Section 6: Mutual funds and hedge funds

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1. Basic structure of the notes

- High-level summary of theoretical frameworks to interpret empirical facts.
- Per asset class, we will discuss:
    1. Key empirical facts in terms of prices (unconditional and conditional risk premia) and asset ownership.
    2. Interpret the facts using the theoretical frameworks.
    3. Facts and theories linking financial markets and the real economy.
    4. Active areas of research and some potentially interesting directions for future research.
- The notes cover the following asset classes:
    1. Equities (weeks 1-5).
        - Discount rates and the term structure of risk (week 1)
        - The Cross-section and the factor zoo (week 2) -based Asset Pricing (week 3)
        - Production-based asset pricing (week 4)
        - Demand-based asset pricing (week 5)
    2. Mutual funds and hedge funds (week 6).
    3. Volatility (week 7).
    4. Government bonds (week 8).
    5. Corporate bonds and CDS (week 9).
    6. Currencies and international finance (week 10).
    7. Commodities (week 11).
    8. Real estate (week 12).

2. Main Questions

- Enormous literature on mutual funds and hedge funds in empirical asset pricing. As always, our coverage is by necessity selective and incomplete.
- Reflects the fact that the asset management industry is massive, and has grown enormously since the financial crisis. AUM at the top-500 global asset managers was $113 trillion at the end of 2022. This is up from $32 trillion at the end of 2009. That's a compound annual growth rate (CAGR) of 10%.
- Trend is likely to continue as wealth grows in emerging markets (esp. China and India) and wealth inequality grows.
- Concentrated industry: top-20 account for $50 trillion. Blackrock is #1 with $8.6 tr, Vanguard #2 with $7.2 tr, Fidelity #3 with $3.7 tr., State Street #4 with $3.5 tr, JMPC #5 with $2.8tr.
- 60% of AUM among top-500 manager assets is in North-America
- 35% is passively managed, a share that keeps increasing
- One main question is whether **mutual/hedge fund managers have skill**. In other words, can they systematically out-perform a passive investment strategy?
  - What constitutes a passive strategy has changed over time
  - First, there were low-cost index funds (Vanguard was a pioneer in the mid-1970s)
  - Then there were low-cost style funds (think Vanguard small value fund, Vanguard International Equities Fund, Vanguard Total Bond Fund, etc.)

- Then there were ETFs; now there are more ETFs than stocks. ETFs allow investors to implemented sophisticated trading ideas at low cost.
  - Smart-beta products now exceed $1 trillion in AUM.
- Several large mutual fund families have slashed their fees for plain-vanilla index funds to nearly zero (e.g. Fidelity offers free stock index and bond index funds since August 2018).

- There are interesting questions about the **industrial organization of the mutual fund industry**. How to explain the size distribution of funds and fund families (firms), rising concentration of large firms, competition between active and passive management, fee structures, and valuation of asset management firms.

- A third main question is how the growth of passive strategies affects the **efficiency of markets**.
  - Who will make markets efficient when all investors are passive (the Stiglitz paradox)?
  - Should passive funds get involved in corporate governance?

3. Mutual Fund Performance

3.1. *What does theory say?*

- In the seminal Berk and Green (2004) model, there is skill and yet no alpha.
- Here is the **setup**
  - MF investors and managers are symmetrically informed
  - Funds are born with skill α^i, the ability to out-perform a benchmark investment strategy
  - Fund return in excess of passive benchmark is $R_t^i = \alpha^i + \epsilon_t^i$. This return is *before fees*.
  - Skill distribution $\alpha^i \sim \mathcal{N}(\phi_0, \gamma^{-1})$ and idiosyncratic risk ("luck") $\epsilon_t^i \sim \mathcal{N}(0, \omega^{-1})$
  - Managers incur costs from trading $C(q)$, independent from skill, but convex in AUM q: $C'(q) > 0$, $C''(q) > 0$.
  - Intuition: the larger they become, the more dispersed their information acquisition strategy becomes (smaller information advantage), but the more price impact they have.
  - Investors pay a fixed mutual fund fee f per dollar AUM q.
  - After-fee returns investors receive per dollar invested:

$$r_{t+1} = R_{t+1} - \frac{C(q_t)}{q_t} - f = R_{t+1} - c(q_t)$$

- Investors (and managers) need to infer α^i from observed history of portfolio returns $\{R_s\}_{s=0}^t$, which mix skill and luck. Using Bayesian updating, posterior mean of management ability at time t is ϕ_t.
- Investors supply assets perfectly elastically to funds with positive ϕ_t. They withdraw all assets from funds with negative expected excess returns.
- Funds incur a fixed cost of operation F as well. When fund revenues do not cover the fixed cost, the fund exits. Funds with $\phi_t < \overline{\phi}$ will exit. Threshold s.t. marginal firm breaks even:

$$fq_t = q_t^*(\overline{\phi})\overline{\phi} - C(q_t^*(\overline{\phi})) = F$$

- Exiting firms are replaced with new firms drawn from the initial α distribution.

• **Implications**

- In equilibrium, $E_t[r_{t+1}] = 0$. All funds earn zero expected excess return *after fees*. Investors are indifferent between all actively-managed mutual funds of various skill levels and passive investments.
- Intuition: Funds with the highest skill have positive excess returns more frequently, investors upwardly revise their estimate of the manager's skill, they allocate more AUM to those firms. This process continues until the high-skill funds have so much decreasing returns (price impact) that they cannot longer profitably invest the last dollar after-fees.
- **The funds with the highest skill have the highest AUM**. This is an equilibrium theory of size distribution of MFs.

- Highly skilled funds also tend to be older: they have survived for a long time because they are good.
- Net alpha is **not a good measure of manager skill**. The competitive allocation of assets to funds + DRS at the fund level results in skill co-existing with zero net α.
  No alpha $\not\Rightarrow$ No skill!
- Fund captures all of the value added, investor captures nothing. Equilibrium is Pareto efficient.
- Equilibrium is consistent with a fixed expense ratio f, regardless of skill. As in data: mutual funds charge very similar fees, and usually there are no performance fees.
- Flow-performance relationship:

$$\frac{q_t - q_{t-1}}{q_t} = \frac{r_t}{f}\left(\frac{\omega}{\gamma + t\omega}\right) + \frac{r_t^2}{4f^2}\left(\frac{\omega}{\gamma + t\omega}\right)^2$$

  * Little noise in returns (high ω) relative to precision of prior about alpha γ, high signal-to-noise ratio ω/γ, large belief revision, large in- or outflow.
  * As fund age t increases, less uncertainty about fund skill. Flows to young firms respond more dramatically to performance than flows to mature funds: more belief revisions.
  * Higher fees make flows less sensitive to performance.
  * Non-linear: more (less) response to extreme positive (negative) performance, *as long as fund survives*.
- Fund managers optimally decide what fraction of AUM to invest actively versus passively. High-skill funds with superior past track record invest more passively. This reduces risk to investor. The conditional volatility of after-fee

returns (tracking error) decreases in fund age, as in data.

- Calibration
  - Fees f of 1.5%, consistent with data.
  - Idiosyncratic return volatility of 20% ($\omega = 25$) to match fund return volatility of around 9%.
  - Priors on alpha before fees are centered around $\phi_0 = 6.5\%$ mean alpha, with cross-sectional standard deviation of 6% ($\gamma = 277$).
  - High mean in priors of 6.5% is required to match the high survival rates in the first few years in the data.
  - High precision in priors of 277 is needed to match slope of flow-performance relationship of 2-year old funds to estimates from Chevalier and Ellison (1997).
  - These parameters imply that about 80% of funds have high enough skill (alpha before fees=gross alpha) to recover the fees they charge.

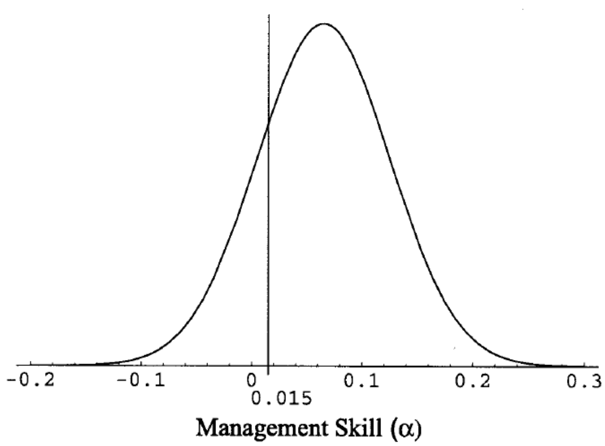


Fig. 4.—Distribution of management skill. The vertical line marks the level of the management fee—1.5 percent. Approximately 80 percent of the area below the curve lies to the right of this line. The parameter values (mean and precision) are $\phi_0 = 0.065$ and $\gamma = 277$.

3.2. Empirical evidence on mutual fund returns

- Standard data set: CRSP mutual fund data set of actively managed U.S. equity mutual funds. Exclude index funds. Data starts in 1962, but systematic monthly return coverage only starts in 1984. Literature usually starts sample in 1984.
  - Survivorship free: include funds that are no longer alive, but were at some point in the sample.
  - Exclude funds that were below \$5mi in AUM initially, but not if they fall below the threshold later in sample.
- Standard performance analysis uses a monthly Fama-French 3-factor or Carhart (1997) 4-factor model:

$$R_t^i - R_t^f = \alpha^i + \beta_M^i (R_t^M - R_t^f) + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \beta_{MOM}^i MOM_t + e_t^i$$

  More recently, literature began adopting the Fama French 5-factor model or the Hou, Xue, and Zhang 4-factor model.
- The literature has generally found little evidence for significantly positive alpha for the average mutual fund, not only after-fees, consistent with Berk and Green, but also *before fees*.
- The zero average alpha before fees (gross alpha) result makes sense as an equilibrium outcome.
- Why? Since passive investments by definition earn a zero alpha, the **aggregate/average active MF portfolio must also earn zero alpha before fees**.
  Note: This argument assumes absence of other investors, such as households or other institutions that hold equity, and who might have *negative* average alphas.

- Fama and French (2010) find that the value-weighted portfolio of actively managed U.S. equity mutual funds indeed is very close to the market portfolio and earns zero alpha.

- The sample is 1984-2006. We focus on vw-avg MF portfolio panel:

Table II

Intercepts and Slopes in Variants of Regression (1) for Equal-Weight (EW) and Value-Weight (VW) Portfolios of Actively Managed Mutual Funds

The table shows the annualized intercepts ($12 * a$) and t-statistics for the intercepts ($t(Coef)$) for the CAPM, three-factor, and four-factor versions of regression (1) estimated on equal-weight (EW) and value-weight (VW) net and gross returns on the portfolios of actively managed mutual funds in our sample. The table also shows the regression slopes (b, s, h, and m, for $R_M - R_f$, SMB, HML, and MOM, respectively), t-statistics for the slopes, and the regression R^2, all of which are the same to two decimals for gross and net returns. For the market slope, $t(Coef)$ tests whether b is different from 1.0. Net returns are those received by investors. Gross returns are net returns plus 1/12$^{\text{th}}$ of a fund's expense ratio for the year. When a fund's expense ratio for a year is missing, we assume it is the same as other actively managed funds with similar assets under management (AUM). The period is January 1984 through September 2006. On average there are 1,308 funds and their average AUM is \$648.0 million.

	$12 * a$						
	Net	Gross	b	s	h	m	R^2
EW Returns							
Coef	−1.11	0.18	1.01				0.96
$t(Coef)$	−1.80	0.31	1.12				
Coef	−0.93	0.36	0.98	0.18	−0.00		0.98
$t(Coef)$	−2.13	0.85	−1.78	16.09	−0.24		
Coef	−0.92	0.39	0.98	0.18	−0.00	−0.00	0.98
$t(Coef)$	−2.05	0.90	−1.78	16.01	−0.25	−0.14	
VW Returns							
Coef	−1.13	−0.18	0.99				0.99
$t(Coef)$	−3.03	−0.49	−2.10				
Coef	−0.81	0.13	0.96	0.07	−0.03		0.99
$t(Coef)$	−2.50	0.40	−5.42	7.96	−3.22		
Coef	−1.00	−0.05	0.97	0.07	−0.03	0.02	0.99
$t(Coef)$	−3.02	−0.15	−5.03	7.78	−3.03	2.60	

- The vw-average MF portfolio has a market beta around 1.

- FF3 alpha is 0.13% per year before fees, 0.4 standard deviations above 0. FF3 alpha is -0.81% per year after fees, 2.5 sd below 0.

- Carhart alpha is -0.05% per year before fees, 0.15 sd below 0. Carhart alpha is -1.00% per year after fees, 3.0 sd below 0.

- Market factor captures 99% of variation in monthly MF returns, with essentially no exposure to SMB, HML, MOM.

- Berk and Green predicts that the average alpha before fees (gross alpha) is positive. But the data suggest it is zero. After-fee alpha (net alpha) is zero in the model, but negative in data.

- Berk and Green model also predicts that *most* active MF managers should have positive alpha before fees (80%, recall graph).

- In contrast, the adding up constraint logic of Fama and French (2010) implies that if there are some funds with positive gross alpha, there must be equal mass with negative gross alpha.

- Key empirical challenge is to distinguish skill from luck. Given thousands of funds observed over 40 years, many will have very good returns purely by chance.

- Common approach is to test for **persistence** in mutual fund returns. Rank funds into deciles based on past (abnormal) performance. Then see how well each decile does over next 1, 3, 6, 12, 24, ... months. These tests suggest that **very few funds persistently outperform**.

  - But, ranking funds based on short-term past performance is largely sorting on noise, which makes for low power in these persistence tests.

- Alternative is to bootstrap long histories of individual fund returns to infer existence of superior and inferior funds. Comparing distribution of bootstrapped fund returns with $\alpha = 0$ to actual return distribution. This is what Fama and French (2010) do.

- For net $\alpha = 0$, the null hypothesis is that every manager has just enough skill to recover expense ratios they charge investors.

- Simulated versus actual distribution of net alpha *t-statistics* (conditional on funds exceeding \$5mi AUM, \$250 mi, and \$1 billion):

Table III

Percentiles of $t(\alpha)$ Estimates for Actual and Simulated Fund Returns: January 1984 to September 2006

The table shows values of $t(\alpha)$ at selected percentiles (Pct) of the distribution of $t(\alpha)$ estimates for actual (Act) net and gross fund returns. The table also shows the percent of the 10,000 simulation runs that produce lower values of $t(\alpha)$ at the selected percentiles than those observed for actual fund returns (% < Act). Sim is the average value of $t(\alpha)$ at the selected percentiles from the simulations. The period is January 1984 to September 2006 and results are shown for the three- and four-factor models for the \$5 million, \$250 million, and \$1 billion AUM fund groups. There are 3,156 funds in the \$5 million group, 1,422 in the \$250 million group, and 660 in the \$1 billion group.

	5 Million			250 Million			1 Billion		
Pct	Sim	Act	%<Act	Sim	Act	%<Act	Sim	Act	%<Act
3-Factor Net Returns									
1	−2.50	−3.87	0.08	−2.45	−3.87	0.10	−2.39	−4.39	0.01
2	−2.17	−3.42	0.06	−2.13	−3.38	0.13	−2.09	−3.55	0.09
3	−1.97	−3.15	0.07	−1.94	−3.15	0.12	−1.91	−3.36	0.07
4	−1.83	−2.99	0.06	−1.80	−3.04	0.10	−1.78	−3.16	0.07
5	−1.71	−2.84	0.08	−1.69	−2.91	0.10	−1.67	−2.99	0.10
10	−1.32	−2.34	0.05	−1.31	−2.37	0.10	−1.30	−2.53	0.08
20	−0.87	−1.74	0.03	−0.86	−1.87	0.04	−0.86	−1.98	0.03
30	−0.54	−1.27	0.06	−0.54	−1.41	0.06	−0.54	−1.59	0.02
40	−0.26	−0.92	0.05	−0.27	−1.03	0.07	−0.27	−1.19	0.02
50	−0.01	−0.62	0.04	−0.01	−0.71	0.06	−0.01	−0.82	0.03
60	0.25	−0.29	0.11	0.25	−0.39	0.19	0.24	−0.51	0.05
70	0.52	0.08	0.51	0.52	−0.08	0.25	0.52	−0.20	0.08
80	0.85	0.50	3.20	0.84	0.37	1.68	0.84	0.25	0.85
90	1.30	1.01	8.17	1.29	0.89	5.19	1.28	0.82	4.81
95	1.68	1.54	30.55	1.66	1.36	14.17	1.64	1.34	17.73
96	1.80	1.71	40.06	1.76	1.49	17.24	1.74	1.52	26.33
97	1.94	1.91	49.35	1.90	1.69	25.92	1.87	1.79	42.86
98	2.13	2.17	58.70	2.08	1.90	30.43	2.04	2.02	50.07
99	2.45	2.47	57.42	2.36	2.29	43.92	2.31	2.40	63.11

- Left tail *much lower* in data than under the no-skill null. Even worse for the large funds.
- Right tail shows no evidence of unusual skill.
- At the 80th percentile of manager skill distribution, less than 1% of simulations produce $t(\alpha)$ values below the observed one. Vast majority of managers appear not to have enough skill to recoup expenses.
- Only the 98th and 99th percentiles are consistent with distribution of zero net alpha model. Glimmer of hope that there are a few right-tail funds that occasionally outperform after fees.
- Far cry from Berk and Green prediction that most MF managers have enough skill to recover costs, so MF investors earn at least zero net alpha in every fund.

- Null hypothesis for **gross** $\alpha = 0$ is that funds have no skill to beat the benchmark (or just enough skill to cover costs not charged as part of the expense ratios).

- Left tail of actual $t(\alpha)$ still to the left of the average from the simulations. Some managers' actions result in negative alpha relative to passive benchmarks.

- Right tail shows outperformance of benchmark before fees.

- Above the 60th percentile, funds have enough skill to beat the benchmark in at least 56% of simulations, rising to more than 90% of simulations at the 96th and higher percentiles.

	5 Million			250 Million			1 Billion		
Pct	Sim	Act	%<Act	Sim	Act	%<Act	Sim	Act	%<Act
3-Factor Gross Returns									
1	−2.49	−3.07	4.11	−2.45	−3.16	3.16	−2.39	−3.29	1.88
2	−2.17	−2.68	4.79	−2.13	−2.67	6.01	−2.09	−2.70	5.64
3	−1.97	−2.48	4.20	−1.94	−2.51	4.47	−1.91	−2.51	5.12
4	−1.83	−2.31	4.41	−1.80	−2.35	4.68	−1.78	−2.33	5.77
5	−1.71	−2.19	4.15	−1.69	−2.18	5.99	−1.67	−2.18	6.52
10	−1.32	−1.72	5.75	−1.31	−1.77	5.94	−1.30	−1.86	4.15
20	−0.87	−1.10	13.61	−0.86	−1.24	7.18	−0.86	−1.43	2.52
30	−0.54	−0.71	20.03	−0.54	−0.79	15.10	−0.54	−1.00	4.28
40	−0.26	−0.36	29.74	−0.27	−0.43	23.84	−0.27	−0.59	10.25
50	−0.01	−0.06	38.87	−0.01	−0.15	26.28	−0.01	−0.28	13.48
60	0.25	0.28	56.05	0.25	0.14	31.47	0.24	0.05	21.21
70	0.52	0.63	71.81	0.52	0.48	43.62	0.52	0.35	26.70
80	0.85	1.06	85.21	0.84	0.88	58.14	0.84	0.79	44.31
90	1.30	1.59	90.01	1.29	1.41	69.39	1.28	1.34	60.63
95	1.68	2.04	92.10	1.66	1.81	72.89	1.64	1.78	70.37
96	1.80	2.20	93.73	1.76	1.93	73.44	1.74	1.96	77.00
97	1.94	2.44	95.97	1.90	2.19	84.36	1.87	2.22	85.47
98	2.13	2.72	97.29	2.08	2.47	89.30	2.04	2.37	83.72
99	2.45	3.03	96.66	2.36	2.83	90.95	2.31	2.97	94.63

- Right-tail evidence is much weaker for larger funds, consistent with decreasing returns assumption in Berk and Green.

- However, weeding out of unskilled fund managers should also lead to left tails that are less extreme for large funds. Not true in data.

- Now repeat the simulations under the null that there truly is some skill (gross alpha) centered around 0: $\alpha^i \sim \mathcal{N}(0, \sigma)$. What does σ need to be to generate actual distribution of $t(\alpha)$? Best fit for left-tail and right-tail of the distribution are for $\sigma = 1.25\%$.

- This implies that about 1/6th of funds have true gross alpha above 1.25% per year, and only 2.5% of funds have gross alpha above 2.5% per year.

- A lot of the right-tail performance is due to very small funds.

- The large sample of funds (3,156) gives these simulations power. We can be quite confident that $\sigma \in [0.75\%, 1.75\%]$.

- In a similar simulation study, Kosowski, Timmermann, Wermers, and White (2006) find a somewhat larger group of funds that outperforms. Fama and French (2010) argue this is in some part due to Kosowski et al.'s data exclusion rules inducing survivorship bias, and in other part due to differences in the sample (1972-2002). Latter could be due to biases in CRSP data before 1984. Or maybe there were simply more high-skilled funds present in the early days.

- In conclusion, average gross alphas are about zero and average net alphas about equal to minus the expense ratio. Second, there is little evidence that a substantial group of mutual funds systematically outperforms, at least unconditionally.

3.3. *Information acquisition and conditional performance*

- Natural to think of mutual funds as investors whose job it is to acquire information about future asset values and use that information to invest in high-valued assets.
- But clearly, not all MFs are good at this. Only a fraction of them are skilled. Define skill as having the ability to profitably process information in order to outperform other investors.
- Adding up constraint: skilled MF managers outperform at the expense of unskilled MF managers and unskilled households.
- Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) set up an equilibrium model of the MF industry along these lines. Unskilled households are modeled as noise traders.
  - Skilled MF managers choose to rationally allocate a fixed information processing capacity between learning about aggregate (macro) news or learning about firm-specific news.
  - Optimal information acquisition strategy is to learn about aggregate shocks in recessions and about firm-specific shocks in expansions.
  - Recessions are times when aggregate shocks become relatively larger, making them more valuable to learn about.
  - Model delivers predictions for:
    * conditional covariance of MF portfolio holdings with macro shocks and firm-specific earnings shocks
    * cross-fund holdings and return dispersion
    * fund excess returns

- Motivated by this theory, Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) propose a new definition of skill: general cognitive ability to pick stocks or time the market. Not innate talent, but skills obtained from data analysis.

- Prior work studies stock picking ability and market timing ability in isolation, as two different talents. Little empirical evidence for the presence of unconditional market timing skills. Only a little bit better for unconditional stock picking skill.

- Theory suggests that optimal strategy is conditional on the business cycle: skilled managers should be market timing in recessions and stock picking in expansions.

- Data indeed shows that the average fund's Timing is higher in recessions and average fund's Picking is higher in expansions.

- Quantile regressions show that the effect of the business cycle on Timing (Picking) are much stronger in the higher percentiles of the Timing (Picking) distribution.

- More powerful test of the theory: the **same** funds that are good at Timing in recessions should be good at Picking in expansions. (They need not be good at Timing in expansions or Picking in recessions.)

- This is in fact what the data shows. The top funds switch strategies.

Table IV

The Same Funds Switch Strategies

We divide all fund-month observations into recession and expansion subsamples. *Expansion* = 1 − *Recession*. *Top* is an indicator variable equal to one for all funds whose *Picking* in expansion is in the highest 25^{th} percentile of the distribution, and zero otherwise. Control variables, sample period, and standard errors are described in Table I.

	Timing		Picking	
	Expansion (1)	Recession (2)	Expansion (3)	Recession (4)
Top	−0.001	0.037	0.059	−0.054
	(0.004)	(0.013)	(0.005)	(0.017)
Log(Age)	0.009	−0.015	−0.001	0.027
	(0.002)	(0.006)	(0.002)	(0.007)
Log(TNA)	−0.001	0.004	−0.001	−0.024
	(0.001)	(0.003)	(0.001)	(0.003)
Expenses	0.571	0.981	−0.985	−3.491
	(0.322)	(1.085)	(0.366)	(1.355)
Turnover	0.010	0.009	0.013	−0.005
	(0.003)	(0.008)	(0.004)	(0.012)
Flow	0.058	−0.852	0.127	−0.054
	(0.024)	(0.112)	(0.036)	(0.092)
Load	0.124	0.156	0.104	0.504
	(0.050)	(0.162)	(0.054)	(0.197)
Size	−0.009	−0.057	0.011	0.023
	(0.002)	(0.006)	(0.002)	(0.007)
Value	−0.018	−0.057	0.027	0.107
	(0.003)	(0.010)	(0.003)	(0.011)
Momentum	−0.007	−0.148	0.031	−0.007
	(0.003)	(0.010)	(0.004)	(0.011)
Constant	0.018	0.055	−0.022	−0.159
	(0.001)	(0.005)	(0.002)	(0.006)
Observations	204,311	18,354	204,311	18,354

- Effects are similar at the manager level, suggesting that these skills are a feature of the manager not just the fund.

- Top funds tend to be: smaller, younger, with higher expense ratios, more active (higher turnover, fewer stocks, more stock and industry concentration), and with managers that are more likely to have an MBA and to depart later to a hedge fund.

- These top funds outperform: annual FF4 alpha is 0.7%.

- They market time by adjusting their portfolio prior to the onset of recessions: (i) holding stocks with lower beta, (ii) holding more defensive industries, and (iii) holding more cash.

- Suggests a new Skill Index, where w_t is real-time recession probability of Chauvet and Piger, and Timing and Picking are standardized in the cross-section and time series.

$$SkillIndex_t^j = w_t Timing_t^j + (1 - w_t) Picking_t^j$$

- This Skill Index predicts MF returns: A one-std increase improves CAPM alpha by 2.4% per year, relative to mean of -0.5% (column 1).

Table IX

Skill Index Predicts Performance

The dependent variables are, respectively, the fund's cumulative CAPM, three-factor, or four-factor alpha, calculated from a 12-month rolling-window regression. The regression window is $t-10$ to $t+2$ for one month ahead and $t+1$ to $t+13$ for one year ahead. For each fund, we form *Skill Index* defined in equation (7). *Picking* and *Timing* are defined in Table I, except that they are normalized so that they are mean zero and have a standard deviation of one over the full sample. The other control variables, sample period, and standard error calculation are the same as in Table I.

	One Month Ahead			One Year Ahead		
	CAPM Alpha (1)	Three-Factor Alpha (2)	Four-Factor Alpha Alpha (3)	CAPM Alpha (4)	Three-Factor Alpha (5)	Four-Factor Alpha (6)
Skill Index	0.202	0.103	0.094	0.197	0.090	0.091
	(0.038)	(0.019)	(0.017)	(0.028)	(0.023)	(0.013)
Log(Age)	−0.027	−0.022	−0.033	−0.014	−0.008	−0.023
	(0.007)	(0.005)	(0.006)	(0.007)	(0.005)	(0.006)
Log(TNA)	0.025	0.005	0.008	−0.012	−0.018	−0.012
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Expenses	−3.347	−8.139	−8.040	−5.571	−9.423	−9.475
	(1.026)	(0.797)	(0.755)	(0.983)	(0.748)	(0.660)
Turnover	−0.041	−0.075	−0.065	−0.007	−0.050	−0.048
	(0.010)	(0.010)	(0.008)	(0.012)	(0.011)	(0.009)
Flow	2.226	1.585	1.436	0.106	0.163	0.164
	(0.156)	(0.095)	(0.091)	(0.114)	(0.084)	(0.071)
Load	−0.655	−0.037	−0.271	−0.576	0.250	−0.009
	(0.189)	(0.134)	(0.143)	(0.174)	(0.122)	(0.132)
Size	−0.031	0.016	0.012	−0.061	−0.005	−0.005
	(0.024)	(0.008)	(0.009)	(0.028)	(0.010)	(0.010)
Value	0.237	0.010	0.045	0.235	0.034	0.074
	(0.030)	(0.019)	(0.017)	(0.036)	(0.025)	(0.021)
Momentum	0.246	0.158	0.157	0.098	0.056	0.088
	(0.042)	(0.031)	(0.025)	(0.031)	(0.030)	(0.025)
Constant	−0.032	−0.056	−0.042	−0.044	−0.071	−0.058
	(0.023)	(0.017)	(0.020)	(0.024)	(0.018)	(0.021)
Observations	219,321	219,321	219,321	187,659	187,659	187,659

- If this is true cognitive ability, it should persist. Otherwise, it is luck. Sort mutual funds based on Skill Index into quintiles. Then track returns in next 1, 3, 6, 12 months.

- Bottom panel shows that skill persists. Q5-Q1 significant until 9 months later.

- In contrast, *time-invariant* market timing and stock picking skills do not display persistence.

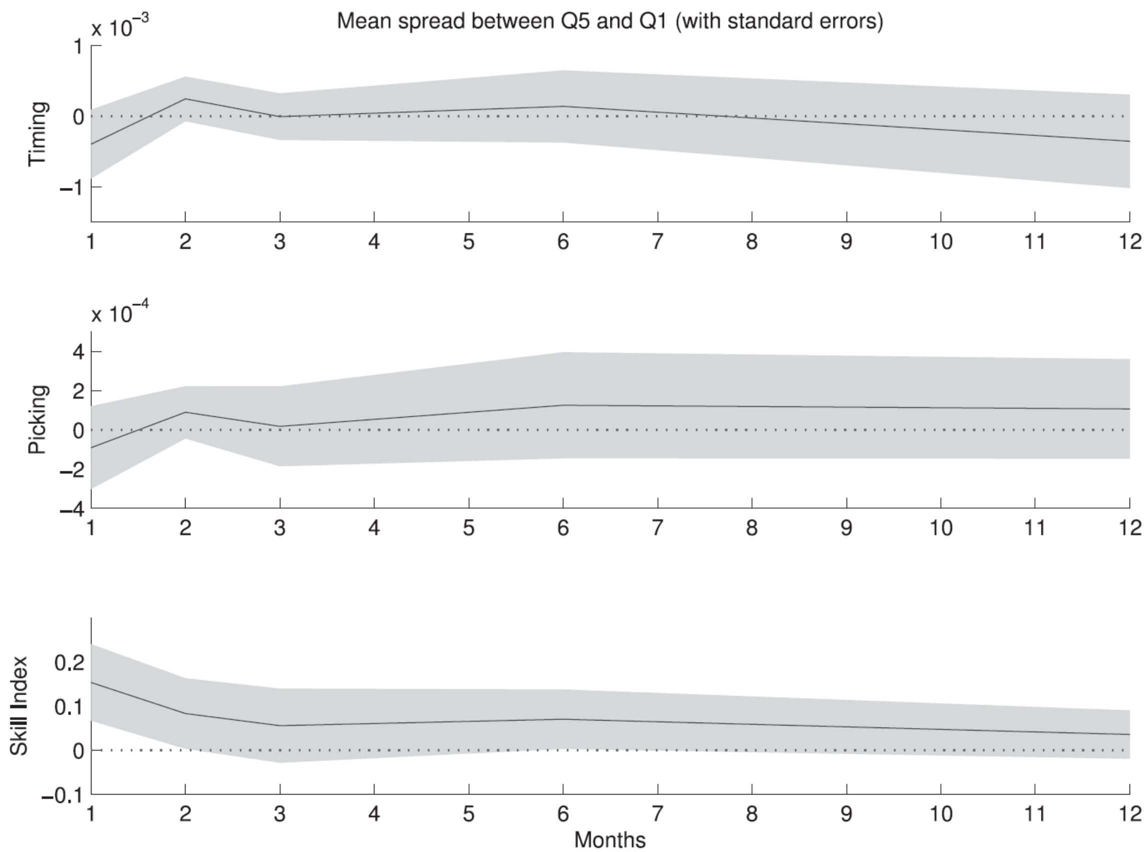


Figure 1. Persistence of *Timing*, *Picking*, and *Skill Index*. We rank funds into quintiles based on their *Timing*, *Picking*, or *Skill Index* score at time 0. Next, we subtract the average score in quintile 5 (Q5) from that in quintile 1 (Q1) in each of the following 12 months. We report that difference in the postformation period. A positive difference indicates persistent skill. The shading shows two standard errors on either side of the point estimate (solid line).

3.4. *The debate on measuring skill goes on*

- Berk and Binsbergen (2015) argue that a MF manager's skill is the value it extracts from markets.
- A manager who runs a huge fund with a small gross α may add more value than a manager who runs a small fund and has a large α.
- Value added is defined as excess return over passive benchmark, i.e., gross alpha, times AUM:

$$V_t^i = q_{t-1}^i (R_t^i - R_t^B)$$

- For a fund that exists for T^i periods, **S**kill is estimated as

$$\widehat{S}^i = \frac{1}{T^i} \sum_{t=1}^{T^i} V_t^i$$

- Gross alpha is only the correct measure of skill if all the funds have the same size. Large dispersion in AUM belies this.
- Paper makes some data improvements
  - combines and cross-checks CRSP and Morningstar data sets to obtain better return, AUM, and expense ratio data
  - does not exclude funds that hold non-US stocks; the AUM of funds holding only US stocks falls from 45% in 1977 to 25% in 2011.
  - uses Vanguard funds as benchmarks, but only in years after these funds are introduced.

- Value added is zero at the median, but average is $270,000 per month. Ten percent of funds add more than $750,000/month in value. These 10% control 25% of the assets.

Table 3

Value added ($\hat{S}_i$). For every fund in our database, we estimate the average monthly value added, $\hat{S}_i$. The cross-sectional mean, standard error of mean, t-statistic and percentiles are the statistical properties of this distribution. Percent with less than zero is the fraction of the distribution that has value added estimates less than zero. The cross-sectional weighted mean, standard error of the weighted mean and t-statistic are computed by weighting by the number of periods the fund exists, that is, they are the statistical properties of $\overline{S}_W$ defined by Eq. (9). The numbers are reported in Y2000 $ millions per month.

	Vanguard benchmark	FFC risk measure
Cross-sectional weighted mean	0.27	0.25
Standard error of the weighted mean	0.05	0.06
t-statistic	5.74	3.94
Cross-sectional mean	0.14	0.10
Standard error of the mean	0.03	0.03
t-statistic	4.57	3.43
1st percentile	−3.60	−3.93
5th percentile	−1.15	−1.43
10th percentile	−0.59	−0.77
50th percentile	−0.02	−0.03
90th percentile	0.75	0.70
95th percentile	1.80	1.98
99th percentile	7.82	6.76
Percent with less than zero	57.01%	59.70%
Total number of funds	5974	6054

- Cross-sectional correlation between value added and gross alpha is only 23%.
- Under null of no skill, value added should not be persistent. But paper finds persistence up to 10 years out.
- Concludes that a group of skilled managers exists. Investors know (can learn) who the skilled managers are, and reward them with high flows and fee revenues. Investors do not share in the fruits of this skill.

3.5. Are mutual fund managers paid for skill?

- Even if (some) managers are skilled, it is not obvious that managers can capture the rents from that skill. Their employers, the fund families (firms), might capture the rents instead.
- The literature typically considers the fund and the manager to be one and the same, as if every firm only had one fund and the fund manager were the owner of the firm.
- But fund families have many funds, and managers are typically the employees, not the owners. Little is known about the second layer of delegation: from firm owners to fund managers.
- Making this distinction requires data on compensation of managers, which typically is not available. Ibert, Kaniel, Van Nieuwerburgh, and Vestman (2018) is the first paper to use data on actual mutual fund manager compensation for the universe of Swedish actively managed mutual funds. Tax registry data.
- Main empirical specification:

$$\log(L_{m,t}) = \alpha_m + \beta \log(REV_{m,t}) + \gamma \log(1 + R^{abn}_{m,t-1}) + \delta X_{m,t-1} + \epsilon_{m,t}$$

- Finds that manager compensation responds *very little* to fund performance (R^{abn}), whether measured by excess return, factor alpha, or value-added.
  - A one-XS-stdev increase in performance increases MF manager pay by 3%, or 0.04 XS-stdev of pay.
  - Including lagged abnormal returns strengthens pay-for-performance (PPS) a bit, but it remains economically small.
  - PPS 5 times smaller than in Berk and Green simulation.

- Manager compensation is more responsive to fund size (REV).
  - elasticity of pay to REV is 0.15. A 1% increase in fund revenue increases pay by 0.15%.
  - a one xs-stdev increase in revenue increases pay by 25%, or 0.4 xs-stdev of pay.
  - That is, the manager's *share* of revenue falls by 0.85% when the fund's AUM increases by 1%.
  - Ex.: Fund AUM goes from $450 to $900 million, fee revenue goes from $6.2 to $12.4 million, manager pay goes from $210,000 to $241,200. Fund family captures 99.5% of dollar revenue increase, manager only 0.5%. Managerial pay falls from 3.3% to 1.9% of revenue.
- In Berk and Green, AUM is a perfect measure of skill. AUM in turn is driven by past out-performance. This need not be true in the real world.
- Is sensitivity of pay to AUM driven by the part of AUM that is due to past superior return, or driven by the part that is orthogonal to past returns?
- Empirical finding: Coefficient on component of REV orthogonal to past performance remains nearly unaffected and strongly significant.
  - This component could capture the effect of advertising, marketing, and sales skills which attract investor flows, regardless of investment out-performance.
- PPS strengthens but remains economically weak.
  - Adding up coefficients: only 2% increase in wages from non-trivial 1% alpha achieved 3 years in a row.

– Same regression in Berk and Green model-simulated data show coefficient that is 50% larger in model than in data.

– And some of this is a sample selection effect.

Table 3
Decomposing the effect of revenue on pay

	(1) $\log(L_{m,t})$	(2) $\log(L_{m,t})$	(3) $\log(L_{m,t})$	(4) $\log(L_{m,t})$	(5) $\log(L_{m,t})$	(6) $\log(L_{m,t})$	(7) $\log(L_{m,t})$
$\log(REV_{m,t})$	0.141***			0.140***			
	(0.0194)			(0.0195)			
$\log(REVorth_{m,t})$		0.144***	0.134***		0.144***	0.144***	0.130***
		(0.0194)	(0.0257)		(0.0193)	(0.0193)	(0.0255)
$\log(1+R^{abn}_{m,t})$						0.0646	0.253
						(0.151)	(0.194)
$\log(1+R^{abn}_{m,t-1})$				0.148	0.327*	0.325*	0.586**
				(0.176)	(0.174)	(0.170)	(0.236)
$\log(1+R^{abn}_{m,t-2})$							0.583***
							(0.200)
$\log(1+R^{abn}_{m,t-3})$							0.274*
							(0.158)
Constant	7.173***	9.509***	9.074***	7.212***	9.563***	9.561***	9.141***
	(0.595)	(0.639)	(0.894)	(0.602)	(0.646)	(0.645)	(0.904)
Manager FE	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	No
N	2,898	2,883	1,932	2,898	2,883	2,883	1,932
Adjusted R^2	0.229	0.233	0.182	0.229	0.234	0.234	0.190

See Table 2. The second, fifth, and sixth columns use as the independent variable the part of log revenue that is orthogonal to abnormal returns at time t and $t-1$. The third and seventh columns additionally orthogonalize revenue to abnormal returns at times $t-2$ and $t-3$.

- Ibert, Kaniel, Van Nieuwerburgh, and Vestman (2018) suggest that literature needs to shift its attention to the fund family.

- Firm-level variables strong determinants of MF manager pay:

  – Firm fixed effects and firm-year fixed effects

  – Firm revenue that is driven by all *other* managers

  – Firm profitability (bonus pool)

  – Whether the fund belongs to a large commercial bank

3.6. The role of marketing in driving fund flows

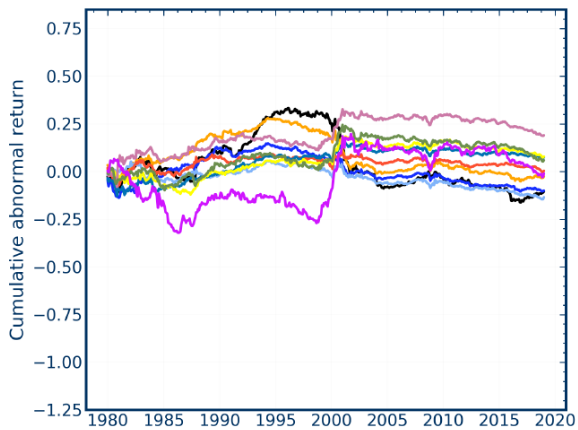
- Roussanov, Ruan, and Wei (2021) make progress in understanding the role of marketing for fund flows.
- About 1/3 of the \$100 bi in total mutual fund revenue is spent on marketing: sales loads and distribution costs (12b-1 fees).
- Is marketing a wasteful **rat race** which distorts the allocation of assets towards under-performing funds, or does it enable capital to flow to more skilled managers by alleviating search costs?
- Households have to search for funds. Heterogeneity in search costs captures differing investor sophistication. Generalizes IO model of Hortacsu and Syverson (2004) who study the market for S&P500 index funds.
- Funds choose fees and marketing spending. Marketing increases the likelihood that a customer finds that fund, but lowers the profits of the fund.
- Model nests Berk and Green's frictionless market with rational investors when the search frictions are turned off.
- Relative to the Berk and Green model, the data has far too many large unskilled funds, while the top-10% alpha firms are too small relative to the frictionless model.
- Model with search frictions finds that marketing expenses are nearly as important as expense ratios or fund performance for explaining the variation in fund size (AUM).

- Search costs estimated to be high: 39 basis points (lower return) to sample an additional mutual fund. That's 2/3 of average gross alpha.
- Marketing is effective at raising fund size: 1bp increase in marketing expenses raises AUM by 1%. Slightly higher for high-skill funds, slightly lower for low-skill funds. Complementarity between marketing and skill. Marketing alone can explain 10% of cross-sectional variation in fund size.
- Counter-factual exercise that prohibits marketing. Current rules cap it at 1% of AUM.
  - Shows that marketing reduces welfare due to the arms race it entails; 80bps increase in welfare (in units of returns) when marketing is prohibited.
  - Without marketing, there would be more price competition and the average expense ratio would be 80bps rather than 160bps.
  - Index funds would become larger as a share of the market.
    - More investors would know of the index fund once active funds cannot obfuscate through marketing.
    - Active funds would become more attractive because they would be cheaper. Their gross alphas would be higher because decreasing returns (they represent a smaller share of new market equilibrium).

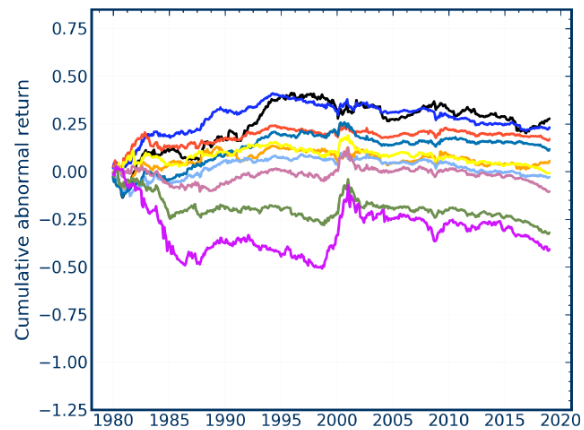
3.7. Machine-learning skill of MF managers

- Kaniel, Li, Pelger, and Van Nieuwerburgh (2023) use a neural network (see week 2) to analyze what attributes predict the **abnormal** return of mutual fund managers
  - Use 4-factor alpha as measure of skill (results are robust to other alpha definitions)
  - Include about 90 characteristics of the stocks the MF holds
  - Include characteristics of the MF: AUM, turnover, expense ratio, fund (abnormal return) momentum , etc.
  - Include MF family characteristics
- Find that only fund and fund family characteristics predict fund abnormal returns, not stock characteristics.
  - Fund momentum and fund flow are two key predictors.
  - Predictability is stronger in high sentiment periods.
- Predictability is long-lasting: SR only decays by half 36 months later.
- Important to predict abnormal returns, rather than total fund returns. Total fund returns have much stronger factor structure, and stock characteristics help to pick up that factor structure.

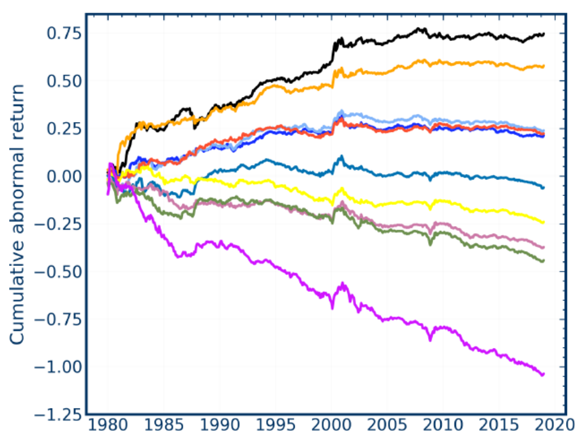
Figure 7: Cumulative abnormal returns for different information sets.



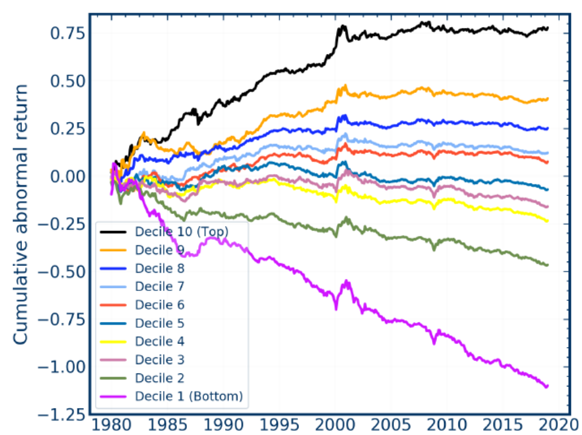
(a) Stock-specific characteristics



(b) Stocks-specific characteristics + sentiment



(c) Fund-specific characteristics



(d) Fund-specific characteristics + sentiment

4. Hedge Fund Returns

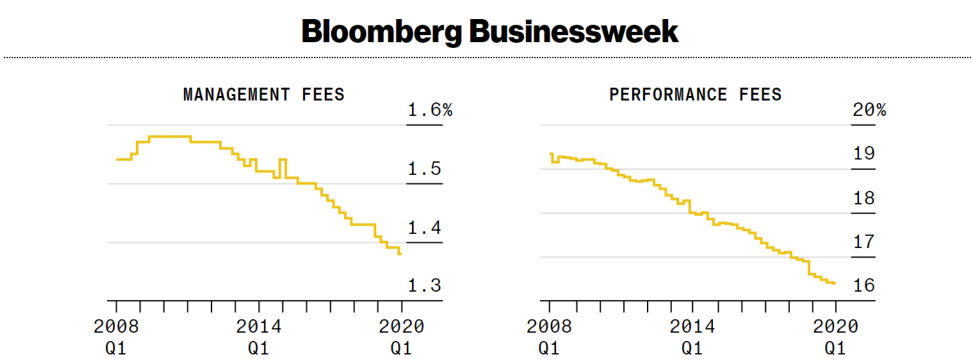
4.1. Stylized Facts

- Hedge funds are much smaller than mutual funds, with $5 trillion in AUM in 2023 (includes $320 billion in fund of funds). Up from $1.8 trillion in 2013.

- Spread over many strategies:

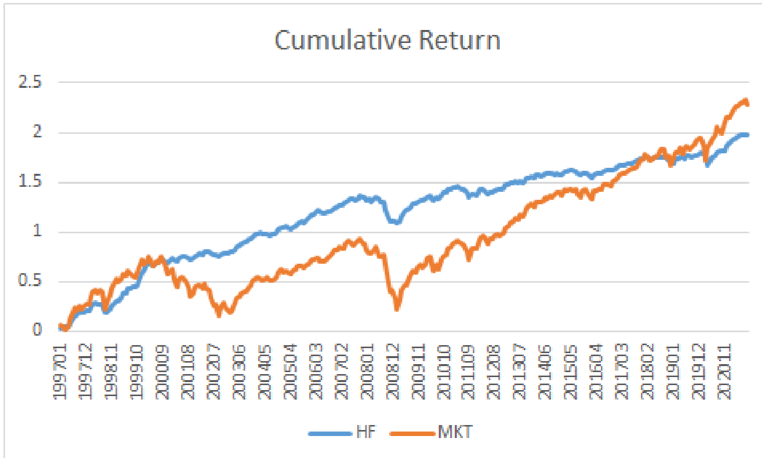
Assets Under Management	4th Qtr. 2023	3rd Qtr. 2023	2nd Qtr. 2023
Hedge Funds*	$5051.6B	$4959.1B	$5138.7B
Fund of Funds	$323.7B	$323.3B	$335.2B
Sectors			
Balanced (Stocks & Bonds)	$719.6B	$706.5B	$764.8B
Convertible Arbitrage	$32.5B	$35.2B	$37.6B
Distressed Securities	$19.4B	$19.7B	$16.0B
Emerging Markets	$420.4B	$416.6B	$434.2B
Equity Long Bias	$310.7B	$305.2B	$310.6B
Equity Long/Short	$149.1B	$139.7B	$144.5B
Equity Long-Only	$583.3B	$556.1B	$574.4B
Equity Market Neutral	$53.2B	$52.3B	$49.6B
Event Driven	$226.5B	$229.7B	$241.8B
Fixed Income	$967.0B	$954.9B	$973.1B
Macro	$151.2B	$149.8B	$153.8B
Merger Arbitrage	$73.8B	$83.8B	$91.2B
Multi-Strategy	$688.5B	$687.5B	$694.9B

- Hedge funds have come under pressure over lack of out-performance, esp. in light of their high fees ("2&20") and the more sophisticated passive strategies now available to investors.
  - Hedge funds returned 9.3% in 2023, much less than the 26% return on S&P500. Hedge funds returned 10.2% in 2021, much less than the 28.4% return on S&P500. Also under-performance in 2020 (11.1% vs. 16.6%).
  - Hedge funds should do best when volatility is high and stock and bond returns are fairly low.
  - Hedge funds outperformed in 2008: -18.3% versus -38.5% for the S&P500. Hedge fund marketeers now play on investor fear about next crisis.
  - Hedge funds also outperformed in 2022: -8.2% versus -18.1%
- Fund-of-fund strategies' AUM down from $446 bn in 2011 to $320 bn in 2023. Fund-of-funds = fees-on-fees!
- In response to investor pressure, hedge funds have been lowering both management and performance fees



Hedge-fund fees fall to an all-time low. Source: HFR

- Barclays Hedge Fund index. Cumulative returns net of fees, January 1997-Sept 2021: 197%. CRSP-vw stock market: 229%.



- Hedge fund returns compared to Fama-French 5 factor returns:

TABLE 1
HEDGE FUND AND FF-5 RETURNS

	HF	Mkt-Rf	SMB	HML	RMW	CMA	Rf
Full sample: 1997.01-2021.09							
E[R]	8.24	8.65	2.33	0.58	3.68	2.26	1.91
Std[R]	7.11	15.90	11.11	11.54	9.94	7.30	
SR	0.89	0.54	0.21	0.05	0.37	0.31	
First half: 1997.01-2009.03							
E[R]	9.41	0.64	3.25	3.40	5.46	4.52	3.40
Std[R]	7.75	16.92	12.69	12.60	12.79	8.74	
SR	0.78	0.04	0.26	0.27	0.43	0.52	
Second half: 2009.04-2021.09							
E[R]	7.09	16.49	1.42	-2.18	1.93	0.05	0.45
Std[R]	6.43	14.54	9.34	10.37	5.97	5.51	
SR[R]	1.03	1.13	0.15	-0.21	0.32	0.01	

- Consistently lower volatility than stock market, somewhat lower returns in second half of sample period, but higher Sharpe ratio.

- CAPM: $\alpha = 0.32\%$ per month (t-stat 3.6), $\beta_M = 0.29 << 1$, $R^2 = 43.3\%$.

- FF-3: $\alpha = 0.31\%$ (t-stat 3.9), $\beta_M = 0.27^*$, $\beta_{SMB} = 0.12^*$, $\beta_{HML} = -0.07^*$, $R^2 = 48.0\%$.

- FF-5: $\alpha = 0.37\%$ (t-stat 4.4), $\beta_M = 0.25^*$, $\beta_{SMB} = 0.09^*$, $\beta_{HML} = -0.02$, $\beta_{RMW} = -0.10$, $\beta_{CMA} = -0.04$, $R^2 = 49.2\%$.

- Significant out-performance over full sample (4.4% per year), low market beta, a bit of small-stock exposure, no other factor exposure.

- First half of sample from 1997.01-2009.03: FF-5: $\alpha = 0.42\%$ (t-stat 3.5), $\beta_M = 0.35^*$, $\beta_{SMB} = 0.19^*$, $\beta_{HML} = -0.09$,$\beta_{RMW} = 0.06$, $\beta_{CMA} = 0.01$, $R^2 = 75.0\%$.

- Second half of sample from 2009.04-2021.09: FF-5: $\alpha = 0.32\%$ (t-stat 3.0), $\beta_M = 0.20^*$, $\beta_{SMB} = -0.02$, $\beta_{HML} = 0.02$, $\beta_{RMW} = -0.22^*$, $\beta_{CMA} = -0.01$, $R^2 = 25.5\%$.

- HF strategies became less profitable (10bp per month) and much less correlated with FF5 factors since GFC (R^2 fell from 75% to 25%).

- Results for the value-weighted Dow Jones Credit Suisse (DJSC) Broad Hedge Fund Index and the equal-weighted HFRI Fund Weighted Composite Index are similar.

- This evidence suggests that hedge fund returns cannot readily be replicated by portfolios combining traditional risk factors.

- The positive net alphas for the average hedge fund could mean that markets are inefficient.

- Or the risk factor model for hedge funds may be misspecified.

- Hedge funds may have **non-linear, option-like exposures** to standard factors. Specifically, hedge fund strategies are akin to writing out-of-the-money put options. As long as the crash does not materialize, you earn the option premium. When it does, you get wiped out. This manifests itself as skewness in returns and left-tail risk.
  - See Mitchell and Pulvino (2001), Fung and Hsieh (2001) and Agarwal and Naik (2004).
  - A survey of the recent empirical hedge fund literature is Agarwal, Mullally, and Naik (2015).

- One branch of literature uses asset-based style benchmarks, bottom-up strategies that combine stocks and bonds to try to replicate hedge fund returns. The most well-known is the 9-factor model of Fung and Hsieh (2004).

- The main takeaway from this literature is that the alpha of hedge funds following rule-based strategies is significantly lower after accounting for the risks spanned by the benchmarks, transaction costs, and fees. Other strategies' alphas are harder to explain away by this approach, e.g., macro strategies.

- Another branch directly includes higher-moments of stock returns as factors (vol, skewness, kurtosis), macro uncertainty (Bali, Brown, and Caglayan, 2014), or volatility of the aggregate volatility factor (Agarwal, Arisoy, and Naik, 2019).
  Finds that these factors are related to cross-section and time-series of hedge fund returns.

- This evidence suggests that in the aggregate, hedge fund investors may be specializing in bearing downside market risk and/or aggregate uncertainty risk. They demand compensation for this in equilibrium. That is the alpha we find in linear factor regressions.

- This makes sense if the end users of hedge fund investments hold concentrated portfolios. This concentration premium is particularly large if the specialized asset/strategy has more downside risk than the market factor.

- Jurek and Stafford (2015) constructs the returns on a simple strategy that starts with some equity capital (margin), writes a put option on the S&P500 index, invests the proceeds in the risk-free rate, and sells the option at the end of the month.

- The leverage (L) in the strategy is either 2x or 4x.

- This simple option-writing strategy replicates HF returns very well.

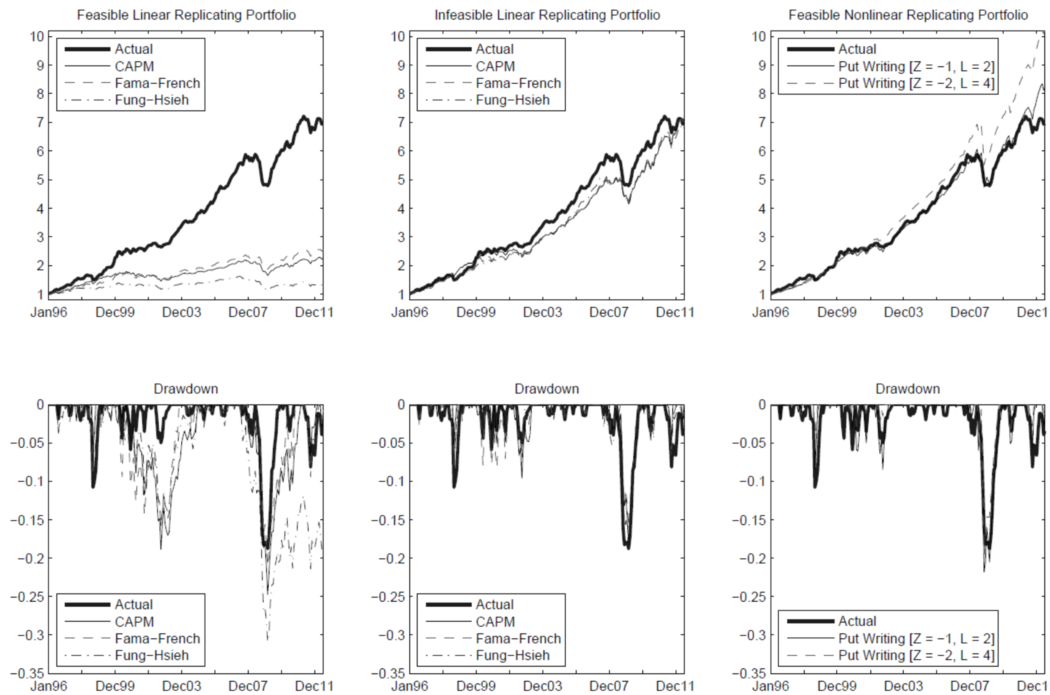


Figure 1. Replicating the risks and returns of the HFRI Fund Weighted Composite Index. The top panels plot the cumulative value of $1 invested in the HFRI Fund Weighted Composite Index (pre-fees; "Actual"), along with various replicating strategies. The left panel shows the cumulative return based on the fitted values from three common factor models (CAPM, Fama-French/Carhart, Fung-Hsieh) exclusive of the estimated intercept (feasible linear replication). The middle panel repeats the plot based on the fitted factor models, but returns are cumulated inclusive of the estimated intercept (infeasible linear replication). The right panel plots the returns to the two put-writing strategies (feasible nonlinear replication). Relative to the [Z=-1, L=2] put-writing strategy, the [Z=-2, L=4] strategy applies a higher amount of leverage to options that are written further out of the money. The bottom panels plot the corresponding monthly drawdown series for the hedge fund index and the replicating strategies.

4.3. Data Issues

- Hedge fund return data have some well-known issues:
  - Unconditional *return smoothing* that reflects asset illiquidity and discretion in marking portfolios to market. May hide downside risk exposure. Jurek and Stafford (2015) show that smoothing two monthly observations (Aug 98 and Oct 08) is enough to obscure downside market risk.
  - Survivorship bias.
  - Selection bias: young, small, and poorly performing funds may never enter the data set.
  - Incubation bias: when (successful) funds make it into the data set, historical returns are also made available for these funds (backfilling). These returns are better than average, another form of selection bias.

5. The Rise of Passive Investing

- In his presidential address to the AFA, Stambaugh (2014) documents the decline in stocks directly held by individuals.

Figure 1. Individual equity ownership. The solid line plots annual values for the fraction of the U.S. equity market that is owned directly by individuals. The dotted line plots a linear trend fit through the data points.

- as well as the decline in active asset management, or equivalently, the rise in passive investment (indexing)

- These trends have continued since publication of this paper.

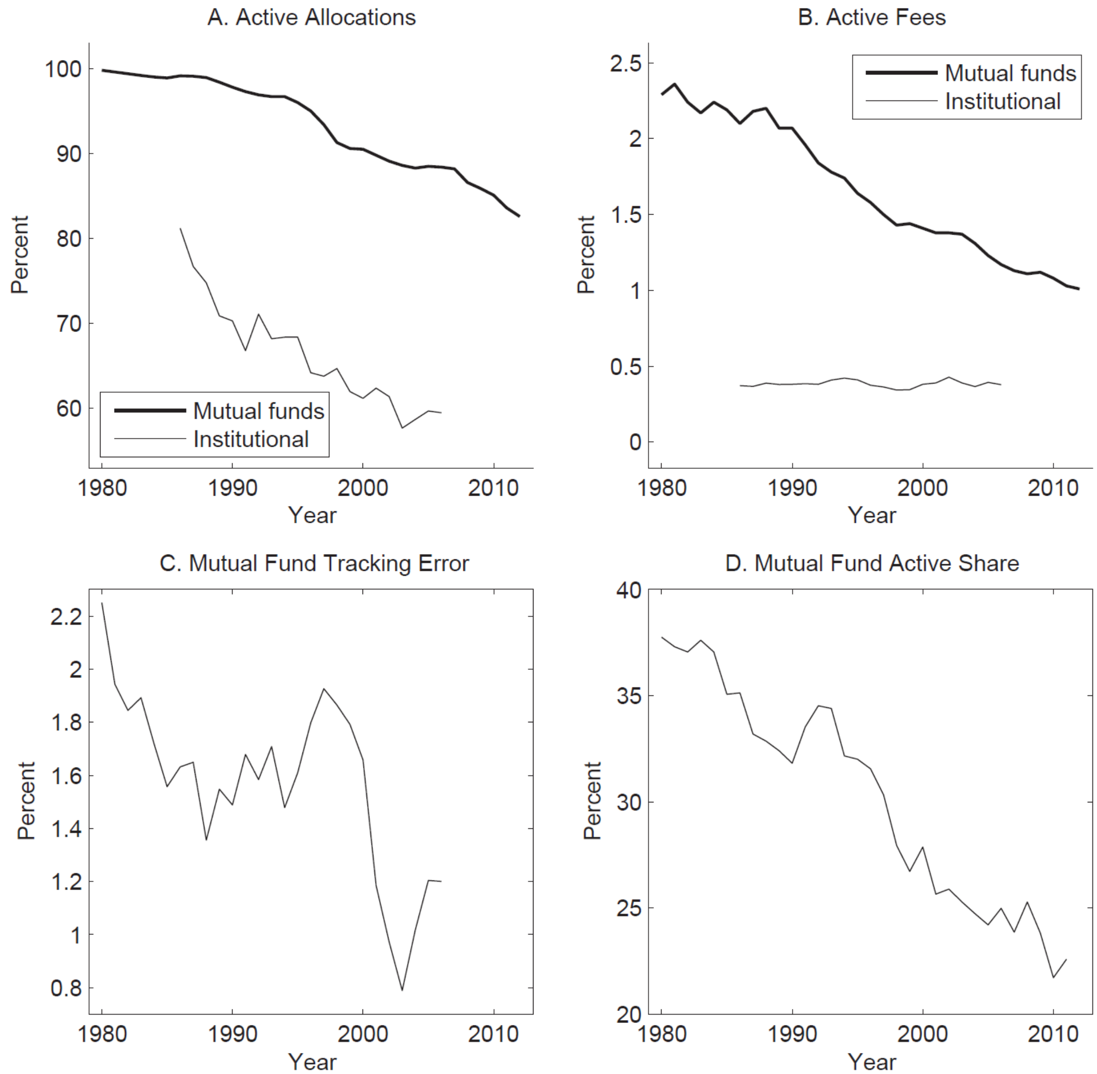


Figure 2. Trends in active management. Panel A plots the fraction of equity mutual fund assets that are actively managed (thicker line) and the fraction of institutionally owned equity that is actively managed (thinner line). Panel B plots the aggregate cost to investors of owning active equity mutual funds (thicker line) and the aggregate fee paid by institutional investors for active equity management. Panel C plots the estimated tracking error of the aggregate portfolio of active equity mutual funds. Panel D plots the estimated active share of that portfolio.

- Stambaugh argues these two trends are related. A decline in noise trading by individuals, and the mispricing it generates, has reduced the capacity for profitable active management. The footprint of active management shrinks as a result.

5.1. *Role of indexing on price informativeness*

- Most trading is done by institutions, and many asset managers are "benchmarked" to an index.
- Breugem and Buss (2019) studies the effect of benchmarking on information acquisition and on price informativeness, defined as deviations of price from fundamental value.
- Benchmarked investors with *CARA* preferences have an information-insensitive hedging demand for stocks in the index. This reduces the effective supply of shares in *all* investors' portfolios that are sensitive to private information. This information-scale effect reduces value of private information, and leads to a decline in the amount of information acquired. Price informativeness declines.
- Benchmarked investors with *CRRA* preferences have limited willingness to speculate, so that sensitivity of portfolio w.r.t private information declines. They not only acquire less information, but also trade less aggressively on that information. This risk-taking effect leads to a further decline in value of private information and adversely affects information aggregation.
- In equilibrium, benchmarked investors are less well informed than non-benchmarked investors and earn lower expected returns.
- As the fraction of AUM in benchmarked portfolios increases, the "average" investor becomes less informed and trades less aggressively on information. Less information is aggregated in prices. The return gap between investors widens.

- Stock prices rise due to the hedging demand from benchmark investors (information scale effect) but fall due to the decline in price informativeness/increase in posterior uncertainty (risk-taking effect). Which effects dominates depend on cost of acquiring information. If it is low, prices may fall when benchmarking increases, and expected excess returns rise.

- Information scale effect is only present for stocks in the index; the overall effect is stronger for these firms.

5.2. Role of Corporate Governance

- While outside the realm of this empirical asset pricing course, there is an interesting discussion in corporate governance about the role that large passive investors like Blackrock, Fidelity, or Vanguard ought to play in the corporate governance of the firms they own. They are after all the largest shareholders of most firms.

- Edmans, Levit, Reilly (2019) argue that large investors that own large stakes in many firms can strategically choose which stakes to sell when they are hit with a liquidity shock. The choice of which position to exit is a threat that improves price informativeness and corporate governance. This offsets the weakening of corporate governance through diversification/dilution.

- Azar, Schmalz, and Tecu (2018) document that common ownership of stocks leads to higher product prices. They interpret the evidence as anti-competitive behavior; large shareholders exert pressure on their portfolio companies to reduce competition with each other. They could instead result from better governance, leading to superior product quality.