "high water mark" provision, have long lock-up periods, do not employ leverage, and little "skin in the game"
- Gao, Gao, and Song (2018, RFS) construct a measure of expectations about occurrence of a rare disaster to proxy for the risk faced by HFs providing extreme event insurance
- They construct a rare disaster index (RIX) based on implied vols of out-of-the-money puts on various indices from sectors including banking, precious metals, housing, oil service, and utilities

Tail Risk Exposure

- Gao, Gao, and Song (2018, RFS) find that the providers of this insurance earn higher returns, even during recessions



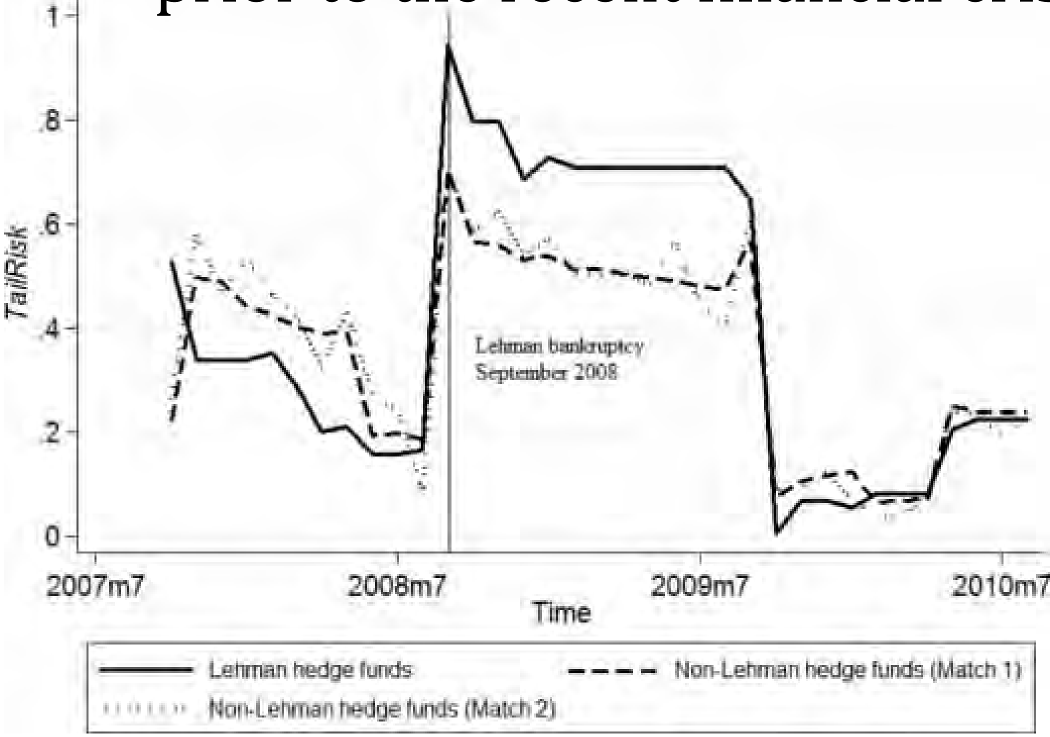
- A potential reason for this difference is that their measure is based on options and can capture ex-ante expectations of future tail risk
- Agarwal, Ruenzi, and Weigert (2017, JFE) propose a different non-parametric measure of tail risk derived from the lower tail dependence of HF and market returns, scaled by the ratio of their ES

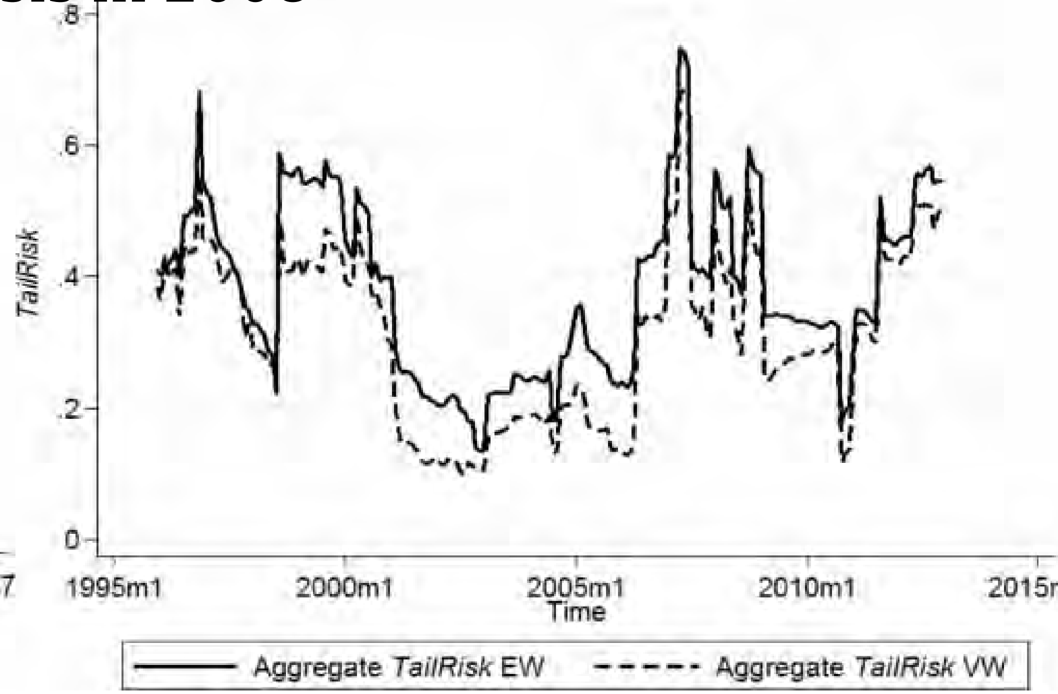
$$TailRisk = \lim_{q \to 0} P\left(r_i \le F_i^{-1}(q) \,|\, r_m \le F_m^{-1}(q)\right) \frac{|ES_{r_i}|}{|ES_{r_m}|}$$

- Their tail risk measure can explain both the cross-sectional and time-series variation in fund returns

Tail Risk Exposure

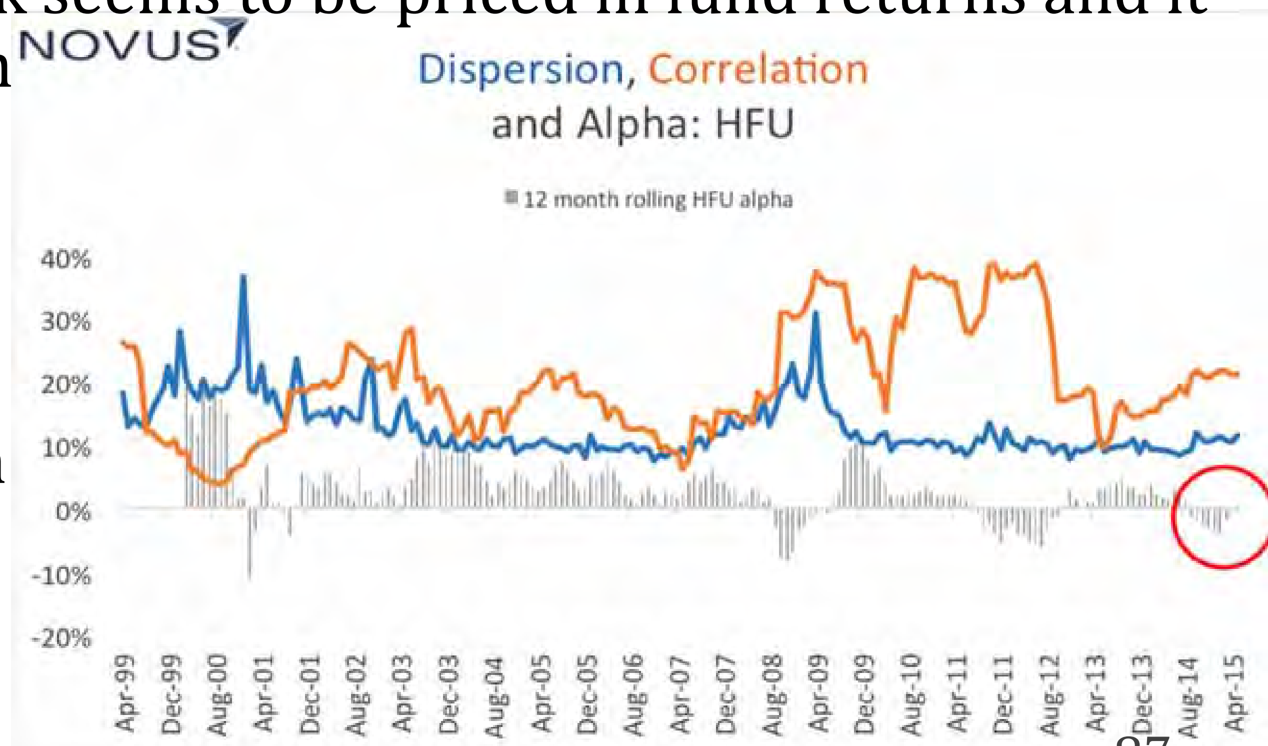
- Using the equity positions of HFs, they provide evidence of a direct link between tail risk and their investments in tail-sensitive stocks
- The spread between the portfolios of HFs with the highest and the lowest past tail risk amounts to 4.7% per annum after controlling for common risk factors à la Fung and Hsieh (2004, FAJ)
- Because funds can mitigate the tail risk by taking long positions in put options, they observe that funds time tail risk by reducing it prior to the recent financial crisis in 2008





Tail and Correlation Risk Exposure

- Buraschi, Kosowski, and Trojani (2014, RFS) construct a measure of correlation risk based on the prices of OTC correlation swaps
  - Correlation swaps pay the difference between observed correlations and the correlation swap rate
  - Market prices of swaps allows to accurately price correlation risk
- They find that the HF industry as a whole is exposed to significant correlation risk, particularly in the case of long-short equity funds
- Negative correlation risk seems to be priced in fund returns and it is highly correlated with tail risk
- Funds with high corre-lation risk tend to do poorly in periods of economic distress when correlations between assets increase

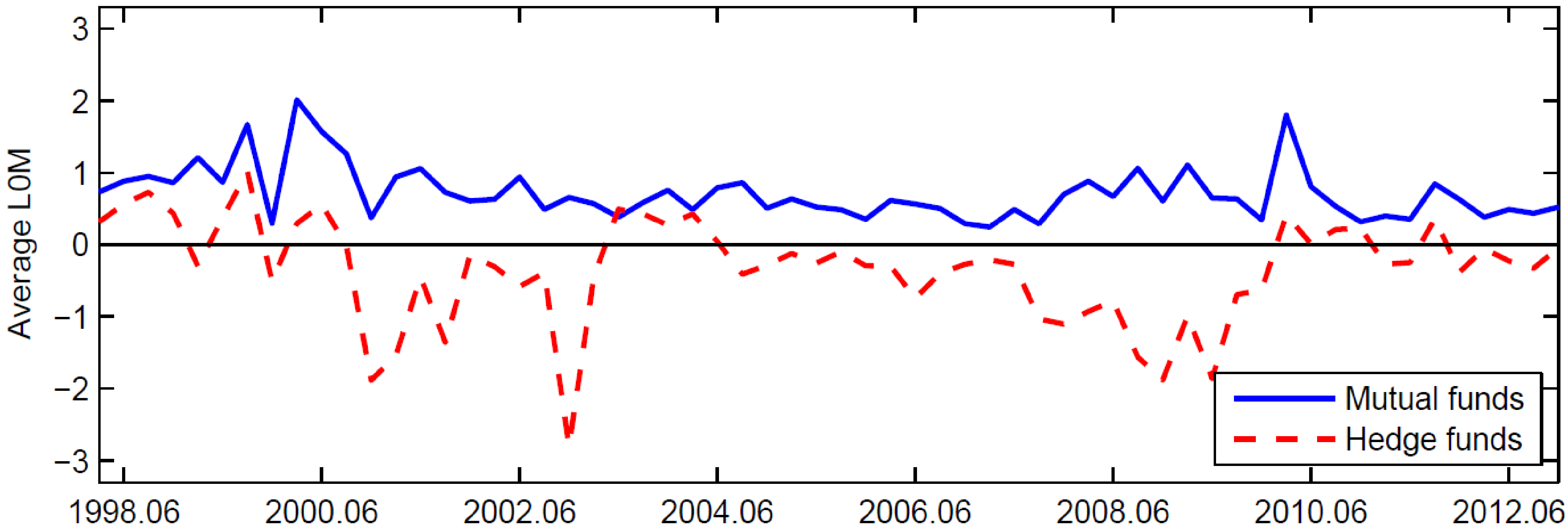


Hedge Funds and Momentum

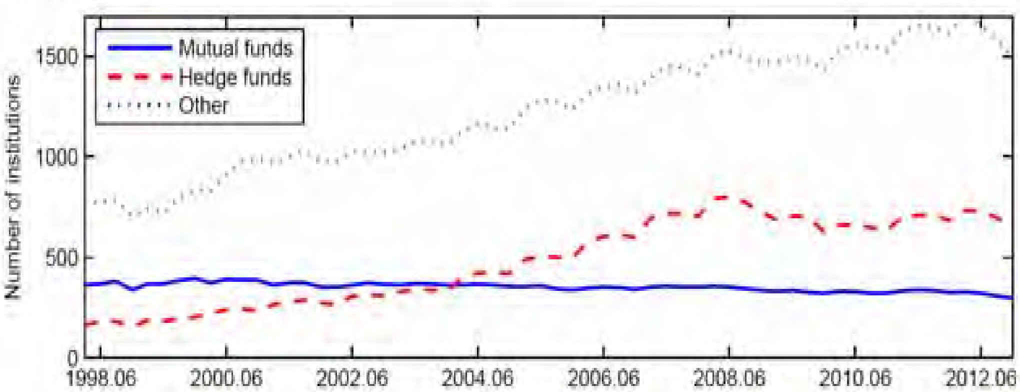
- Grinblatt, Jostova, Lubomir, and Philipov (2016) document that HF managers are not momentum investors: for almost 2/3 the managers, stock purchases tend to be contrarian, although their tendency to sell recent winners is less pronounced
- The style of contrarian HFs is persistent and highly profitable
  - 80% of contrarian HFs in first half of sample are also in the second
  - Despite the documented profitability of momentum, contrarian HFs exhibit top performance: their quarterly portfolio rebalancing generates a significantly positive alpha, outperforming both MFs and the approximately 1/3 of HFs that follow momentum strategies
- 2/3 of MF managers follow momentum strategies; in contrast to HFs, momentum MFs outperform contrarian MFs
  - HFs' success as contrarian investors comes at the expense of MFs: the highest alpha to contrarian HF buys comes from stocks that MFs sell
  - Consistent with Chen, Hanson, Hong, and Stein (2008) show that HF returns are higher in months when the MF sector is in distress
  - MFs cater to retail investors' demand for `fashionable' stocks, which may provide trading opportunities for contrarian HFs

Hedge Funds and Momentum

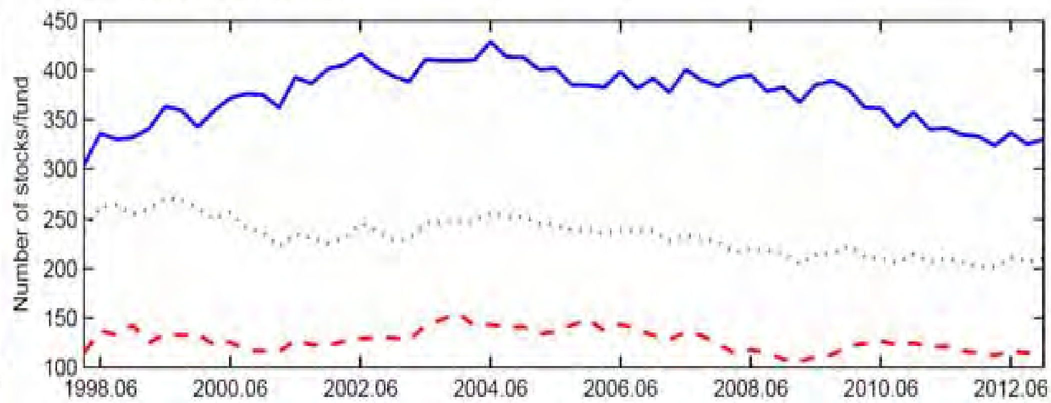
Plot A: Momentum measures (L0M) for mutual and hedge funds



Plot A: Number of funds



lot B: Number of stocks per fund



Are Hedge Funds a Distinct Asset Class?

- One reason for the growth of the industry is investors' desire for an asset class that has low correlation with systematic risk factors
- Several studies have examined the relation between HFs' exposure to systematic risk factors and their performance
- Titman and Tiu (2011, RFS) examine the relation between past R^2 and future fund performance, as the low R^2 funds have higher Sharpe ratios, higher information ratios, higher alphas, and higher manipulation-proof performance measures than the high R^2 funds

As skill (measured by 4-factor alpha) decreases, factor exposure (as measured by r-squared and individual factor coefficients) increases.

Figure 8. Median characteristics of 4-factor alpha quintiles as of December 2014

			Median Multivariate Coefficient			
4-Factor Alpha Quintile	Median Annualized 4-Factor Alpha	Median R^2	Beta to MSCI World Index	Small - Large	Value - Growth	Winners - Losers
(Highest 4F Alpha) 5	9.14%	0.31	0.30	0.19	0.02	0.05
4	4.44%	0.35	0.29	0.16	0.02	0.04
3	2.07%	0.48	0.34	0.16	-0.08	0.01
2	-0.80%	0.54	0.50	0.25	-0.09	-0.02
(Lowest 4F Alpha) 1	-7.10%	0.54	0.72	0.49	-0.32	-0.28

Note: All data based on the trailing 60 months as of December 2014. Funds are sorted into 4-factor alpha quintiles based on regressing their net returns (less the risk-free rate) against excess returns to the equity market (MSCI World Index – interpolated 1-month return on BofA ML 3-month Treasury Index), Value (MSCI World Value Index - MSCI World Growth Index), Size (MSCI World Small Cap Index - MSCI World Large Cap Index), and Momentum (float-weighted return of top half of price performers in the MSCI World Index from previous 12 months - float-weighted return of bottom half of price performers in the MSCI World Index from previous 12 months). Median statistics are then calculated for all funds in each quintile over the same time period (trailing 60 months as of December 2014). All hedge funds included are classified as "Equity Hedge" funds by HFRI and have continuous returns for the 60 months ended December 2014. Source: HFRI, MSCI, FactSet.

Are Hedge Funds a Distinct Asset Class?

Relative measures of 4-factor alpha and R-squared have significant implications for subsequent returns.

Figure 5. Annualized average 25th month peer-relative subsequent return

4- Factor Alpha$_{t-1}$	R^2_{t-1}: Low	2	3	4	High	**All**	**Low-High**
Low	-2.27%	-3.45%	-2.85%	-2.41%	-4.63%	**-2.94%**	**2.36%**
2	-2.35%	-2.79%	-1.79%	-0.44%	-1.22%	**-1.51%**	**-1.13%**
3	-1.84%	-1.17%	-0.92%	0.43%	-0.24%	**-0.74%**	**-1.60%**
4	0.22%	0.47%	-0.11%	0.72%	0.68%	**0.09%**	**-0.46%**
High	4.81%	4.46%	6.37%	4.46%	4.41%	**4.95%**	**0.39%**
All	**0.20%**	**0.04%**	**0.29%**	**0.31%**	**-0.92%**	**0.00%**	**1.12%**
High-Low	**7.08%**	**7.92%**	**9.23%**	**6.87%**	**9.04%**	**7.89%**	

*Note: On a rolling monthly basis, funds are sorted simultaneously into r-squared quintiles and 4-factor alpha quintiles based on regressing their net returns (less the risk-free rate) against excess returns to the equity market (MSCI World Index – interpolated 1-month return on BofA ML 3-month Treasury Index), Value (MSCI World Value Index - MSCI World Growth Index), Size (MSCI World Small Cap Index - MSCI World Large Cap Index), and Momentum (float-weighted return of top half of price performers in MSCI World Index from previous 12 months - float-weighted return of bottom half of price performers in MSCI World Index from previous 12 months). 25th month returns are then adjusted by subtracting out the universe-wide peer median monthly return, and then a cross-fund, cross-time average is taken across all data points in the basket and annualized (monthly average return * 12). Sample period includes test months from 1/2000 to 12/2014 (180 months). All hedge funds, open or closed, included are classified as "Equity Hedge" funds by HFRI and have at least 25 months of continuous returns. Source: HFRI, MSCI, FactSet.*

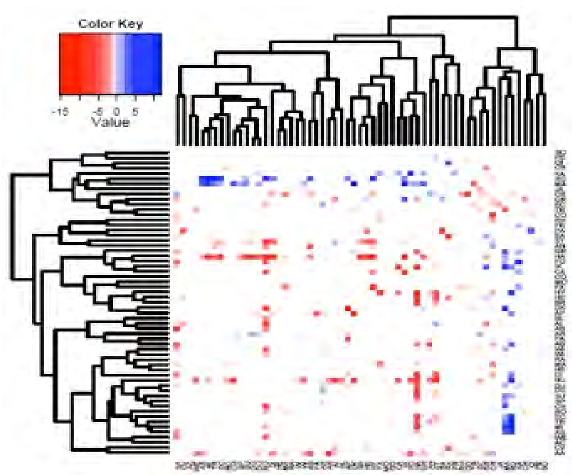
4-factor alpha is a proxy for skill while the R-squared to the 4 factors is a proxy for factor dependence.

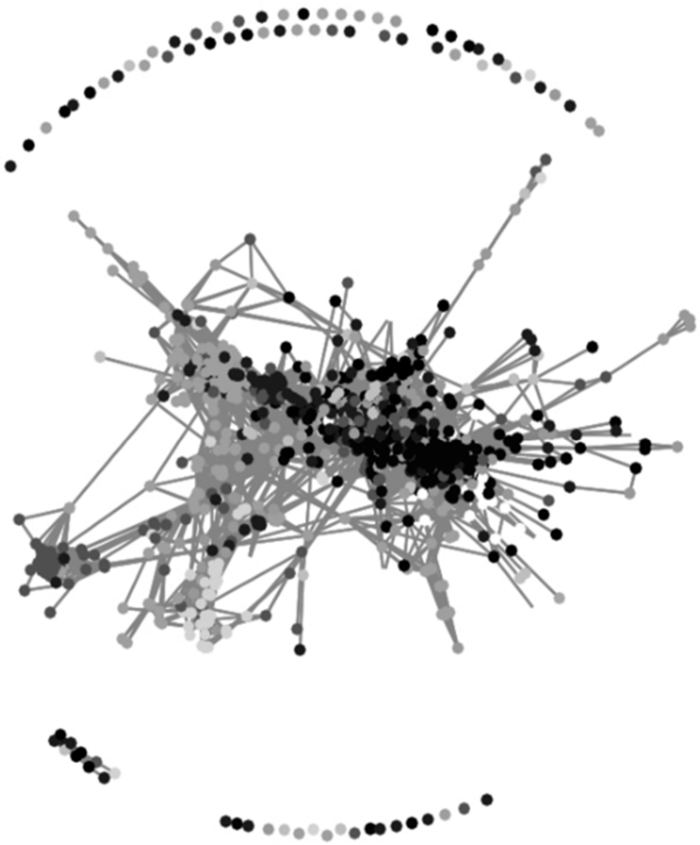
Figure 2. Hedge fund classification framework

		R^2 to 4 Factors (Factor Dependence): Low	High
4-Factor Alpha (Skill)	Low	*"Honest Loser"*	*"Smoke and Mirrors"*
	High	*"Pure Skill"*	*"Polluted Skill"*

Are Hedge Funds a Distinct Asset Class?

- Yet, Bollen (2013, JFQA) compares the performance of funds with zero R^2 to funds with higher R^2 and concludes that differences in per-formance (in favor of zero-R^2) is due to an omitted risk factor
- Low R^2 funds have a higher probability of failure and are exposed to significant downside risk
- Sun, Wang, and Zheng (2012, RFS) create correlation clusters
- Funds with returns that are less correlated to their clusters outperform those whose returns are more correlated
- Difference btw. sub-sequent 1Y returns of top and bottom quintiles of funds sorted by distinctiveness index is 6%





Cluster plot of the TASS hedge fund database, 1995, with funds positioned relative to one another according to similarity in strategic focus and investor approach attributes

Are Hedge Funds a Distinct Asset Class?

- The benefit of including HFs in diversified ptfs are illustrated here

Measure	Portfolio I	Portfolio II	Portfolio III	Portfolio IV
Annualized return	9.64%	10.43%	7.86%	9.01%
Annualized std. dev.	7.94%	7.09%	8.29%	7.28%
Sharpe ratio	0.67	0.87	0.43	0.65
Minimum monthly return	–6.25%	–6.39%	–5.61%	–5.87%
Correlation w/HFCI	0.59	0.69	0.51	0.62

- The Sharpe ratio of a balanced ptf with US stocks and bonds (0.67, Portfolio I) increases to 0.87 when HFs are added (Portfolio II)
- Similarly, when HFs are added to a balanced portfolio of world equities and bonds (Portfolio III), the Sharpe ratio increases significantly from 0.43 to 0.65 (Portfolio IV)
- Although inclusion of HFs ⇒ mean–variance improvement, Amin and Kat (2003, JFQA) have shown that including hedge funds can also frequently lead to lower skewness and higher kurtosis