28E35700 Alternative Investments

Hedge Funds: Empirical Facts

Spring 2024

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Agenda

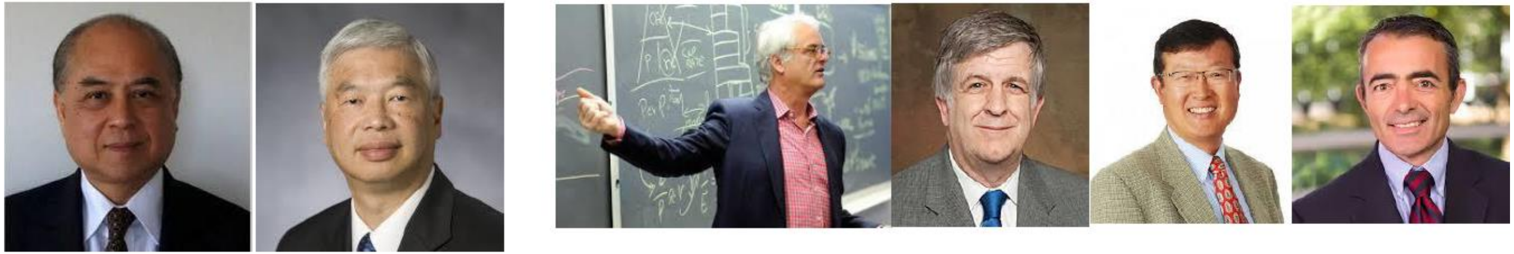
- **Hedge fund data**
  - Commercial data vendors vs confidential regulatory data
- **Aggregate Hedge Fund Performance**
  - Alphas, Betas and Fees
  - Declining Performance
  - Listed vs Non-Listed funds
- **Performance Persistence**
  - Bayesian Alphas vs Relative Alphas
  - Out-of-sample, Data availability and Frictions (Share restrictions)
- **The Performance of the ”Secretive” Non-Listed Funds**

References

1. Joenväärä, Kauppila, Kosowski and Tolonen (2021, CFR). Hedge Fund Performance: Are Stylized Facts Sensitive to Which Database One Uses?
2. Brown, G., Joenväärä, J., Lundblad, C., and Maxwell, R. (2024, WP) Optimal Hedge Fund Portfolio Selection
3. Bollen N., Joenväärä J. and Kauppila M. (2021, FAJ). Hedge Fund Performance: End of an Era.
4. Joenväärä J., Kosowski R. and Tolonen P. (2019, JFQA). The Effect of Investment Constraints on Fund Investor Performance.
5. Bollen N., Joenväärä J. and Kauppila M. (2024, CFR). Decreasing Returns to Scale has Eroded Hedge Fund Performance Persistence.
6. Barth, Joenväärä, Kauppila, and Wermers (2024, R&R RFS). Hedge Fund Industry Is Bigger (and Has Performed Better) Than You Think.

Hedge Fund Researchers

Bill Fung & David Hsieh   Will Goeztmann , Stephen Brown, Bing Liang, Nick Bollen

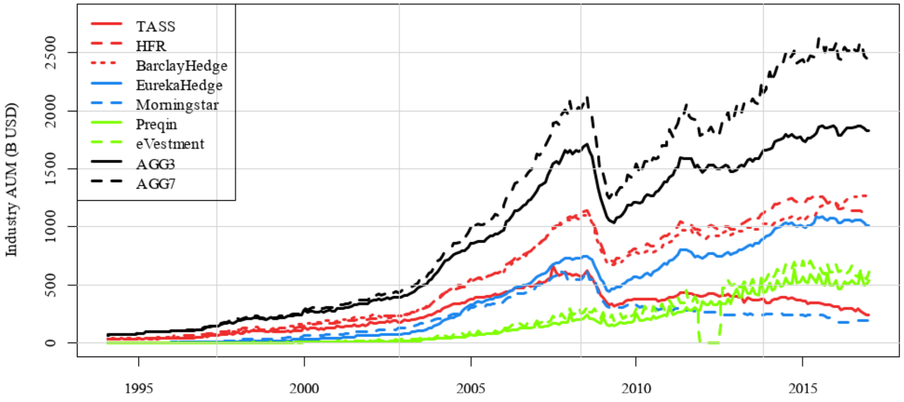


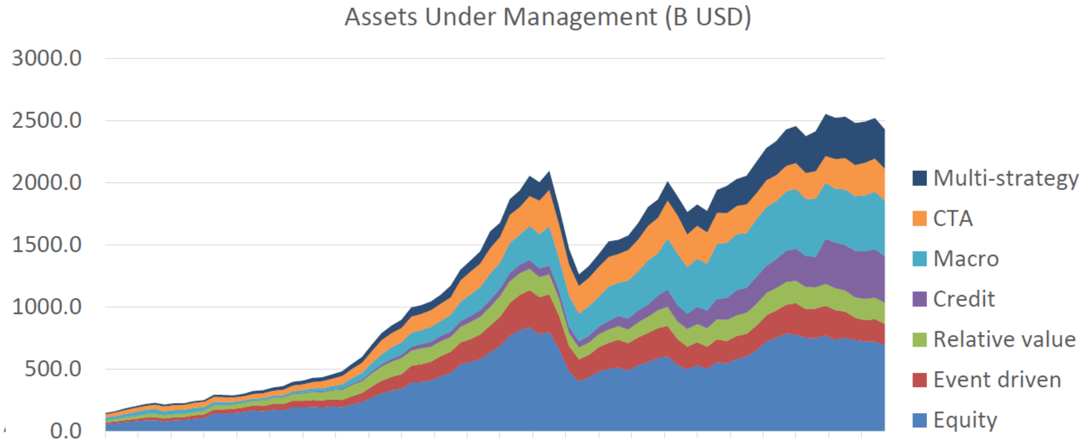
Melvyn Teo, Vikas Agarwal, Robert Kosowski, George Aragon, Cristian Tiu, Russ Wermers

HF Population

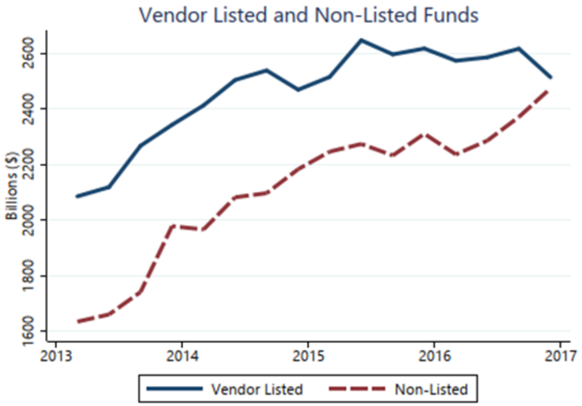
$5T in Total (+ $2.5T from Form PF Funds)

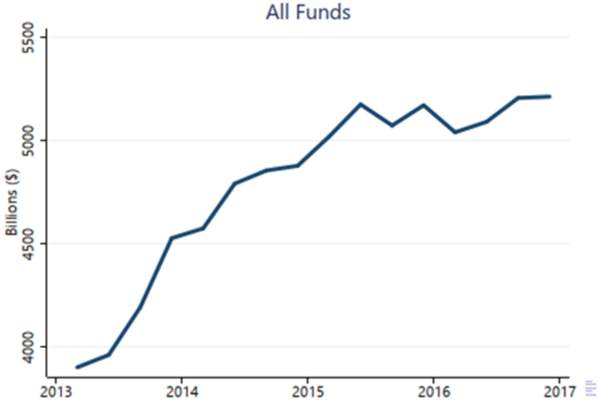
$2.5T in Commercial Databases ($0.5T are UCITS HFs)





Suorce: Joenväärä, Kauppila, Kosowski and Tolonen (2021)





Suorce: Barth, Joenväärä, Kauppila and Wermers (2022)

Why report to a commercial database?

- **Attract capital, build reputation**
  - But HFs will wait for a good track record before starting to report → backfill bias
  - HFs with poor performance stop reporting → survivorship bias
- **Many of the best HFs do not report to databases, e.g., Renaissance Medallion, Caxton, DE Shaw, SAC, Citadel, etc.**
  - Thus, HF databases do not contain the worst left-hand tail or the best right-hand tail and are biased toward mediocrity.
- **Role of consultants:**
  - Albourne Partners, Aksia, Blackstone, Cambridge Associates, HSBC,…
  - Provide information on funds to most sophisticated clients

Aggregate Performance

Critical Finance Review, 2021, 10: 271–327

Hedge Fund Performance: Are Stylized Facts Sensitive to Which Database One Uses?

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[2]*University of Oulu, Finland; mikko.kauppila@oulu.fi*
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[4]*University of Oulu, Finland; pekka.tolonen@oulu.fi*

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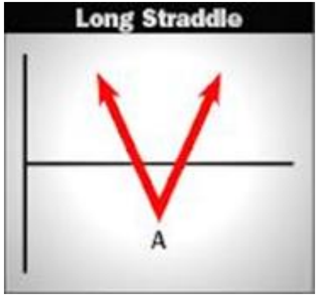
Fung and Hsieh (*FAJ* 2004) 7-Factor Alpha

1. **S&P 500 (SP)**
2. **Russell 2000 – S&P 500 (SCLC)**

3. **Trend follower: Currency (PTFSFX)**
4. **Trend follower: Bonds (PTFSBD)**
5. **Trend follower: Commodity (PTFSFX)**

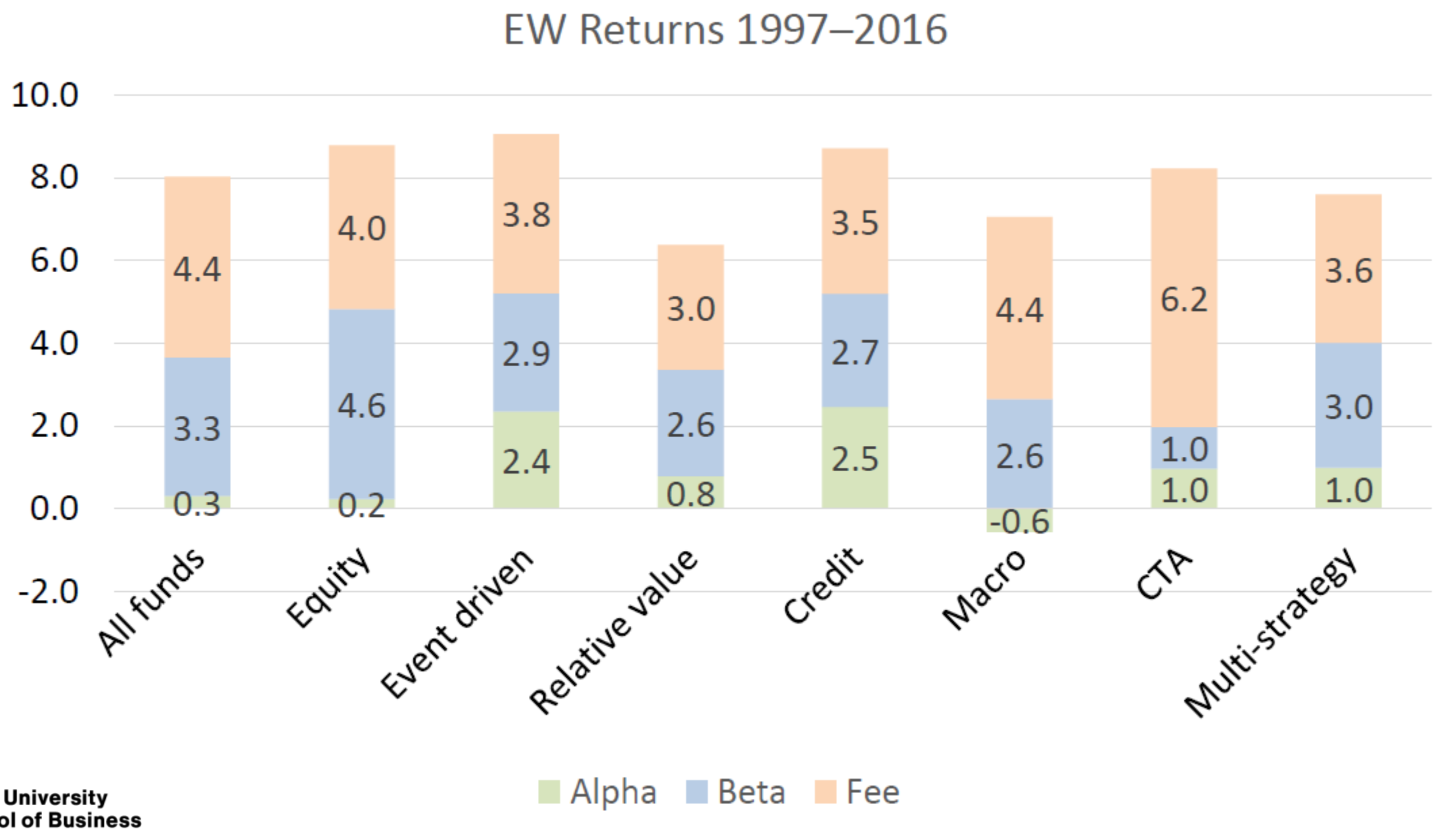
Returns of "look-back" straddles that capture payoffs related to the maximum or minimum values of underlying variables



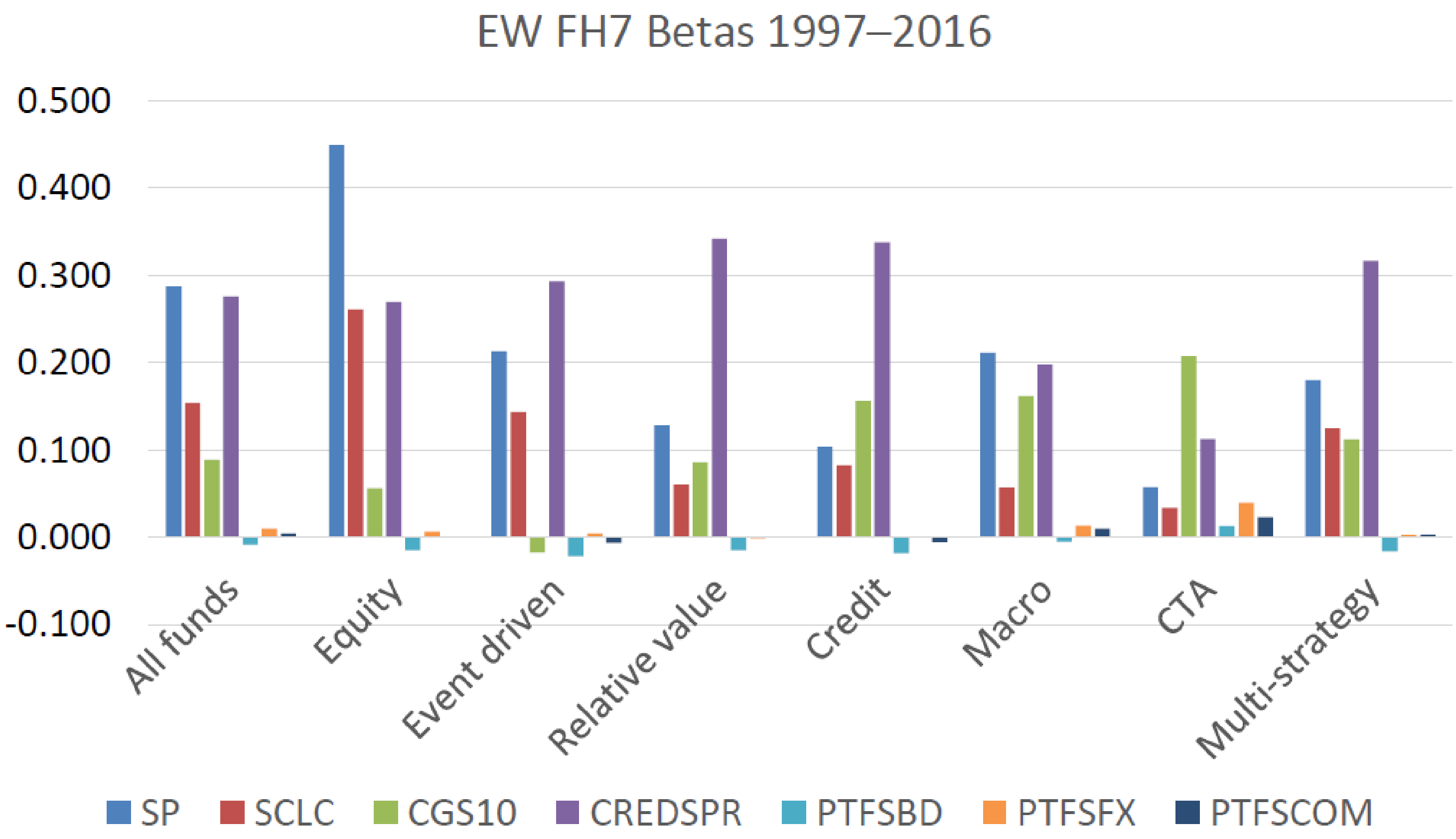
6. **Change in 10-year Treasury Yield (CGS10)**
7. **Change in Credit Spread = Baa yield - 10-year Treasury Yield (CREDSPR)**

Hsieh's Hedge Fund Data Library - Hedge Fund Risk Factors (duke.edu)

Fung-Hsieh Alphas, Betas and Fees



Fung-Hsieh Factor Loadings

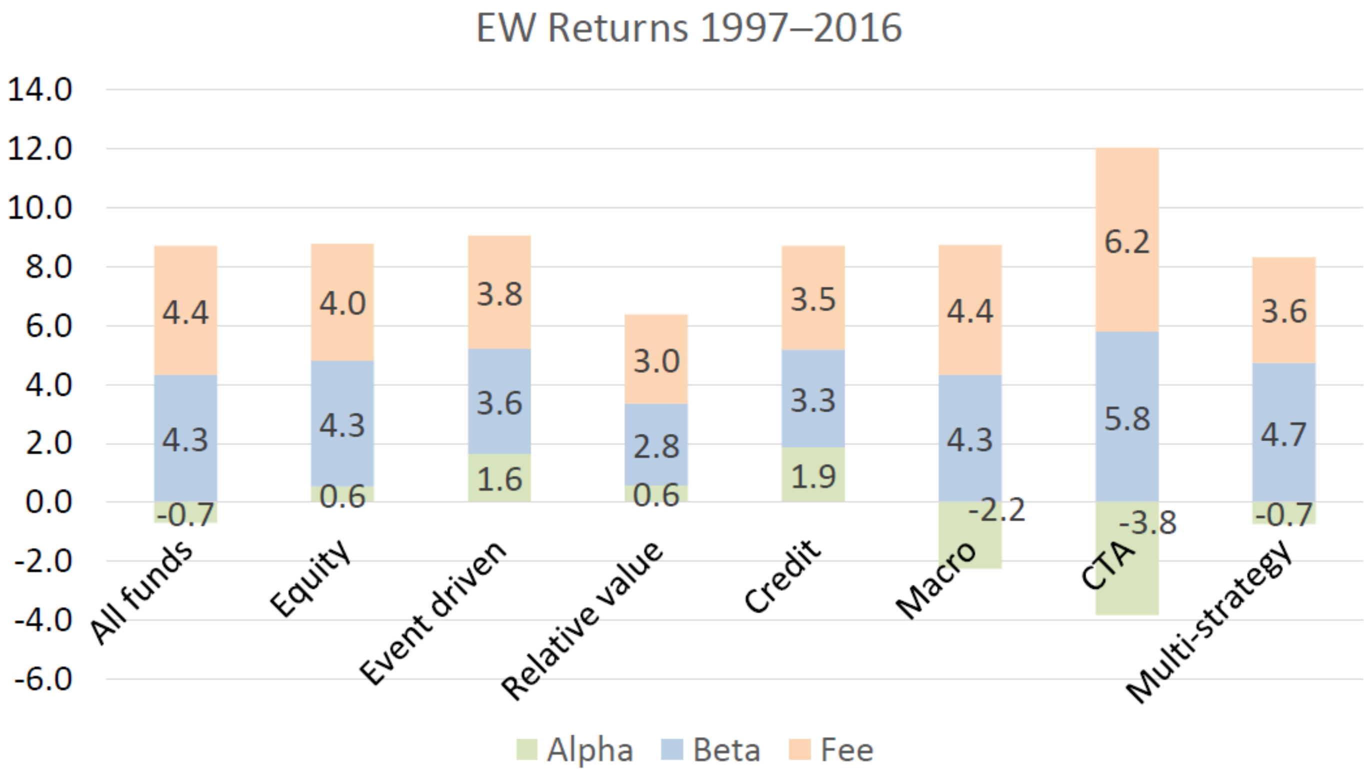


Global 7-Factor Model

1. Global equity market excess return **(Market), Size factor (SMB)**, and **Value factor (HML)** of Fama and French (2012)
2. Global cross-sectional momentum **(MOM)** of Asness, Moskowitz, and Pedersen (2013)
3. Global time-series momentum **(TSMOM)** of Moskowitz, Ooi, and Pedersen (2012)
4. Global betting-against-beta **(BAB)** of Frazzini and Pedersen (2014)
5. Liquidity risk **(P-S Liq)** of Pastor and Stambaugh (2003)

- **Clearly this model is ad-hoc as well, but …**
  - Compared to the Fung–Hsieh benchmark, the alternative global benchmark consistently yields a higher adjusted R-squared.

Global 7-Factor Alphas, Betas and Fees



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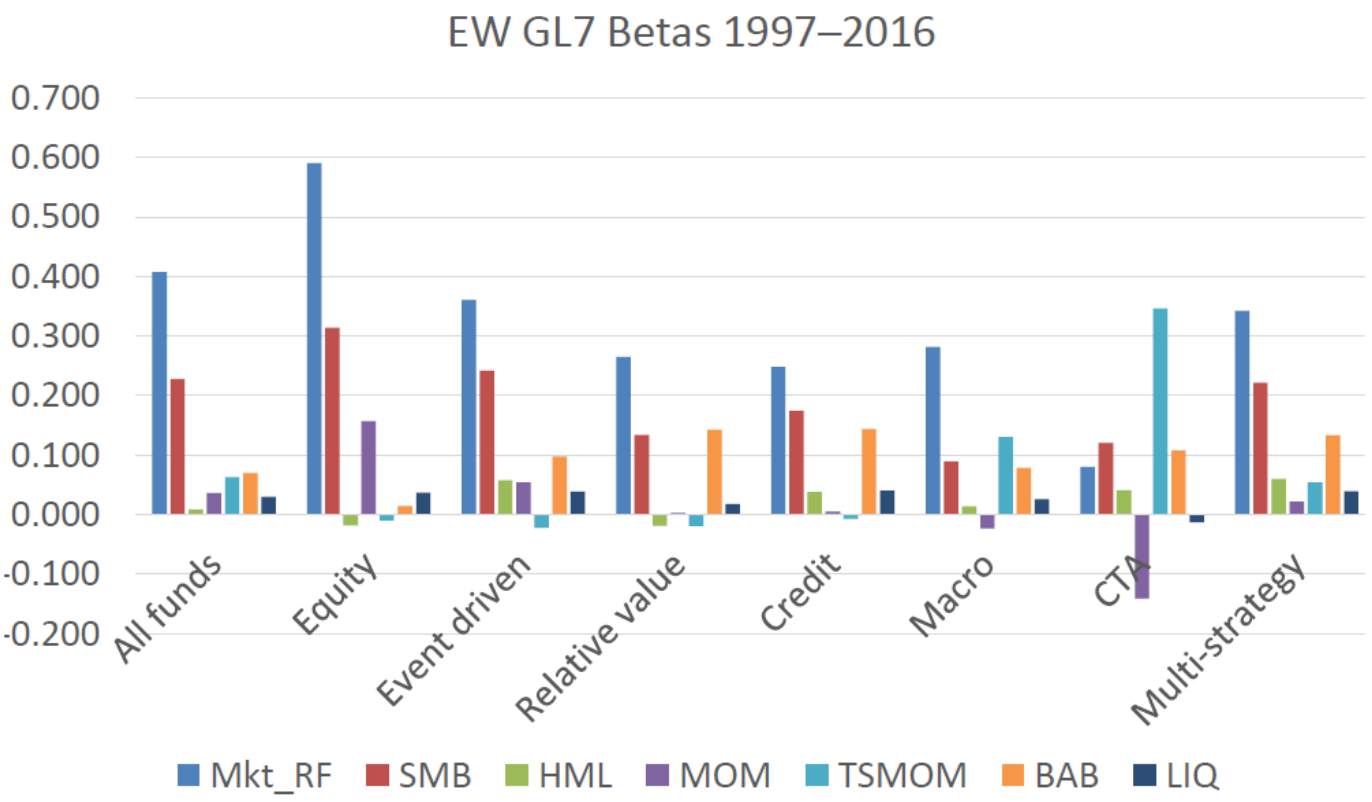
Global 7-Factor Loadings



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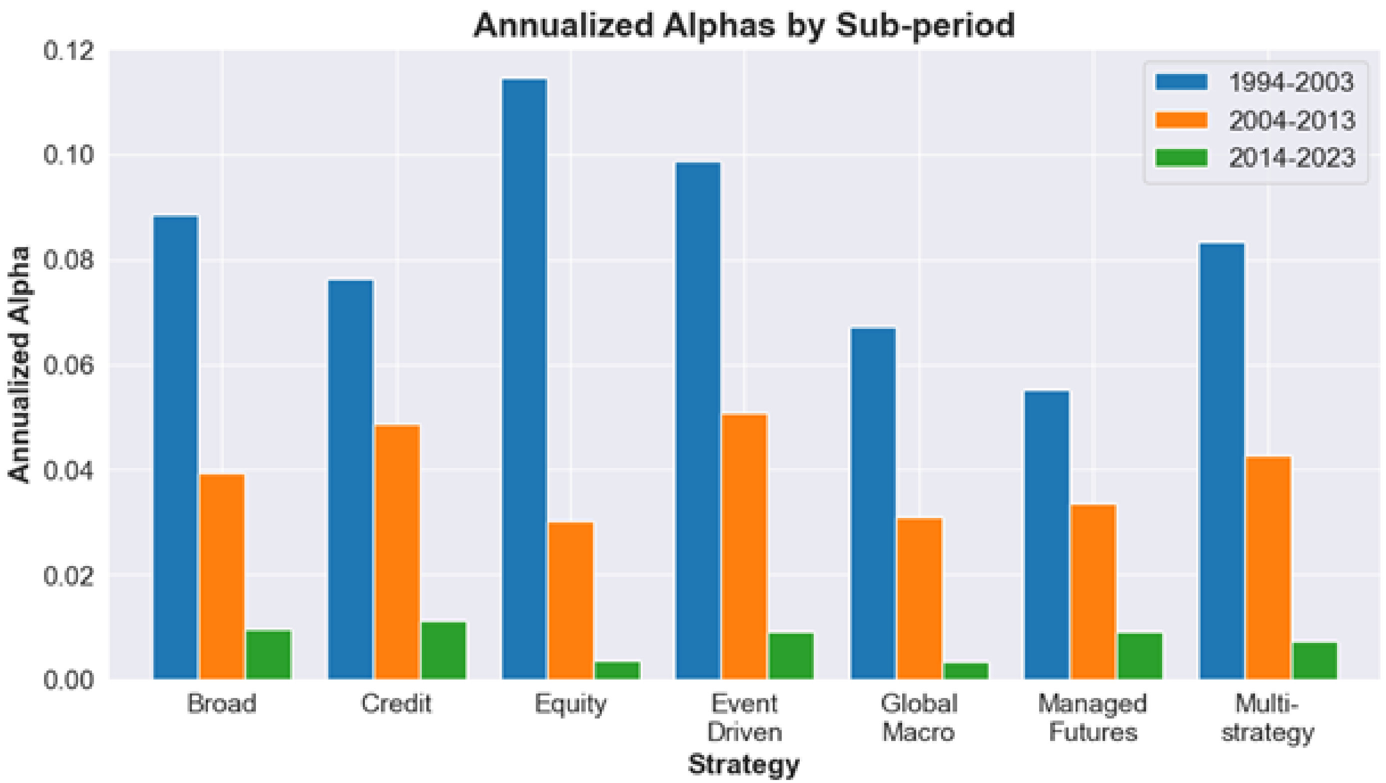
Declining Alphas by sub-periods



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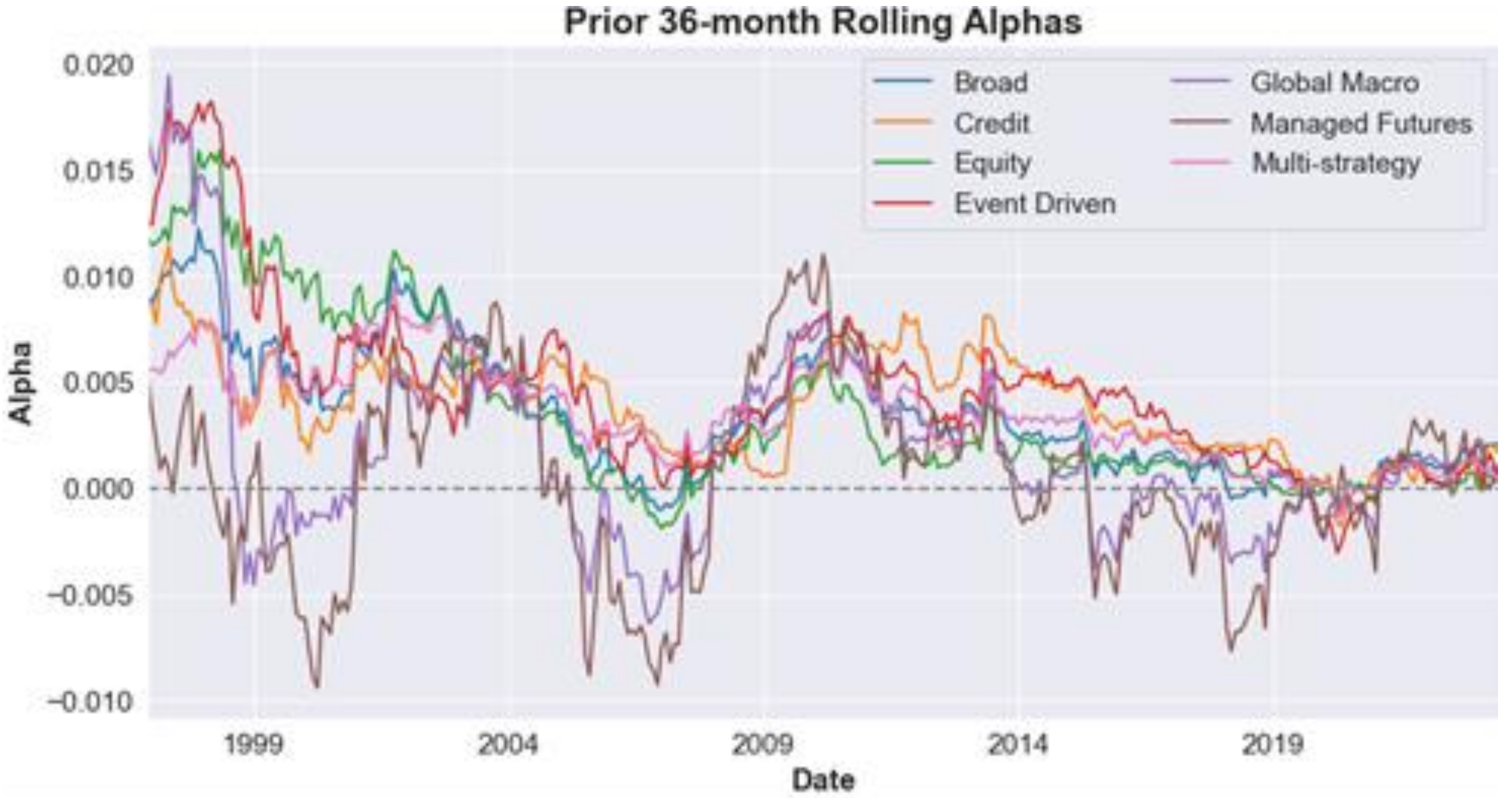
Declining Alphas over time



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Time-varying Market Betas

Performance Persistence: Best Funds Deliver “Alpha”

Early Evidence of Performance Persistence

THE JOURNAL OF FINANCE • VOL. LXV, NO. 1 • FEBRUARY 2010

Do Hot Hands Exist among Hedge Fund Managers? An Empirical Evaluation

RAVI JAGANNATHAN, ALEXEY MALAKHOV, and DMITRY NOVIKOV*

ABSTRACT

In measuring performance persistence, we use hedge fund style benchmarks. This allows us to identify managers with valuable skills, and also to control for option-like features inherent in returns from hedge fund strategies. We take into account the possibility that reported asset values may be based on stale prices. We develop a statistical model that relates a hedge fund's performance to its decision to liquidate or close in order to infer the performance of a hedge fund that left the database. Although we find significant performance persistence among superior funds, we find little evidence of persistence among inferior funds.

Journal of Financial Economics 84 (2007) 229–264

Do hedge funds deliver alpha? A Bayesian and bootstrap analysis☆

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Available online 2 January 2007

Abstract

Using a robust bootstrap procedure, we find that top hedge fund performance cannot be explained by luck, and hedge fund performance persists at annual horizons. Moreover, we show that Bayesian measures, which help overcome the short-sample problem inherent in hedge fund returns, lead to superior performance predictability. Sorting on Bayesian alphas, relative to OLS alphas, yields a 5.5% per year increase in the alpha of the spread between the top and bottom hedge fund deciles. Our results are robust and relevant to investors as they are neither confined to small funds, nor driven by incubation bias, backfill bias, or serial correlation.

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Jagannathan et al. (*JF* 2010) Style Index Alpha

- **Regress fund excess returns on the market and two HFR style indices:**

$$R_t = \alpha + \beta_m R_{m,t} + \beta_1 R_{1,t} + \beta_2 R_{2,t} + \varepsilon_t$$

- **The first style index is the fund's self-reported style the second is selected to maximize model fit**
- **Jagannathan et al. also apply a number of econometric techniques to deal with excess smoothing and censoring of poor returns due to fund failure**

Kosowski et al. (*JFE* 2007) Bayesian Alpha

- **Step 1: regress two non-benchmark assets on the FH seven factors using data back to January 1995**

$$R_{n,t} = \alpha_n + \sum_{k=1}^{7} b_n R_{k,t} + \varepsilon_{n,t} \quad n = 1,2$$

- **Step 2: regress hedge fund returns on benchmark and non-benchmark assets using a 24-month window**

$$R_{p,t} = \delta_p + \sum_{n=1}^{2} \beta_{p,n} R_{n,t} + \sum_{k=1}^{7} \beta_{p,k} R_{k,t} + u_{p,t}$$

- **Step 3: compute hedge fund's benchmark adjusted alpha**

$$\alpha_p = \delta_p + \sum_{n=1}^{2} \beta_{p,n} \alpha_n$$

- **Estimation is conducted in a Bayesian framework – we use the posterior estimate of α divided by its posterior standard error**

The Decline in Hedge Fund Performance Persistence

NICOLAS P.B. BOLLEN*, JUHA JOENVÄÄRÄ† and MIKKO KAUPPILA‡

This version: April 4, 2024

ABSTRACT

This paper successfully replicates Kosowski, Naik, and Teo (2007) and Jagannathan, Malakhov, and Novikov (2010), two seminal studies of hedge fund performance persistence. We show that top funds continue to persist in a more recent sample, even when using novel "real-time" data that approximates an investor's actual information set. The persistence available to investors has substantially weakened, however, and is only observed when using Kosowski et al.'s Bayesian alpha to predict performance. We identify the econometric source of the superiority of Kosowski et al.'s methodology and show that the decline in performance persistence is associated with decreasing returns to scale for superior funds.

JEL Classifications: G11, G23

Keywords: performance persistence, decreasing returns to scale, replication, hedge funds

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Procedure for Testing Performance Persistence

1.

Estimation period

- Estimate fund-level alpha t-statistics (24-month window)

2.

Portfolio sorts

Sort funds into quantile portfolios based on past performance

3.

Performance evaluation (post-rank)

Calculate post-ranking alphas (EW,VW) for portfolios

Out-of-sample Persistence: Jan 2003 – June 2020

Panel A. Sort by Bayesian alpha t-statistic

Portfolio	Mean	Vol	Alpha	t-stat	p-val
1%ile	8.70	6.89	5.78	3.48	0.00
5%ile	7.62	6.70	4.21	3.43	0.00
Decile 1	6.41	6.63	2.85	2.45	0.01
Decile 2	4.63	7.14	0.50	0.46	0.32
Decile 3	4.44	7.42	0.12	0.11	0.45
Decile 4	4.08	7.40	−0.20	−0.18	0.57
Decile 5	4.10	7.43	−0.25	−0.25	0.60
Decile 6	3.64	7.82	−0.99	−0.94	0.83
Decile 7	3.87	8.42	−0.93	−0.83	0.80
Decile 8	3.38	8.61	−1.47	−1.15	0.87
Decile 9	2.57	8.59	−2.24	−1.64	0.95
Decile 10	2.20	8.80	−2.34	−1.53	0.94
95%ile	1.93	8.64	−2.35	−1.43	0.92
99%ile	2.37	9.97	−1.71	−0.69	0.75
Δ 10%	4.21	5.27	5.19	3.80	0.00
Δ 1%	6.33	8.38	7.49	3.13	0.00

Panel B. Sort by Relative alpha t-statistic

Portfolio	Mean	Vol	Alpha	t-stat	p-val
1%ile	5.91	5.16	3.50	2.99	0.00
5%ile	5.05	6.37	1.58	1.31	0.10
Decile 1	4.58	6.68	0.93	0.76	0.22
Decile 2	4.91	7.22	0.91	0.71	0.24
Decile 3	4.34	7.62	0.06	0.04	0.48
Decile 4	4.31	7.57	−0.07	−0.05	0.52
Decile 5	4.56	7.99	0.01	0.01	0.49
Decile 6	3.93	8.10	−0.90	−0.79	0.78
Decile 7	3.78	8.16	−1.01	−0.92	0.82
Decile 8	3.13	8.10	−1.57	−1.37	0.91
Decile 9	2.68	8.04	−1.82	−1.58	0.94
Decile 10	3.34	8.02	−1.17	−1.12	0.87
95%ile	3.53	8.07	−1.03	−0.88	0.81
99%ile	4.34	7.76	0.29	0.20	0.42
Δ 10%	1.25	3.64	2.11	2.12	0.02
Δ 1%	1.56	5.63	3.21	2.17	0.02

Are Persistence Test Assumptions Realistic?

- **Academic studies assume ”year-end” rebalancing without “lags”**
  - Alphas are estimated using a 24-month Windom (Jan – Dec)
  - HFs invest in illiquid assets → Valuations take time → Reporting lags
  - DD takes often time → Some large HF investors can overcome this
  - HFs imposed share restrictions (lockups, notice periods and redemption periods) and during the extraordinary times there are gates and suspensions to redeem.

- **Blackstone Hires Limin Wang as a Managing Director in Quantitative Research**
  - Limin Wang: “It is realistic to assume that it takes a one quarter to rebalance. We use one-quarter lag in our simulations / back-tests.”

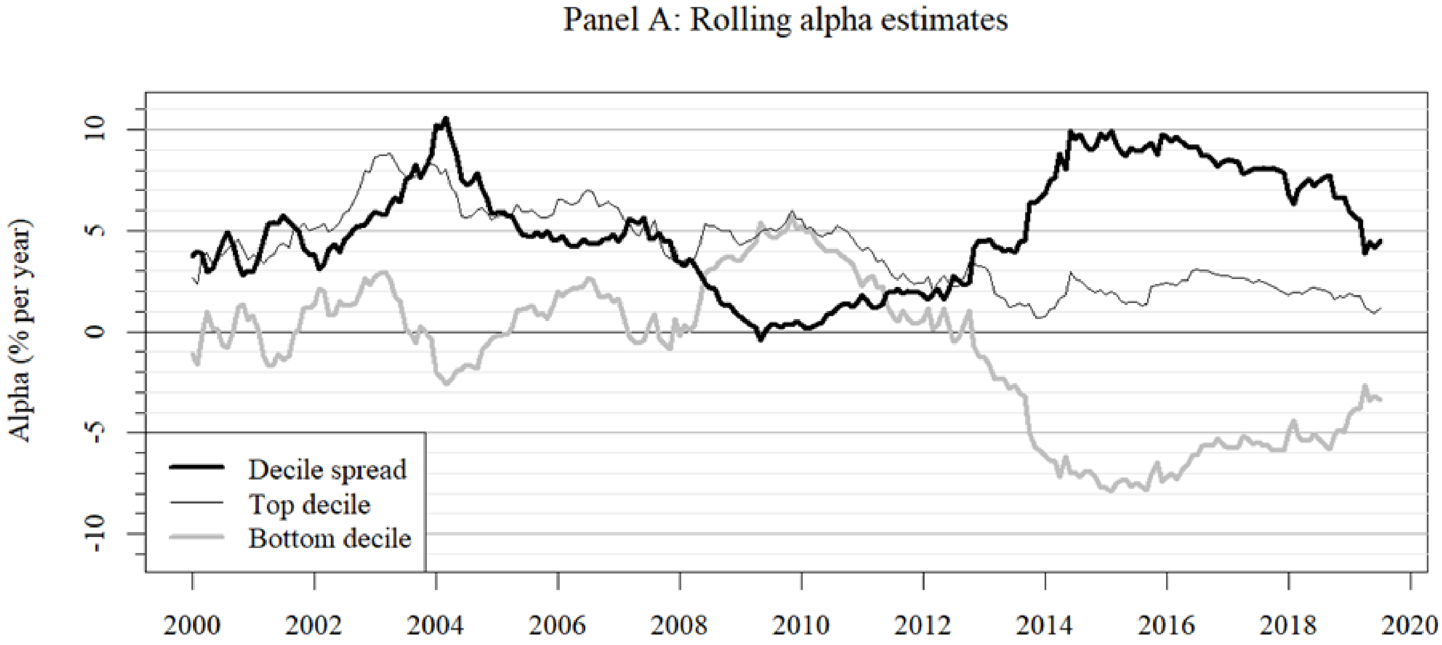
Realtime Persistence of Bayesian Alphas

- **At each portfolio formation date, we only use data from the prior December database snapshots.**
  - Annual December snapshots from TASS (2008–2019), BarclayHedge (2006–2019), and EurekaHedge (2006–2019).
- **Although the spreads are significant, the top portfolio is significant only for 1%**
- **Very weak evidence for Bayesian alphas (no evidence for Relative Alphas, not reported here)**

Bayesian alpha *t*-statistic

Portfolio	Mean	Vol	Alpha	*t*-stat	*p*-val
1%ile	5.92	5.40	4.09	3.22	0.00
5%ile	3.86	5.62	1.67	1.27	0.10
Decile 1	3.19	5.63	0.93	0.85	0.20
Decile 2	2.51	6.53	−0.12	−0.09	0.54
Decile 3	2.03	7.51	−1.04	−0.77	0.78
Decile 4	1.82	7.11	−1.26	−1.14	0.87
Decile 5	2.71	6.84	−0.13	−0.14	0.55
Decile 6	2.28	7.49	−0.64	−0.58	0.72
Decile 7	2.00	7.93	−1.45	−1.23	0.89
Decile 8	1.53	8.14	−2.04	−1.62	0.95
Decile 9	0.93	8.47	−2.79	−1.93	0.97
Decile 10	−0.10	8.39	−3.36	−2.16	0.98
95%ile	−0.05	8.53	−3.10	−1.86	0.97
99%ile	−1.04	10.51	−3.30	−1.17	0.88
Δ 10%	3.29	4.85	4.29	3.33	0.00
Δ 1%	6.96	8.72	7.39	3.05	0.00

5-year rolling FH7alphas of portfolios ranked by KNT Bayesian alpha



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Exploiting Predictability: Adding HFs to a Balanced Portfolio

Financial Analysts Journal | A Publication of **CFA Institute**
https://doi.org/10.1080/0015198X.2021.1921564

Research

Hedge Fund Performance: End of an Era?

Nicolas P.B. Bollen, Juha Joenväärä, and Mikko Kauppila

Nicolas P.B. Bollen is the Frank K. Houston Professor of Finance at Vanderbilt University, Nashville, Tennessee. Juha Joenväärä is an assistant professor of finance at Aalto University, Helsinki, Finland. Mikko Kauppila is a doctoral candidate at the University of Oulu, Oulu, Finland.

Data and methodology

- We consolidate six major commercial databases **(BarclayHedge, EurekaHedge, eVestment, Hedge Fund Research, Lipper TASS, and Morningstar).**
- **Our data** consist of static fund characteristics and monthly time series of USD-converted net-of-fees returns and AUM **from January 1994 through December 2016.**

- We **benchmark hedge funds** against an equally weighted portfolio consisting of **the S&P 500 and the Vanguard Total Bond Market Index fund (VBTIX)—**hereafter, called the "stock/bond portfolio"
- We divide our data **two subperiods** demarcated by **the December 2007/January 2008 breakpoint** that coincides with the timing of Warren Buffett's bet and, more importantly, defines two subperiods that **both contain a full stock market cycle**.

Methodology

1. **Simulate a random selection of 15 funds each year from the top quintile as ranked by the predictor variables and repeated the process 1,000 times.**
2. **Measure the benefit of an allocation to HFs by comparing the performance of an equally weighted "stock/bond portfolio"—with the performance of a multi-asset-class portfolio that included a 20% allocation to hedge funds selected by the competing predictor variables.**
3. **Given the diversification potential of a hedge fund allocation, we computed two utility-based measures to assess the value added for risk-averse investors.**

Table 1. Hedge Fund Performance Predictors

Category	Measure	+/–	Description
Broad skill measures	Alpha	+	Intercept from a regression against FH factors.
	SDI	+	Strategy distinctiveness index of Sun, Wang, and Zheng (2012).
Timing skill measures	Market	+	Market timing following Treynor and Mazuy (1966). Loading on squared S&P 500 excess return, controlling for FH factors.
	Volatility	–	Volatility timing following Chen and Liang (2007). Loading on the interaction of S&P 500 excess return and level of volatility (VIX), controlling for FH factors.
	Liquidity	+	Liquidity timing following Cao, Chen, Liang, and Lo (2013). Loading on the interaction of S&P 500 excess return and level of liquidity, controlling for FH factors.
	Macro	+	Macroeconomic timing skill of Bali et al. (2014). Loading on their macroeconomic uncertainty index.
Incentive measure	ΔOption	+	Dollar increase in the value of next year-end incentive options per dollar increase in fund return, following Agarwal et al. (2009).

Notes: The "+/–" column indicates whether, based on existing literature, we expected the measure to be related to higher (+) or lower (–) future performance. Predictors based on regression coefficients (including intercepts) were always precision-adjusted; that is, we used the *t*-values of the coefficients. The dependent variable in all regressions is the fund excess return. "FH factors" refers to the seven-factor model of Fung and Hsieh (2004). All measures are based on a 24-month rolling window except the incentive measure, which is based on a fund's full history until the ranking month.

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Delta method of Fleming et al. (JF 2001)

- **"Delta" method of Fleming et al. (*JF* 2001)**
  - Can be interpreted as the incremental value of one risky investment over another risky investment expressed as a certainty equivalent
  - Based on quadratic utility with various levels of risk aversion (γ)
- **Quadratic utility as a second-order approximation of true utility**
- **Utility of strategy *p* and initial wealth W_0 given by**

$$U = W_0 \sum_{t=1}^{T} \left[R_{p,t} - \frac{\gamma}{2(1-\gamma)} R_{p,t}^2 \right]$$

- **Can be used to compare two investment strategies *p* and *q***

$$\sum_{t=1}^{T} \left[R_{p,t} - \Delta - \frac{\gamma}{2(1-\gamma)} \left(R_{p,t} - \Delta\right)^2 \right] = \sum_{t=1}^{T} \left[R_{q,t} - \frac{\gamma}{2(1-\gamma)} R_{q,t}^2 \right]$$

- **Can be interpreted as the maximum fee an investor would pay to switch from *q* to *p***

Only FH Alpha and Macro Timing add value to multi-asset portfolio

Table 4. Economic Value of a Hedge Fund Investment in a Portfolio Context, January 1997–December 2016

Predictor	Average (pps)	Standard Deviation (pps)	Sharpe Ratio	Alpha (pps)	MPPM (pps)	γ1 (pps)	γ5 (pps)	γ10 (pps)
FH alpha	−0.37	−1.77**	0.13**	0.29**	−0.01	−0.25	0.24	0.88**
Macro timing	−0.42	−1.80**	0.13**	0.31**	−0.05	−0.30	0.19	0.84**
SDI	−1.23**	−2.50**	0.08	−0.12	−0.74**	−1.07**	−0.42	0.43
ΔOption	−0.98**	−2.11**	0.07	−0.13	−0.56*	−0.84**	−0.28	0.46
Market timing	−0.68*	−1.44**	0.04	−0.05	−0.37	−0.58	−0.18	0.36
Volatility timing	−0.81*	−1.60**	0.04	−0.19	−0.47	−0.70*	−0.25	0.34
Random	−0.76	−1.38**	0.02	−0.24	−0.47	−0.67	−0.28	0.24
Liquidity timing	−0.91**	−1.50**	0.01	−0.31	−0.59*	−0.81**	−0.39	0.17

Notes: Listed are differences between performance of a portfolio consisting of a 20% allocation to hedge funds, 30% to the S&P 500, and 50% to the VBTIX and performance of a stock/bond portfolio. Listed also are measures of incremental utility offered by the portfolio over the stock/bond portfolio for three risk aversion levels (γ = 1, 5, 10). Results were averaged across 1,000 simulations of a strategy of randomly selecting 15 funds each year from the top quintile formed by each of the predictors. Predictors were ranked by the differences in Sharpe ratio. Hedge fund returns were de-smoothed and adjusted for delistings. Definitions of predictors are given in Table 1. For the first five statistics, significance was determined by the percentage of simulations in which the portfolio's statistic was higher or lower than that of the stock/bond portfolio. For the last three columns, significance was determined by the percentage of simulations in which the incremental utility provided by the portfolio relative to the stock/bond portfolio was positive. The stock/bond portfolio featured an average return of 7.02%, a standard deviation of 7.58%, a Sharpe ratio of 0.65, an alpha of 0.59%, and an MPPM of 4.03%.

*Significant at the 5% level.

**Significant at the 1% level.

No more higher Sharpe ratios during the second period

Table 5. Benefit of an Allocation to Hedge Funds by Subperiod

Predictor	Average (pps)	Standard Deviation (pps)	Sharpe Ratio	Alpha (pps)
A. January 1997–December 2007				
Macro timing	0.15	−2.02**	0.23**	0.84*
FH alpha	0.14	−1.91**	0.22**	0.65*
SDI	−0.63*	−2.51**	0.15*	0.23
Volatility timing	−0.13	−1.66**	0.14*	0.36
Market timing	0.00	−1.47**	0.13*	0.43
Liquidity timing	−0.07	−1.50**	0.13	0.41
Random	−0.14	−1.58**	0.13	0.33
ΔOption	−0.75**	−2.29**	0.10	−0.04
B. January 2008–December 2016				
FH alpha	−1.00*	−1.64**	0.04	−0.06
ΔOption	−1.27**	−1.93**	0.04	−0.22
Macro timing	−1.12*	−1.59**	0.02	−0.26
SDI	−1.96**	−2.52**	0.00	−0.56
Market timing	−1.50**	−1.44**	−0.06	−0.66
Volatility timing	−1.63*	−1.58**	−0.06	−0.76
Random	−1.53*	−1.20**	−0.09	−0.89
Liquidity timing	−1.95**	−1.56**	−0.12	−1.19

Do Non-listed ”Secretive” HFs Outperform?

The Hedge Fund Industry is Bigger (and Has Performed Better) Than You Think

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*Views and opinions expressed are those of the authors and do not necessarily represent official positions or policy of the Federal Reserve Board of Governors, Federal Reserve System, OFR or Treasury.

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This Paper

- In this paper, we combine vendor data and U.S. regulatory data to provide bias-free estimates of:
  1. Total industry size
  2. Performance, including: alphas, betas, and persistence
  3. Investor flows and industry growth
  4. The flow-performance relationship
- Our data constitute the most comprehensive view of the hedge fund industry to date
- Our data also allow important comparisons between **vendor-listed** and **non-listed** funds
  - Determines the size and sign of cumulative bias in vendor data statistics

Vendor Data

- Vendor data are derived from a manual consolidation of seven common providers:

  1. Lipper TASS
  2. Hedge Fund Research (HFR)
  3. BarclayHedge
  4. EurekaHedge
  5. Morningstar
  6. Preqin
  7. eVestment

- Vendor data are collected through 2016. Includes returns, net assets, average and maximum leverage, fund domicile, and fund strategy, among others

Regulatory (Non-Listed) Data: Form PF

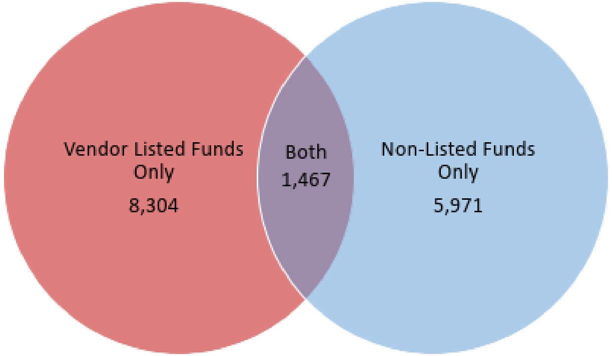
- Dodd-Frank mandated enhanced regulatory reporting for private funds — primarily implemented in Form PF
- Advisers with more than $150 million in regulatory private fund assets provide detailed data annually on the hedge funds they advise.
- *Large Hedge Fund Advisers* ($1.5 billion in hedge fund assets) provide additional data on a quarterly basis for each of their *Qualifying Hedge Funds* ($500M in assets)
  - While reported annually or quarterly, some fields such as returns and asset class exposures, are reported at a monthly frequency
- Form PF data includes gross and net assets, gross and net returns, asset class exposures, types of borrowing, counterparty exposures and creditors, and much more

Combined Data

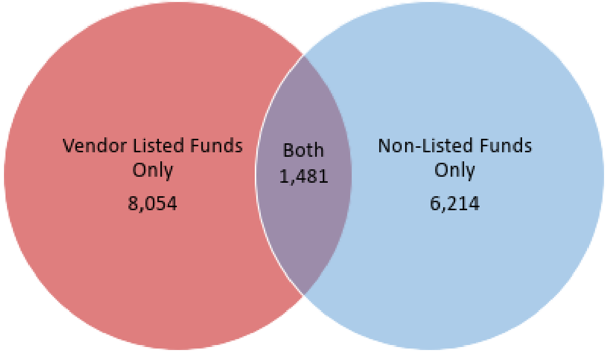
- To estimate the size of the industry, we must combine data without double counting
- But, Form PF is **highly confidential**, and vendor data can only be shared with license holders
- **Our approach**: use Form ADV — a publicly available SEC filing — to get SEC fund identifiers for *each vendor-listed fund*
  - Then use these identifiers to exclude vendor-listed funds from the Form PF data
  - This allows us to combine aggregate statistics from the listed and non-listed data without sharing and without double-counting

Combined Data: Fund Counts

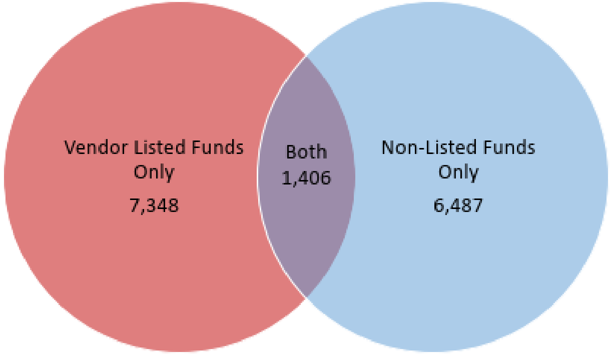
2013



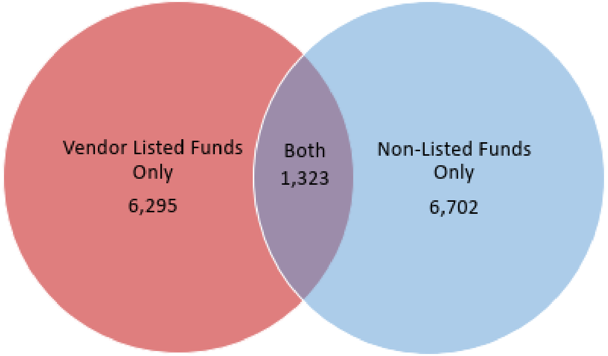
2014



2015

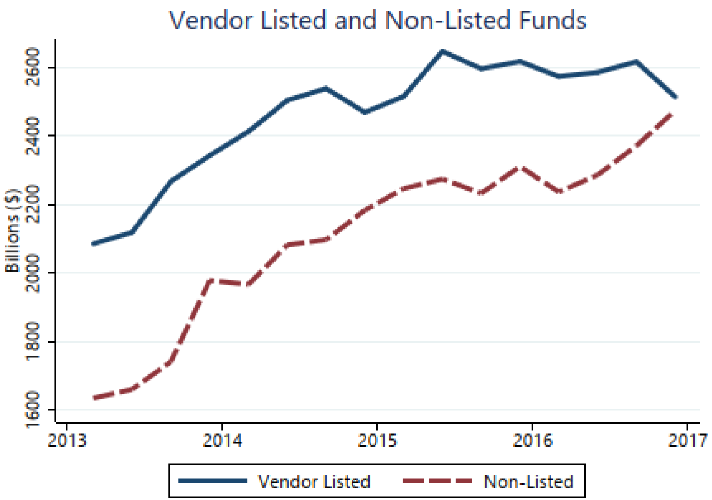


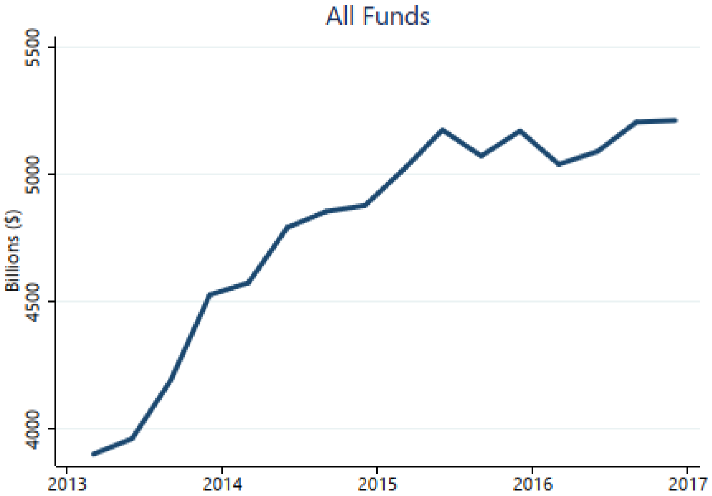
2016



How Large is the Hedge Fund Industry?

- Eurekahedge **$2.23 trillion**
- Barclay Hedge **$2.37 trillion**
- Hedge Fund Research (HFR) **$3.02 trillion**
- eVestment **$3.00 trillion**
- Preqin **$3.14 trillion**
- *SEC Private Fund Statistics **$3.48 trillion**





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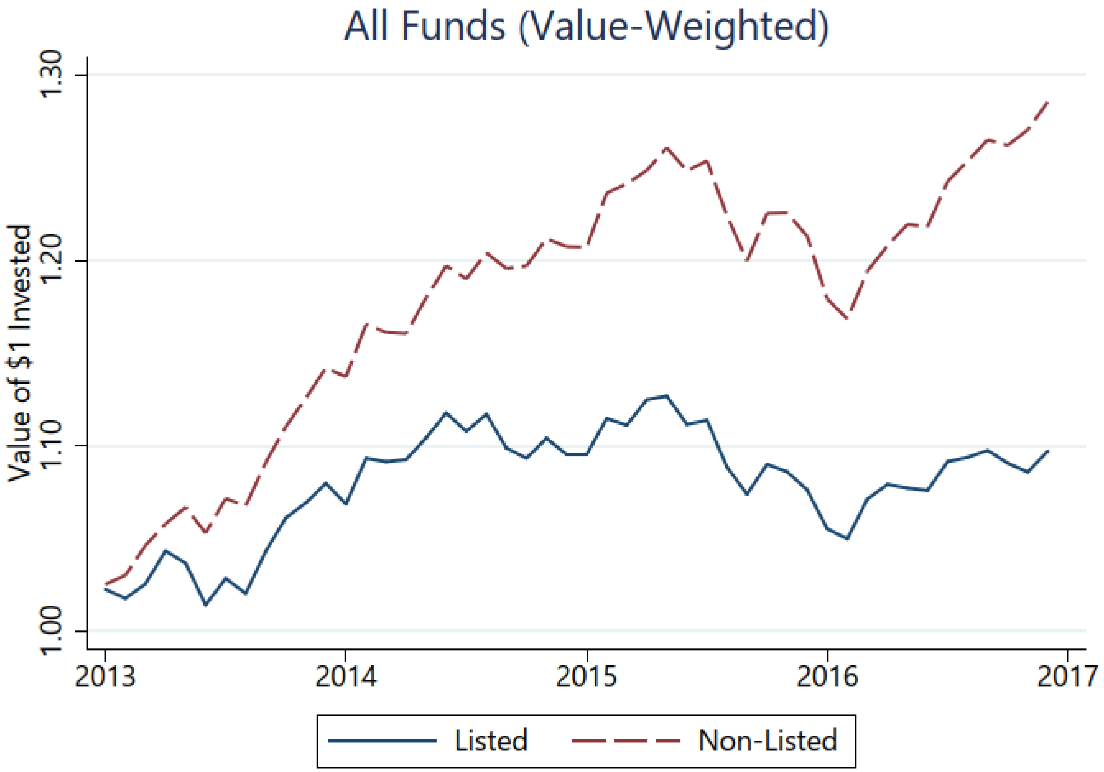
Performance



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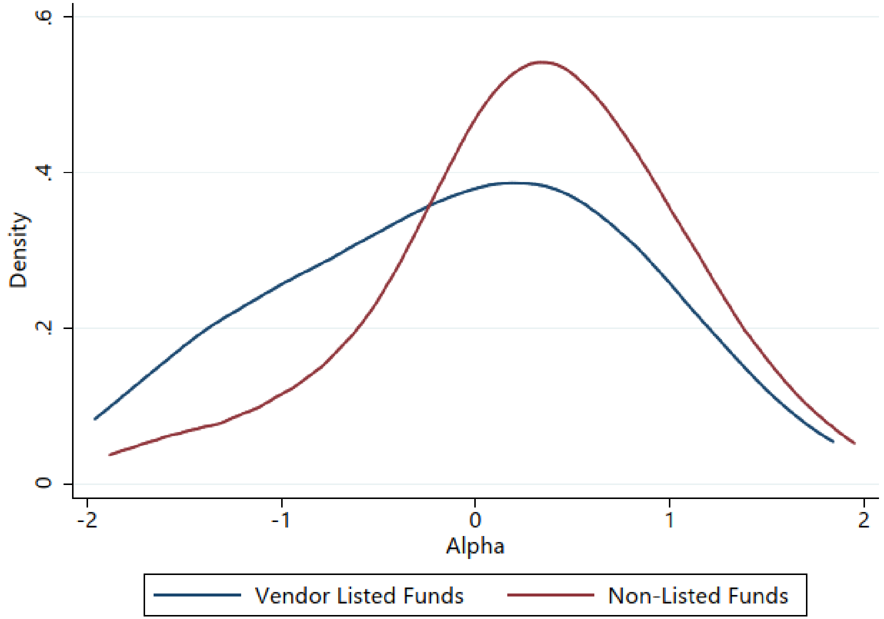
Risk or Risk-Adjusted Returns?

- Superior performance by non-listed funds could result from two sources:
  1. Greater exposure to systematic risk factors
  2. Greater risk-adjusted performance (alpha)
- We use the "Global 7" factor model from Joenvaara et al. (2019): Mkt, SMB, HML, CSMOM, TSMOM, BAB, PSLIQ
- We find risk exposures are **highly similar** between listed and non-listed funds Betas PDF
- We measure alpha through three approaches
  - Jensen's alpha (intercept from factor regression)
  - Bootstrap (non-parametric hypothesis tests)
  - Fama-MacBeth regressions (control for characteristics)

Jensen's Alpha (Monthly)



- Vendor-listed funds: mean = -0.146%, median = -0.086%
- Non-listed funds: mean = 0.470%, median = 0.354%

Can Observables Explain Performance Differences?

- We estimate two-stage Fama-MacBeth regressions:

$$\text{(First Stage: TS)} \quad R_{i,t} = \beta_{0,i} + \beta_i' F_t + \varepsilon_{i,t}; \quad \widehat{\alpha}_{i,t} = \beta_{0,i} + \varepsilon_{i,t}$$

$$\text{(Second Stage: CS)} \quad \widehat{\alpha}_{i,t} = \gamma_{0,i} + \gamma_{1,t} Listed_{i,t} + \phi' Z_{i,t} + \epsilon_{i,t}$$

$$\text{where} \quad \gamma_1 = \frac{\sum_t \gamma_{1,t}}{T}, \quad \text{(w/ Newey-West s.e.)}$$

- We are interested in γ_1 — whether the inclusion of controls attenuates the lower performance of vendor-listed funds

Standard Controls Do Not Explain Differences in Alpha

Dep. Var.	Net Excess Return	Gross G7 Alpha	Net G7 Alpha	Net G7 (GLM Adj.) Alpha	Net FH Alpha	Net FH + Em Mkt Alpha	Net FH + Option Alpha
Listed	**-0.38**	**-0.41**	**-0.45**	**-0.45**	**-0.37**	**-0.28**	**-0.34**
	-4.24	-7.20	-7.97	-6.63	-4.31	-3.17	-3.98

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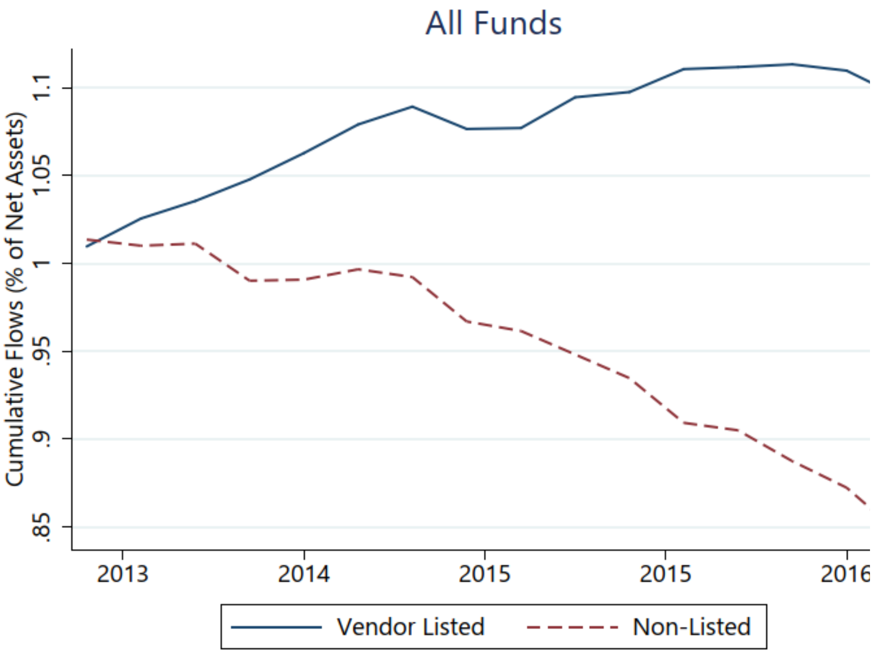
Performance Persistence

Estimation Horizon		3 Months			6 Months			1 Year		
Prediction Horizon		**Non-Listed**	**Listed**	$\widehat{\gamma}_t$	**Non-Listed**	**Listed**	$\widehat{\gamma}_t$	**Non-Listed**	**Listed**	$\widehat{\gamma}_t$
3 Months	Estimate	0.516	0.090	**-0.423**	0.641	0.176	**-0.463**	0.677	0.131	**-0.545**
	t-statistic	10.339	1.971	-6.981	7.603	2.762	-7.707	11.063	0.963	-6.348
6 Months	Estimate	0.507	0.086	**-0.420**	0.618	0.130	**-0.488**	0.660	0.099	**-0.561**
	t-statistic	7.361	2.640	-6.870	6.513	2.026	-9.818	7.984	0.482	-6.188
1 Year	Estimate	0.513	0.063	**-0.453**	0.611	0.087	**-0.528**	0.658	0.119	**-0.545**
	t-statistic	11.688	1.842	-10.382	17.294	0.566	-12.661	21.544	0.457	-5.948
2 Year	Estimate	0.405	0.057	**-0.358**	0.488	0.107	**-0.392**	0.537	0.025	**-0.520**
	t-statistic	6.137	0.906	-12.389	7.666	0.796	-9.497	9.426	0.645	-19.084

- Strong evidence for persistence is found only in non-listed funds

Flows



Flow-Performance Relationship in Hedge Funds

Dep. Var.	Flow (% Qtr)	Flow (% Qtr)	Flow (% Qtr)	Flow (% Qtr)	Flow (% Qtr)	Flow (% Qtr)
Listed	3.553	3.521	-0.900	-5.001	-0.397	-0.828
	9.313	12.813	-1.593	-3.943	-0.741	-1.063
Listed x Performance rank				**0.085**		
				6.472		
Performance rank (percentile)			0.097	0.018		
			18.796	2.411		
Listed x Net excess return						**0.225**
						2.688
Net excess return (% pq)					0.274	0.057
					16.062	0.728
Flow_{t-1} (% pq)			0.161	0.161	0.163	0.163
			29.665	29.673	29.014	28.818
Strategy Controls	No	Yes	Yes	Yes	Yes	Yes
Other Controls	No	No	Yes	Yes	Yes	Yes
Number of observations	109,848	107,276	84,134	84,134	84,134	84,134

Economic Interpretation

- Non-listed reporting funds simultaneously have:
  1. Superior performance, generated through higher alphas
  2. Weaker association between flows and performance
- Our interpretation:
  - Skill is scarce, uncertain, and difficult to signal
  - Managers with uncertain or unproven skill list w/ vendors to generate interest
  - Managers with established/more certain skill do not need to list
  - Because of selection, listed funds have zero alpha on average, while non-listed funds have positive alphas
  - Because listed funds have less certain skill, the association between performance and flows is stronger