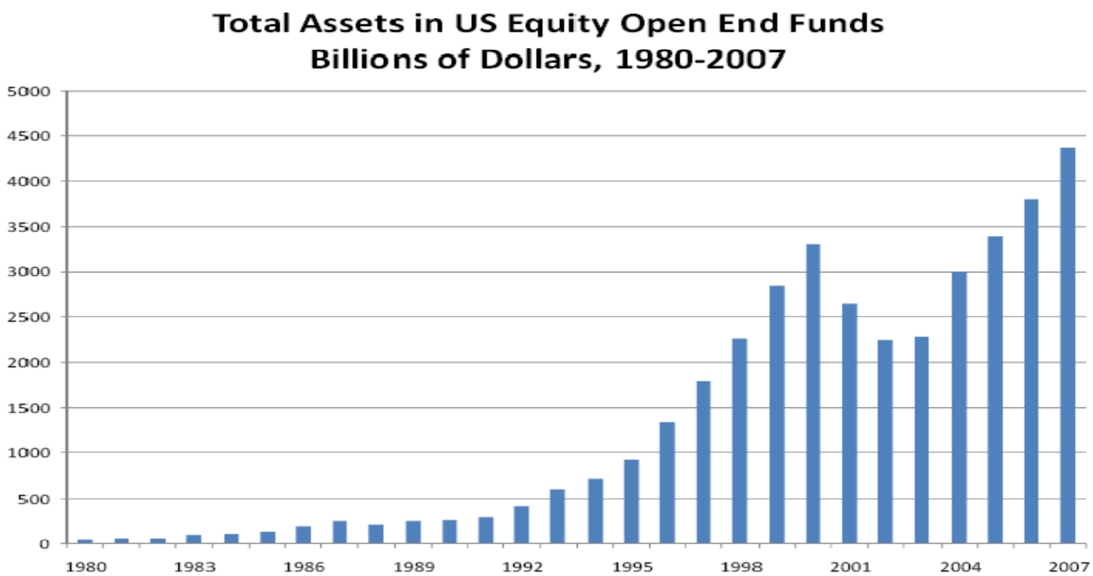
Lecture 8: Mutual Funds

In this lecture, we will discuss

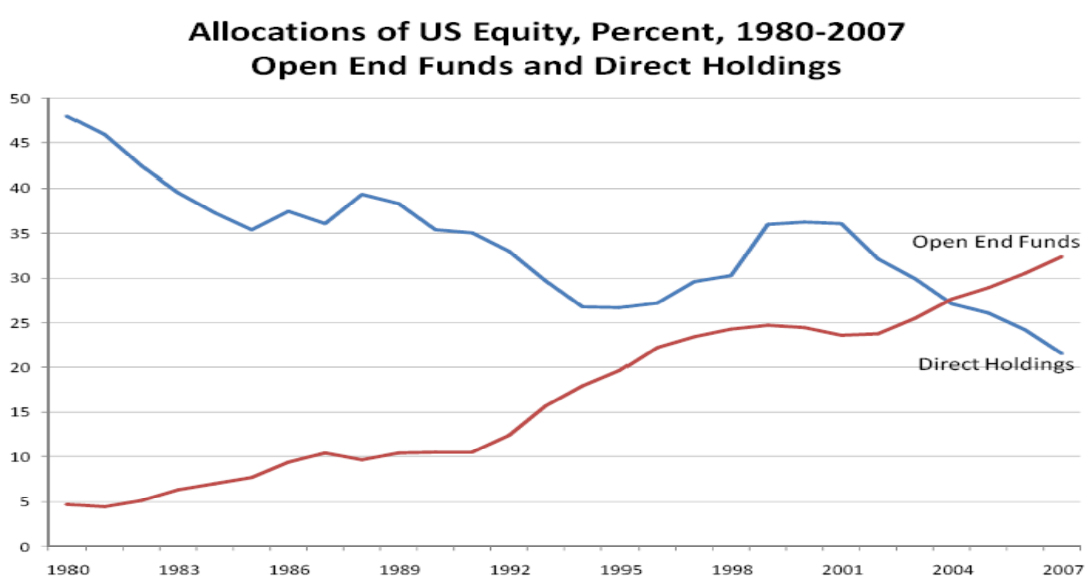
- Performance evaluation techniques
  - based on past returns
  - based on past returns and holdings
- Market timing
- Performance attribution
- Performance persistence
- Performance-flow relations
- Fund families
- Career as a mutual fund manager
- Window dressing

Mutual Fund Growth

- U.S. mutual funds manage \$16.6 trillion (Feb 1, 2017)



- 44% of U.S. households own mutual funds (2007)
  – Growth at the expense of direct holdings



Performance Evaluation

- Key question:
  - How can we identify skilled active fund managers?
- Fund performance depends on
  - Skill: ability to identify and exploit opportunities
  - Scale: size of the fund, size of the industry
  - Risk: betas
  - Luck: underappreciated component
- It is difficult to extract skill from performance
  - Risks are often hidden
  - Luck (good and bad) plays a bigger role in investment performance than most people think

"I returned, and saw under the sun, that the race is not to the swift, nor the battle to the strong, neither yet bread to the wise, nor yet riches to men of understanding, nor yet favor to men of skill; but time and chance happen to them all." Ecclesiastes 9:11.

- There is a performance evaluation industry out there
  - Morningstar, Lipper, etc.
  - Helps investors choose how to allocate funds among different money managers

- Performance is measured relative to a *benchmark*
  - The benchmark should reflect the fund's objectives
- Popular equity fund benchmark choices (Lines, 2016):

Mutual fund benchmarks reported in Morningstar Direct (US equity only), ranked by share of total assets under management (average over 1980-2014). Also shown is the number of funds reporting each benchmark.

Primary Prospectus Benchmark	% of AUM	No. of Funds
S&P 500	57.49	5860
CRSP indices	8.95	38
Other S&P indices	6.68	1437
Russell 1000 Value	5.57	1039
Other Russell indices	5.47	1176
Russell 1000 Growth	4.37	1109
Other US Equity indices	3.17	587
Russell 3000	1.84	636
Russell 1000	1.41	437
Russell 2000	1.35	723
Russell 3000 Growth	1.21	169
Russell 2000 Value	1.00	485
Russell 2000 Growth	0.70	575
Russell 3000 Value	0.67	155
No reported benchmark	0.12	11572

- Sensoy (2009) finds that 31% of equity funds report "questionable" benchmarks in their prospectuses
  - These exist other S&P or Russell size- and B/M-based benchmarks that better match the funds' styles and are more correlated with fund returns

- Good predictors of fund performance: Costs and fees
  - It is hard to make money but easy to lose money
  - Net fund returns are dragged down by expenses (e.g., trading costs) and administrative fees
    * Fees and transaction costs reduce net returns, cutting into profits from active trading
  - Expenses, turnover, and load fees all *negatively* impact fund performance (Carhart, 1997)
    * Expense ratios reduce returns more than 1-for-1
    * Higher turnover reduces performance
    * Load funds underperform no-load funds by about 0.80% per year, on average (and this is before the load fees take their bite!)
  - According to Morningstar (2010), low fees are the best predictor of a mutual fund's future success
- Another good predictor: Fund distribution
  - Direct-sold funds outperform broker-sold funds (Del Guercio and Reuter, 2014)
- When predicting future performance based on past performance, various historical information is used
  - Past *returns* (most common method)
  - Past *returns* and portfolio *holdings*
    * Superior method, but harder to do

Performance Measures Based on Past *Returns*

- **Sharpe ratio**

$$S_P = \frac{\mathrm{E}(R_P) - R_f}{\sigma_P},$$

where $\mathrm{E}(R_P)$ is typically estimated by the portfolio P's historical average return; R_f is the risk-free rate

  - Relevant if *all* of your wealth is invested in P
  - Recall that mean-variance investors maximize the Sharpe ratio of their overall portfolio

- **Alpha**

$$R_{P,t} - R_f \;=\; \alpha + \beta(R_{M,t} - R_f) + \epsilon_{P,t}$$

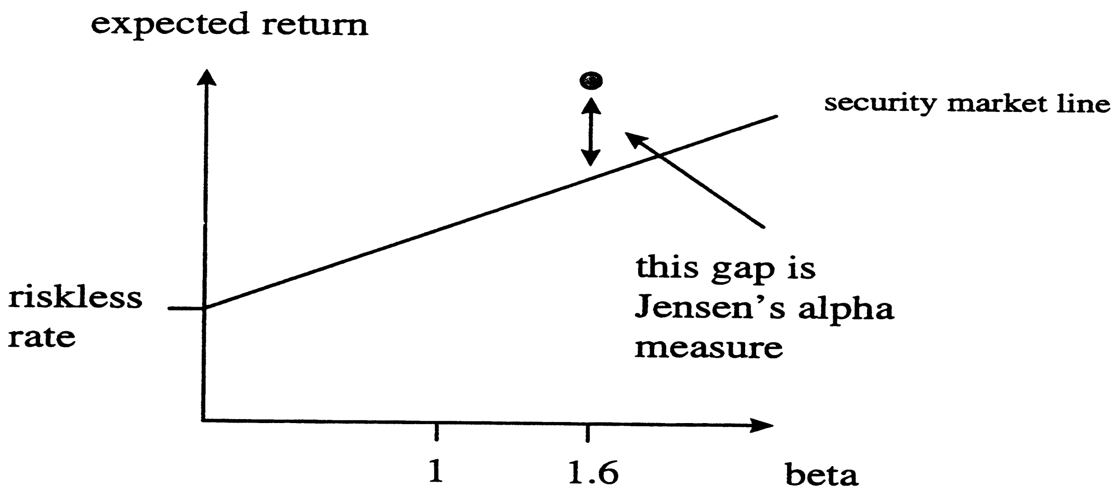
where $R_{M,t}$ is the benchmark return

  - Relevant if you view portfolio P as a potential ingredient in your diversified portfolio
  - Also called Jensen's alpha when M is the market; first used by Jensen (1968)
  - Alpha can be computed with respect to one or multiple benchmarks (e.g., Fama-French)

Some Notes on Alpha

- Alpha can be interpreted as a risk-adjusted (or benchmark-adjusted) average return:

$$\begin{aligned}\alpha &= \mathrm{E}(R_{P,t} - R_f) - \beta \mathrm{E}(R_{M,t} - R_f) \\ &= \mathrm{E}(R_{P,t}) - [R_f + \beta \mathrm{E}(R_{M,t} - R_f)]\end{aligned}$$



  - $\alpha > 0 \Rightarrow$ good, outperformance
  - $\alpha < 0 \Rightarrow$ bad, underperformance

- Information ratio (or "appraisal" ratio):

$$IR_P = \frac{\alpha}{\sigma_\epsilon}$$

- This ratio summarizes the maximum potential improvement in the Sharpe ratio when adding fund P to the benchmark M; recall that

$$S^2_{P+M} = S^2_M + (IR_P)^2,$$

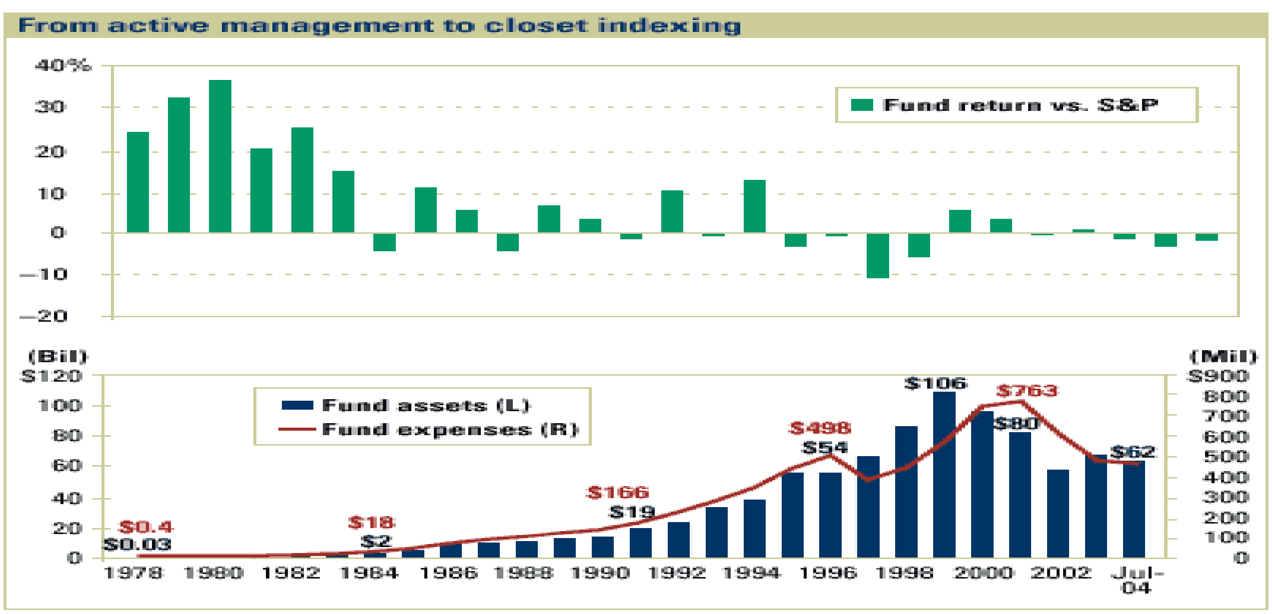
where $P + M$ is the optimal mix of P and M

- Alpha reflects value added through stock picking
  - This interpretation is correct only if β is constant over time (and the benchmark is appropriate)
    - We will analyze time variation in β later
  - Alpha from before-fee returns is the maximum fee the fund can charge (so that the after-fee $\alpha \geq 0$)
- What do mutual fund alphas look like?
  - Roughly half are positive, half negative, before costs
  - Median net alphas (after costs and fees) for 2,609 U.S. equity mutual funds between 7/1963-12/1998 (from Pastor and Stambaugh, 2002):

Investment objective	CAPM α	Fama-French α
Small company growth	-8.45	-0.41
Other aggressive growth	-5.41	-0.37
Growth	-2.17	-0.88
Income	-0.39	-2.03
Growth and income	-0.51	-1.19
Maximum capital gains	-2.29	-0.28
Sector funds	-1.06	-1.84
All funds	-2.13	-1.07

- Median performance is negative after costs and fees!
- These are medians; are there any winners out there?

- **Example:** Fidelity Magellan
  - Managed by Peter Lynch in May 1977 to May 1990
  - How did Magellan fare under Lynch's leadership?
  - How has Magellan fared since Lynch quit?
  - Closet indexing?
    - ∗ In Dec 2002, Magellan charged a 3% load fee and 88bp expense ratio
    - ∗ In Dec 2005, Magellan charged no load fee but still 62bp expense ratio, with only 6% turnover (more than 20 times lower compared to Peter Lynch's turnover in 1990!)
    - ∗ Correlation between Magellan's and the market's excess returns?
  - To find out, play with *magellan.m*.



- There are many active managers out there. A few of them will get high estimated α simply by chance.
  - **Example:** Coin-tossing contest.
  - What is the probability that tossing a fair coin will lead to 10 heads in a row?
  - Now suppose there are 5,000 coin tossers. What is the probability that at least one of them will get 10 heads in a row?
  - Was Peter Lynch just lucky? See Assignment 7.
  - Fama and French (2010) argue that almost all good performers just got lucky

- Some findings based on alpha:
  - Chen, Hong, Huang, and Kubik (2004) find that smaller funds tend to outperform larger funds
    - Diseconomies of scale, illiquidity
    - Teo (2009) finds the same for hedge funds
  - Kacperczyk, Sialm, and Zheng (2005) find that funds whose portfolios are concentrated in fewer industries outperform less concentrated funds
  - Simutin (2014) finds that active funds holding more cash perform better. Superior stock selection.

Estimating Alpha

- The true α is unknown, we can only estimate it
- The usual OLS estimate of α, $\hat{\alpha}$, is imprecise
  - Short return histories and high return volatility $\Rightarrow$ $\Rightarrow$ $\hat{\alpha}$ often has a large standard error
- Improved estimation of α (optional)
  - Use longer historical return series for the benchmark than for the fund being evaluated
    - Can increase precision of $\mathrm{E}(R_{M,t} - R_f)$ in

$$\alpha = \mathrm{E}(R_{P,t} - R_f) - \beta \mathrm{E}(R_{M,t} - R_f)$$

    - Formalized by Stambaugh (1997)
  - Use past returns on non-benchmark passive assets
    - Take a passive asset, e.g. an industry portfolio
    - If this portfolio has some residual correlation with the fund being evaluated, then this portfolio's $\hat{\alpha}$ carries information about the fund's α.
    - Bayesian approach (Pastor and Stambaugh, 2002). Busse and Irvine (2006) show this approach is useful for predicting future alphas
  - Use historical return series for other mutual funds
    - Bayesian approach (Jones and Shanken, 2005)

Performance Measures Based on Past ***Returns*** and Portfolio ***Holdings***

- The **Grinblatt-Titman** performance measure:
  - Fund holds N stocks, $j = 1, \ldots, N$, exists over T periods, $t = 1, \ldots, T$
  - $w_{j,t} \ldots$ weight on stock j when period t begins
  - $R_{j,t} \ldots$ return on stock j in period t
  - The GT measure at time t:

$$GT_t = \sum_{j=1}^{N} (w_{j,t} - w_{j,t-k}) R_{j,t}$$

    * The GT measure is positive if the fund tends to
      - buy stocks before they go up in value
      - sell stocks before they go down in value
    * You can use any $k > 0$; Grinblatt and Titman (1993) use $k = 1$ quarter and $k = 1$ year
  - The GT measure for the whole sample:

$$GT = \frac{1}{T} \sum_{t=1}^{T} GT_t$$

    * $GT > 0 \Rightarrow$ good; $GT < 0 \Rightarrow$ bad
  - The GT measure is not immune to momentum To make it immune, adjust $w_{j,t-k}$ for the buy-and-hold change in the weights between $t - k$ and t: Replace $w_{j,t-k}$ by $w_{j,t-k} \frac{1+R_{j,t-k \to t}}{(1+R_{1,t-k \to t}) \ldots (1+R_{N,t-k \to t})}$

- The **characteristic-based** performance measures (Daniel, Grinblatt, Titman, and Wermers, 1997)
  - Benchmark is based on the characteristics of stocks held by the portfolio being evaluated
    - Characteristics: size, B/M, last-year's return
  - See if the manager is able to pick stocks that outperform stocks with similar characteristics
- Judging fund managers by the company they keep (Cohen, Coval, Pastor, 2005)
  - **Example:** Basketball.
    - Players are taking 10 shots each at the basket
    - Two shooting techniques: one hand or two hands
    - Two-handers' average: 8/10
One-handers' average: 4/10
    - A one-hander and a two-hander have completed 5 shots, and both have scored 4/5
    - Who is more likely to score higher out of 10, the one-hander or the two-hander?
    - Since two-handed shooters tend to score higher, it appears that using both hands improves your ability to achieve a higher average score

      $\Rightarrow$ the two-hander is more likely to win
    - Judge the players' skill not only by their track records, but also by the company they keep

- Analogously, CCP argue that there are groups of managers who use similar techniques, and such managers should deliver similar future performance
- CCP judge a manager's skill by the extent to which her investment decisions resemble the decisions of managers with good track records
- Similar investment decisions are assumed to be made by managers with
  * Similar stock holdings
    - A manager is skilled if her holdings are similar to those of managers who have done well
  * Similar trades
    - A manager is skilled if she buys (sells) stocks that are being concurrently bought (sold) by other managers with good track records
- Two performance measures, based on
  * Similarity in *holdings* (measure δ^*)
  * Similarity in *trades* (measure δ^{**})
- Both measures are constructed in two steps.
  * To estimate the **holdings-based** measure δ^*:
    1. For each stock, define its *quality* as the average $\hat{\alpha}$ of managers holding this stock
    2. Each manager's *skill* is the average quality of stocks held by this manager

* To estimate the **trade-based** measure δ^{**}:
  1. For each stock, define its *quality* as the average $\hat{\alpha}$ of managers who bought this stock recently, minus the average $\hat{\alpha}$ of managers who sold this stock recently
  2. Each manager's *skill* is the average quality of stocks that she bought recently, minus the average quality of stocks that she sold recently

– Both estimates of fund i's skill, $\hat{\delta}_i^*$ and $\hat{\delta}_i^{**}$, are **weighted averages of $\hat{\alpha}$'s** across many funds
  * The weight on $\hat{\alpha}$ of fund j is high if funds i and j have similar portfolios/trades

– Both measures have high precision because they use past returns and portfolio holdings on many funds to evaluate the performance of a single fund

– In the empirical implementation, both measures reveal strong predictability in U.S. fund returns

– These measures can predict future fund returns better than the traditional $\hat{\alpha}$ does!
  * Controlling for $\hat{\alpha}$, both $\hat{\delta}^*$ and $\hat{\delta}^{**}$ significantly predict future fund returns
  * Controlling for $\hat{\delta}^*$ and $\hat{\delta}^{**}$, $\hat{\alpha}$ does not significantly predict future fund returns

Stock quality as a return predictor

- CCP show that *stock quality* computed from mutual fund holdings/trades helps predict *fund returns*
- Wermers, Yao, and Zhao (2012) show that stock quality also helps to predict future *stock returns*
- High-quality stocks tend to have high returns
  - Portfolio strategies generate alphas $> 4\%$ per year
- Recall that high-quality stocks are stocks that are
  - *owned* mostly by high-skilled fund managers
  - *recently bought (sold)* mostly by high-(low-)skilled fund managers

"Follow the leader"

- Pomorski (2006) shows that
  - Mutual funds tend to mimic the trades of high-alpha funds
  - The mimicking is done mainly by funds that are small, young, and poorly-performing in the past
  - A mimicking strategy based on recent trades of the best funds earns an annualized alpha of 4.2% over the quarter after the best funds' trades

Market Timing

- Market timing is attempting to increase (decrease) the portfolio's beta before the market goes up (down)
- Conditional vs. unconditional beta
  - Unconditional beta: β, covariance with the market computed from the whole sample
  - Conditional beta: β_t, covariance at time t
  - It is commonly assumed that $\beta_t = \beta$; not here
- The **Treynor and Mazuy** approach:
  - Allow beta to vary over time...

$$R_{P,t} - R_{f,t} = \alpha + \beta_t(R_{m,t} - R_{f,t}) + \epsilon_t$$

    ...depending on the market's excess return:

$$\beta_t = \beta + \gamma(R_{m,t} - R_{f,t})$$

  - Plug in for β_t:

$$R_{P,t} - R_{f,t} = \alpha + \beta(R_{m,t} - R_{f,t}) + \gamma(R_{m,t} - R_{f,t})^2 + \epsilon_t$$

  - If $\gamma > 0$, the fund has market timing ability
    - Bigger exposure to the market (higher beta) when the market is going up
  - If $\gamma < 0$, the fund times the market in the wrong direction (higher β when the market is going down)!

- The **Henriksson and Merton** approach:
  - Allow beta to vary over time…

    $$R_{P,t} - R_{f,t} = \alpha + \beta_t(R_{m,t} - R_{f,t}) + \epsilon_{1,t}$$

    …depending on the market's excess return:

    $$\beta_t = \begin{cases} \beta + \gamma & \text{if } R_{m,t} > r_{f,t} \quad \text{(upmarket)} \\ \beta & \text{if } R_{m,t} \leq r_{f,t} \quad \text{(downmarket)} \end{cases}$$

  - Plug in for β_t:

    $$R_{P,t} - R_{f,t} = \alpha + \beta(R_{m,t} - R_{f,t}) + \gamma(R_{m,t} - R_{f,t})D_t + \epsilon_t,$$

    where the "dummy" variable D_t is defined as

    $$D = \begin{cases} 1 & \text{if } R_{m,t} > r_{f,t} \quad \text{(upmarket)} \\ 0 & \text{if } R_{m,t} \leq r_{f,t} \quad \text{(downmarket)} \end{cases}$$

  - If $\gamma > 0$, the fund has market timing ability
- You will apply both approaches in Assignment 7
- Empirical evidence on market timing ability is mixed
  - The early studies (e.g., Treynor and Mazuy, 1966, Henriksson, 1984) find no significant timing ability
  - Bollen and Busse (2001) find such ability for 34.2% of funds using daily returns; Jiang, Yao, and Yu (2005) find such ability using holdings data
- **Example:** Fidelity Magellan
  - Was Peter Lynch able to time the market?
  - To find out, play with *magellan.m*.

Performance Attribution

- Attribution is different from evaluation
  - Evaluation measures whether something is good
  - Attribution explains why something occurred

1. Using the fund's past *returns* and *holdings*

- Active fund: A, with return R_A at time t
  Benchmark: B, with return R_B at time t
- Both portfolios are composed of N asset classes (e.g., industries, sectors, stocks vs. bonds, etc.)
- For each asset class, $i = 1, \ldots, N$, define returns
  - $R_{A,i}$, on the active fund's holding of class i
  - $R_{B,i}$, on the benchmark's holding of class i
  - Difference between $R_{A,i}$ and $R_{B,i}$ reflects security *selection* within class i (e.g., stock selection within an industry)
- For each asset class, $i = 1, \ldots, N$, define weights
  - $w_{A,i}$, the active fund's weight in class i
  - $w_{B,i}$, the benchmark's weight in class i
  - Difference between $w_{A,i}$ and $w_{B,i}$ reflects asset *allocation* (e.g., allocating across industries)

- Given this notation, we have

$$\begin{aligned} R_A &= \sum_{i=1}^{N} w_{A,i} R_{A,i} \\ R_B &= \sum_{i=1}^{N} w_{B,i} R_{B,i} \end{aligned}$$

- Decompose the difference between R_A and R_B:

$$\begin{aligned} R_A - R_B &= \sum_{i=1}^{N} w_{A,i} R_{A,i} - \sum_{i=1}^{N} w_{B,i} R_{B,i} \\ &= \underbrace{\sum_{i=1}^{N} (R_{A,i} - R_{B,i}) w_{A,i}}_{\text{security selection}} + \underbrace{\sum_{i=1}^{N} (w_{A,i} - w_{B,i}) R_{B,i}}_{\text{asset allocation}} \end{aligned}$$

(If weights change within period t, then $R_A - R_B$ can differ a little bit from the sum of the two components; the difference is called *activity*.)

- An active fund's return has three basic components:
  1. Investment policy (benchmark return, R_B)
     - How much of the fund's performance is due to the target choice of asset classes (e.g., being a small-stock fund)?
  2. Security selection (or "stock picking")
     - How much is due to picking stocks with higher returns than other stocks in the same asset class?

3. Asset allocation (or "timing")
   - How much is due to timing the asset classes successfully? Did the fund rotate into small stocks just before they went up?

- **Example:** Your fund picks individual stocks and rotates in and out of the technology sector. Your benchmark is 30% technology (and 70% non-technology). At the beginning of year 2015, you put 50% of your capital in technology (and 50% in non-technology). During the year, the technology benchmark return is -10%, the non-technology benchmark return is 10%, and your fund's return is 5%. What are your policy, selection, and timing returns for 2015?
  - $w_{B,1} = 0.3$, $w_{B,2} = 0.7$, $w_{A,1} = 0.5$, $w_{A,2} = 0.5$, $R_{B,1} = -10\%$, $R_{B,2} = 10\%$, $R_A = 5\%$, $N = 2$
  - Policy:
    $$w_{B,1}R_{B,1} + w_{B,2}R_{B,2} = 0.3(-10) + 0.7(10) = 4\%$$
  - Timing:
    $$(w_{A,1} - w_{B,1})R_{B,1} + (w_{A,2} - w_{B,2})R_{B,2} = \\ = (0.5 - 0.3)(-10) + (0.5 - 0.7)(10) = -4\%$$
  - Selection:
    $$\Sigma_{i=1}^{2}(R_{A,i} - R_{B,i})w_{A,i} = R_A - \Sigma_{i=1}^{2} R_{B,i}w_{A,i} = \\ = 5\% - ((-10)(0.5) + (10)(0.5)) = 5\%$$

2. Using the fund's past *returns* only

- In the absence of portfolio holdings, we can conduct *style analysis* by regressing the fund's returns on the returns of various style benchmarks
- **Example:** Four equity style benchmarks
  1. Small-cap value (return R_1)
  2. Small-cap growth (return R_2)
  3. Large-cap value (return R_3)
  4. Large-cap growth (return R_4)
- Also denote
  - $R_0 \ldots$ return on cash
  - $R_A \ldots$ return on the active fund
  - $R_P \ldots$ return on a passive portfolio P with the same style as fund A
- Portfolio P is a combination of the style benchmarks,

$$R_{P,t} = w_0 R_{0,t} + w_1 R_{1,t} + \ldots + w_4 R_{4,t},$$

  where the weights are chosen such that the return on P tracks the return on A as closely as possible
- How can we compute the weights in portfolio P?

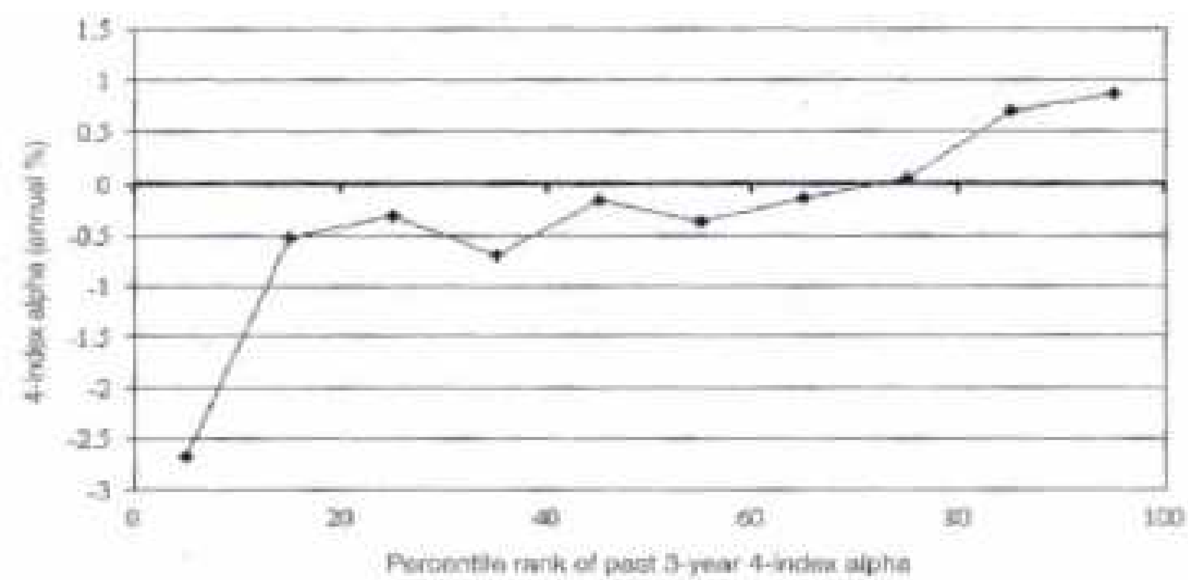
- A popular way to compute these weights is to regress the fund's returns on the style benchmark returns:

$$R_{A,t} = a_0 + a_1 R_{1,t} + \ldots + a_4 R_{4,t} + \epsilon_t$$

  - We can interpret a_i as w_i
  - E.g., if a_1 is large and the other a_i's are tiny, we are most likely looking at a small-cap value fund
- Problems with the regression approach:
  - The a_i's do not necessarily sum to one
  - Some a_i's can be negative, but mutual funds tend to be long-only
- Sharpe (1992) recommends restricted estimation, in which you numerically find the weights that
  - Minimize the tracking error ($\sigma(R_A - R_P)$)
  - Are positive and sum to one
- Now you can do performance attribution, except you substitute the estimated portfolio weights in place of the actual portfolio weights
- **Example:** Fidelity Magellan
  - Did Peter Lynch make bets on any of the value, size, or momentum anomalies?
  - To find out, play with *magellan.m*.

Performance Persistence

- Does performance persist? Does past performance of a fund predict the fund's future performance?
- Early studies found some (fairly weak) persistence.
- Carhart (1997) finds persistence in mutual fund returns, but also that most of this persistence is due to expenses and momentum in stock returns, not skill
  - Momentum in stock returns creates persistence in fund returns, even in the absence of any skill
  - Carhart proposes a "momentum factor" (WML) as a benchmark to take out the momentum effect
  - After accounting for momentum, he finds persistence only among the worst-performing funds, due to their high expenses ⇒ Avoid such funds!



- Cohen, Coval, and Pastor (2005) find strong persistence in year-to-year performance, even among the best-performing funds and even after accounting for momentum in stock returns
  - Sort funds into decile portfolios according to their performance ($\hat{\alpha}$, $\hat{\delta}^{*}$, or $\hat{\delta}^{**}$) over the past year
  - Compute the equal-weighted return for each decile portfolio over the following year
  - Repeat this for each year 1980-2002 to obtain a series of returns for each decile portfolio
  - Compute risk-adjusted returns for each decile:

	Decile										
	1	2	3	4	5	6	7	8	9	10	10-1
	Fama-French Alphas										
$\hat{\alpha}$	-1.62	-0.39	0.00	0.15	0.43	0.75	0.94	1.19	1.62	3.57	5.19
	(-1.62)	(-0.57)	(0.00)	(0.30)	(0.87)	(1.44)	(1.84)	(2.13)	(2.31)	(3.57)	(3.67)
$\hat{\delta}^{*}$	-1.87	-0.91	-0.75	-0.24	-0.01	-0.01	0.18	2.00	2.72	5.48	7.36
	(-1.30)	(-0.87)	(-1.03)	(-0.42)	(-0.02)	(-0.01)	(0.33)	(2.81)	(2.86)	(4.11)	(3.23)
$\hat{\delta}^{**}$	-1.13	-0.27	-0.12	0.37	0.53	0.07	0.97	0.75	1.51	3.32	4.45
	(-1.23)	(-0.45)	(-0.21)	(0.67)	(1.08)	(0.17)	(1.77)	(1.34)	(2.23)	(3.63)	(4.53)
	Four-Factor Alphas (Fama-French + Momentum)										
$\hat{\alpha}$	-1.21	-0.63	0.19	1.13	0.89	0.29	0.65	1.05	1.81	2.48	3.69
	(-1.20)	(-0.80)	(0.31)	(2.13)	(1.81)	(0.54)	(1.29)	(1.68)	(2.63)	(2.60)	(2.64)
$\hat{\delta}^{*}$	-1.58	-0.89	-0.29	-0.11	0.51	0.72	0.67	1.97	1.33	4.30	5.88
	(-1.14)	(-0.81)	(-0.38)	(-0.17)	(0.91)	(1.32)	(1.25)	(2.56)	(1.37)	(3.46)	(2.73)
$\hat{\delta}^{**}$	-0.60	-0.20	0.30	0.38	0.54	0.76	0.18	0.86	1.15	2.92	3.52
	(-0.62)	(-0.31)	(0.47)	(0.81)	(1.10)	(1.56)	(0.32)	(1.55)	(1.66)	(3.11)	(3.25)

- Berk and Green (2004) challenge the traditional wisdom that skilled managers should deliver persistently high risk-adjusted returns. They make 3 assumptions:

  1. Managerial ability is unobservable; investors learn about it by observing the manager's returns
  2. This ability exhibits decreasing returns to scale
  3. Rational investors compete for superior returns

  Under these assumptions, we should not expect to see persistence even if the fund manager is skilled! Logic:

  $$\begin{array}{c}\text{High fund returns}\\ \Downarrow \\ \text{Investors infer that the fund manager is skilled}\\ \Downarrow \\ \text{Investors pour money into the fund}\\ \Downarrow \\ \text{Fund's ability to generate abnormal returns declines}\\ \text{(decreasing returns to scale) until it disappears}\end{array}$$

  A fund that did well in the past will attract new money, but it will not outperform in the future.

  Better-skilled managers perform equally well as less-skilled ones, but they manage larger funds (so they earn higher fees, which are proportional to fund size).

Returns to scale in active asset management

- Two kinds of *decreasing returns to scale*:
  1. **Fund**-level (Berk and Green, 2004)
     - Fund size $\uparrow$ $\Rightarrow$ This fund's performance $\downarrow$
     - Because a larger fund's trades have bigger price impact, hurting the fund's performance
     - Evidence: Mixed, but mostly in favor
  2. **Industry**-level (Pastor and Stambaugh, 2012)
     - Industry size $\uparrow$ $\Rightarrow$ All funds' performance $\downarrow$
     - Because any fund manager's ability to find mispricing declines when there is more competition
     - Evidence: Favorable
       * See Pastor, Stambaugh, and Taylor (2015)
- Pastor, Stambaugh, and Taylor (2015) also find that
  - Active funds have become more skilled over time...
    * Because new funds keep getting better
    * Skill = Alpha adjusted for sizes of fund, industry
  - ...yet their performance has not improved
    * Because industry has grown, more competition
  - Younger funds outperform older funds
  - A fund's performance decreases over its lifetime
    * Due to growing competition
    * Despite learning on the job

Performance-Flow Relations

- Two basic questions:
  1. Does fund performance predict fund flows?
  2. Do fund flows predict fund performance?
- Net fund flow = Fund inflow - Fund outflow
  - How much the fund grows beyond its own return
- Common way of computing net flow in period t:

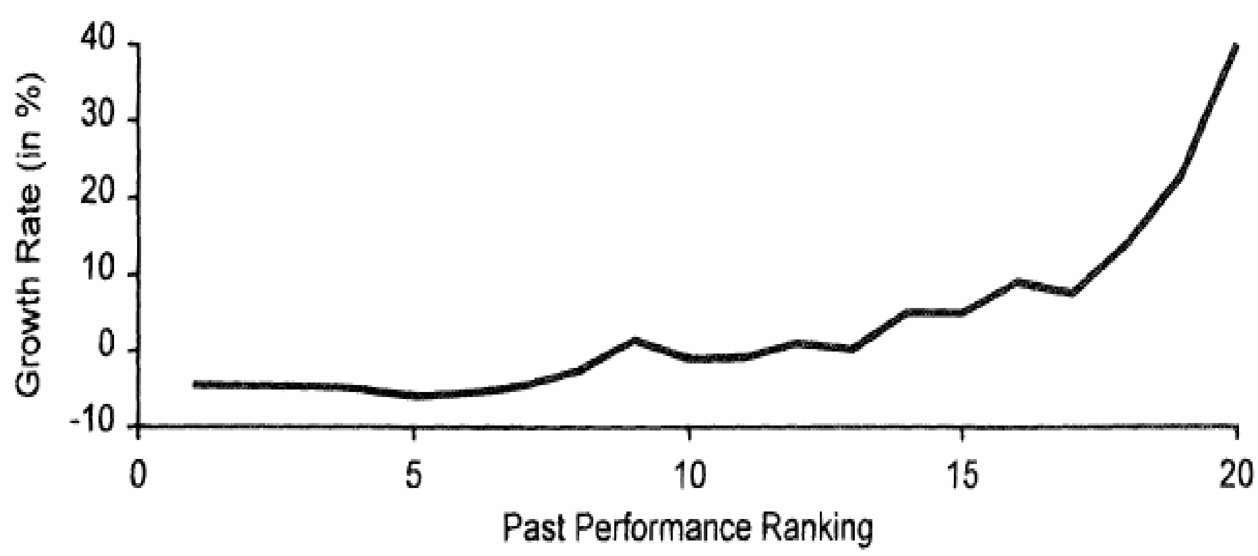
$$\text{Flow}_t = \frac{\text{TNA}_t - \text{TNA}_{t-1}(1 + R_t)}{\text{TNA}_{t-1}},$$

  where TNA_t denotes the fund's total net assets at the end of period t and R_t is the fund's return in period t

Does Fund Performance Predict Fund Flows?

- Yes. Money chases returns.
  - Good performance $\Rightarrow$ Net inflows into the fund
  - Bad performance $\Rightarrow$ Net outflows from the fund
- This positive relation between returns and subsequent flows is good: funds have an incentive to perform well
  - Managers want to manage more money as their compensation is tied to assets under management
  - This positive relation is stronger for high-fee funds

- However, there is a perverse incentive as well, due to nonlinearity in the performance-flow relation.
- The performance-flow relation is *convex*:
  - Good performance $\Rightarrow$ large net inflows
  - Bad performance $\Rightarrow$ not-so-large outflows
- Performance-flow relation (Sirri and Tufano, 1998):



- As a result of this convex relation, fund managers have an incentive to gamble!
  - If I win, a lot of new money flows in
  - If I lose, not much money flows out
  - Similar to an effect in the options market: Higher volatility increases the value of an option
- The convexity in the performance-flow relation is stronger for younger funds (Chevalier and Ellison, 1997) $\Rightarrow$ young funds have a stronger incentive to gamble

- There is evidence that fund managers indeed gamble in response to these incentives (e.g., Brown, Harlow, and Starks, 1996, Chevalier and Ellison, 1997)
  - Funds with the biggest incentives to gamble tend to increase their riskiness in the fourth quarter
  - Family favoritism (see later)

What Else Predicts Fund Flows?

- Advertizing
  - Flows are positively related to 12b-1 fees (Barber, Odean, & Zheng, 2005; Khorana & Servaes, 2012)
    - Do these "marketing" fees make sense?
  - Jain and Wu (2000) find that 294 mutual funds that advertised in Barron's or Money Magazine grew faster than a control group of funds with similar performance prior to the advertising period.
- Load fees
  - Fund flows are negatively related to front-end load fees but unrelated to expense ratios (Barber, Odean, and Zheng, 2005). Investors react to attention-grabbing fees and forget about the less visible fees.

Do Fund Flows Predict Fund Performance?

- Early evidence of the "smart money" effect.
  - Funds with positive net flows subsequently outperform funds with negative net flows (Zheng, 1999; Gruber, 1996) ⇒ fund investors seem able to predict fund performance and invest accordingly
- However, Sapp and Tiwari (2005) show that the "smart money" effect is fully explained by momentum in stock returns (and hence does not reflect investor skill)
  - Funds that hold recent winner stocks receive more new money (because flows chase past returns) and also benefit from stock momentum going forward
  - A momentum factor (Carhart, 1997) eliminates the outperformance of new cash inflows ⇒ the "smart money" effect is not due to smart investors but simply an artifact of momentum in stock returns
- In fact, Frazzini and Lamont (2008) find the opposite evidence of they call the "dumb money" effect.
  - They argue that the "smart money" effect is short-lived (one quarter or less) and that the "dumb money" effect prevails over longer horizons
- Keswani and Stolin (2008) find a smart money effect in the U.K., even after accounting for momentum

- Coval and Stafford (2007) find that fund inflows and outflows move stock prices

$$\begin{gathered}\text{Fund performs very poorly (well)}\\ \Downarrow \\ \text{Large capital outflow (inflow)}\\ \Downarrow \\ \text{Fund decreases (increases) existing positions}\\ \Downarrow \\ \text{Price pressure in the underlying stocks}\end{gathered}$$

  – Investors trading against constrained mutual funds earn significant returns for providing liquidity
  – Future flow-driven transactions are predictable, creating an incentive to front-run the anticipated forced trades by funds experiencing extreme capital flows
    * Future forced trades can be predicted using regressions of flows on past returns (and flows)
    * Consider a strategy that buys stocks likely to be involved in forced purchases and sells stocks likely to be involved in forced sales ("fire sales")
    * This strategy has earned $\alpha > 10\%$ per year!

- Lou (2012) finds that flow-driven trading can explain persistence of mutual fund performance, the smart money effect, and even some of stock price momentum

Funds and Their Families

- Over 90% of all mutual funds are affiliated with fund complexes or "families"
  - Vanguard
  - Fidelity
  - American Funds
  - Franklin Templeton
  - Pimco Funds
  - T. Rowe Price
  - Oppenheimer Funds
  - Putnam
  - Dodge & Cox
  - Columbia
  - ...
- Family affiliation can be good or bad
  - Good: Potential for economies of scale, better research quality, marketing benefits
  - Bad: May distort the incentives of fund managers, inducing them to sacrifice the interest of fund shareholders if the overall family stands to benefit
- 'Favoritism' in fund families

  Gaspar, Massa, and Matos (2006) analyze all active equity mutual funds of the top 50 families of U.S. equity mutual funds from 1991 to 2001, and find that

  - Families transfer performance across funds to favor funds more likely to increase overall family profits
  - These "high-value" funds are funds with
    * High fees
    * High past performance:
      Convex performance-flow relation $\Rightarrow$ a family prefers owning one top-performing fund and one poorly-performing fund to two mediocre funds
  - The performance transfer is achieved in two ways:
    * IPO allocations (preference to high-value funds)
    * Opposite trades across member funds (low-value funds trade in the market to buffer the price pressure of orders by high-value funds, or directly cross buy and sell orders with the high-value funds without going to the open market)

- Affiliated funds of mutual funds (AFs)
  - Offered by most large families, AFs are funds that can only invest in other funds in the family
  - Bhattacharya, Lee, and Pool (2013) find that AFs help other funds in the same family overcome temporary liquidity shocks and thus avoid fire sales

- This insurance provision benefits the family as a whole, but the cost is borne by AF investors

- Evidence of *spillover* effects:

  High fund performance attracts money not only into this fund but also into other funds in the fund's family (Nanda, Wang, and Zheng, 2004)

- Value added by centralized research of fund families
  - Pomorski (2009) analyzes common trades of funds within the same family: when multiple funds within the same family trade the same stock in the same direction, he calls them funds' "best ideas"
  - Finds that best ideas outperform benchmarks by 0.47% per month; the remaining fund trades (not best ideas) fail to beat benchmarks
  - Cohen, Polk, and Silli (2010) define "best ideas" differently, as funds' most aggressive positions, and show again that best ideas outperform

- Incubation bias (Evans, 2010)
  - Fund families tend to start ('incubate') multiple funds and then promote only the subset of funds that get lucky in their first few years
  - Incubated funds' returns are upward-biased

Career as a Mutual Fund Manager

- How much money do mutual fund managers make?

  "Wine makes merry, but money answers all things." Ecclesiastes 10:19.

  2005 figures (based on 10,600 responses to a survey by Russell Reynolds Associates and the CFA Institute):

  - Median mutual fund manager pay: $390,000
  - Stars make much more

- What are the characteristics of a successful manager?

  Chevalier and Ellison (JF 1999) find that

  - Managers who attended higher-SAT colleges have higher risk-adjusted average returns
  - Managers with MBAs outperform the non-MBAs by 0.63% per year (but only by 0.04% after accounting for differences in betas)
  - Younger managers outperform older managers (12 years of age translate into 1% per year)

  Ma, Tang, and Gomez (2015) find that fund managers who receive performance-linked bonuses outperform

  - About 3/4 of managers receive such bonuses

  Chuprinin and Sosyura (2016) find that fund managers who grew up in poor families outperform those who grew up in rich families. Selection effects.

- When do fund managers get promoted or fired?
  - Promotions tend to follow high returns, demotions follow low returns (e.g., Khorana, 1996)
  - Chevalier and Ellison (QJE 1999) find that
    * The probability of termination is more sensitive to performance for younger managers
    * A young manager is more likely to be terminated if his/her fund's sector weightings deviate considerably from those of his peers

    These relations give younger managers an incentive to avoid unsystematic risk and to herd into popular sectors. Consistent with these incentives, they find that younger managers take on less unsystematic risk and hold more conventional portfolios.
  - Annual turnover for mutual fund managers is around 19% per year. That is, out of 100 mutual fund managers at the beginning of the year, 81 will still have the same jobs at the end of the year.
- Are mutual fund managers male or female?
  - In Chevalier and Ellison (JF 1999)'s sample of 492 fund managers, only 7% are women

Window Dressing

- Mutual funds bigger than \$100 million are required to disclose their portfolio holdings on a quarterly basis (section 13(f) of the Securities Exchange Act of 1934)
- *Window dressing* (WD) is the tendency of funds to embellish their portfolios prior to disclosure dates
  - by selling assets that have performed poorly
  - by buying assets that have performed well
  - by buying safer assets than usual

> "Nobody wants to be caught showing last quarter's disasters... You throw out the duds because you don't want to have to apologize for and defend a stock's presence to clients even though your investment judgment may be to hold." A money manager quoted in "The Fine Art of Window Dressing", by S. Jansson, Institutional Investor, 1983, p. 139.

- Lakonishok, Shleifer, Thaler, and Vishny (1991) find weak evidence of WD in a sample of 769 pension funds
- Musto (1999) finds that money market funds hold disproportionately more government securities just before (and fewer just after) portfolio disclosure dates
- Ng, and Wang (2004) find that institutions tend to sell more poorly performing stocks during Q4 than during Q1-3, and buy these stocks back in Q1.

- He, Ng, and Wang (2004) find WD only among institutions that manage other people's money; no WD among those managing their own money
- WD suggests that money managers are evaluated on a broader set of criteria than performance alone
- Carhart, Kaniel, Musto, and Reed (2002) find that mutual fund managers inflate quarter-end stock prices with last-minute purchases of stocks already held
  - This price inflation ranges from 0.5% per year for large-cap funds to over 2% for small-cap funds
  - This temporary return-boosting practice is illegal
  - Trading volume surges in the last few minutes of each quarter, but especially at year-ends
- Ben-David, Franzoni, Landier, and Moussavi (2013) find that hedge fund managers behave similarly
  - Stocks held to the largest extent by hedge funds have higher returns on the last day of the quarter, followed by a reversal the next day
  - Price swings on the order of 30 bp per day
  - Half of the return is earned during the last 20 minutes of the last day of the quarter