17 Week 6 Mutual Funds

17.1 Background

1. It would be natural, and completely sensible, (and good marketing for MBA programs) if funds outperform darts! Pros outperform in any other field.

2. Except for... competition and free entry. The *marginal* fund will be worthless, and the *average* fund may not be very good.

3. The standard empirical approach and view (Jensen 1968):

   (a) There is a big bias problem, and this work is hard! (It's more severe for hedge funds, venture capital funds)

      i. *Survivor* bias: Funds that close are not in database. Funds are more likely to close if they have bad returns

      ii. *Selection* bias. Funds are more likely to report if they have good returns. (Or to report audited returns)

      iii. *Backfill* bias. Often, when a fund is included in a database or index, all past history of that fund is then included. This biases the results towards winners. There were other funds around during the backfill period that lost money and did not get included in the database.

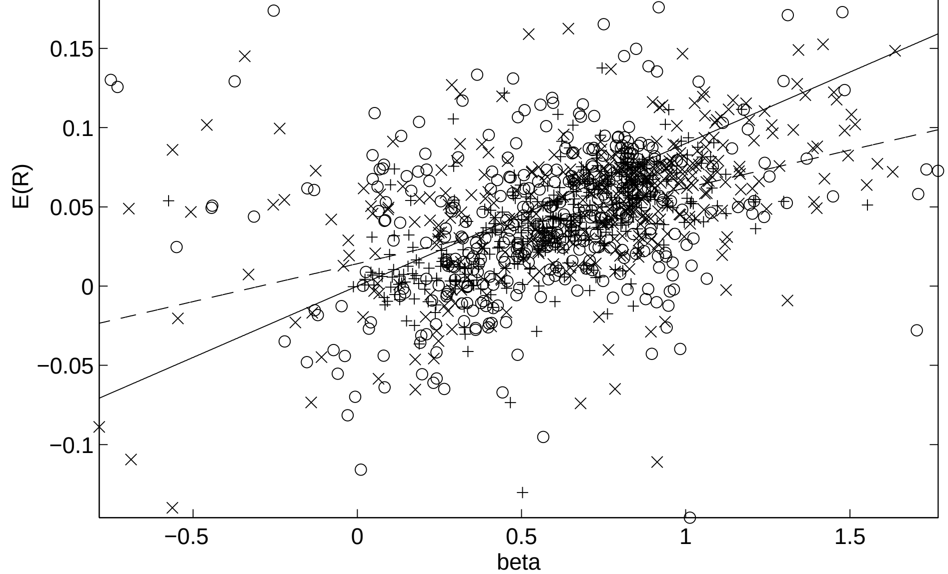
      iv. *Incubator bias.* Fund families start "incubator funds," and then only open the ones that do well. They then report the entire history. It's amazing that the SEC lets them do this. This bias remains in the CRSP database.

      v. (My addition) *Academic interest bias.* We're only interested in hedge funds since they did so well! All t statistics in the Journal of Finance are above 2.1.

   (b) You have to correct for beta. A fund which simply leverages or holds higher beta stocks will seem to outperform with no skill. Thus, run CAPM regressions on funds and examine alphas.

   (c) $\sigma/\sqrt{T}$ again. Returns are so volatile, it's very hard to measure mean returns.

   (d) After addressing all these problems, the standard result: The average fund underperforms S&P by about 1%; typically even before fees.



Notes: Average returns of mutual funds over the Treasury bill rate versus their

(e) "Why the average fund?" you might object. Of course the *average* fund is bad – competition and easy entry into the fund business mean anyone will join. Why aren't we looking at "the good funds?" What about Warren Buffet?

(f) Answer: There is no way to tell after the fact if a given fund was lucky or skillful. We must look at average performance in a group; we have to look at some strategy we might plausibly have used for picking funds ahead of time, and then see what happens to all funds we might have picked.

   i. Just as with stocks, we sort *all* funds at t based on some indicator of "good," then we watch those funds through the following year $t+1$. We have to make sure we include all funds we would have picked at the time, and we have to make sure you keep track of everyone including the losers and the dead in the following year.

   ii. Early answers: They looked (as in practice) at funds that had done well in previous years. They found that there is a random walk in funds too: Past winners are no more likely to keep winning. Here "Good group" means past good performance.

(g) What we can't do: "why is Warren Buffet so good?" (Was he lucky? Where is Elmo Buffet?) "Sure average alpha is bad, but *our* track record is great." (Why does everyone who walks in the door have above average alpha?)

(h) What we can do: Find *everyone* who "looked like" Warren Buffet at t, invest in them through $t+1$, track returns of winners and losers.

4. More background

(a) Most *variation* in *ex-post* fund returns is due to different *strategies* (small, large, value, growth, sector) etc. not to differences in particular stocks that funds pick ("style" not "selection"). Quantitatively, suppose you run

$$R_t^{ei} = \alpha_i + \beta_{im} R_t^{em} + \beta_{i1} f_t^1 + \beta_{i2} f_t^2 + \varepsilon_t^i;\ t = 1, 2....T \text{ for each } i$$

(Here, we're doing a style analysis or variance analysis, so the factors don't have to be "priced" factors. Even before smb and hml, people understood that stocks moved when their industries moved together. The CAPM just says that these betas don't raise expected returns.) Mutual funds hold quite diversified portfolios, so even individual funds (not just portfolios of funds as in Carhart) have very high R^2. More importantly, when you look at average returns in a sample, say 5 years, (E here means a 5 year average)

$$E\left(R_t^{ei}\right) = \alpha_i + \beta_{im} E\left(R_t^{em}\right) + \beta_{i1} E\left(f_t^1\right) + \beta_{i2} E\left(f_t^2\right),$$

then think about how $E(R^{ei})$ varies across mutual funds in that sample, you find almost all variation across funds in $E(R^{ei})$ comes from variation across funds in their β choices and luck-of-the-draw in how the factors f that they load on happen to do, not from variation across funds in the alphas they achieve. (In 5 year samples, many "factors" such as industry that give no long-term average return and thus are not "priced" will nonetheless do well or poorly for 5 years.) Again, "most variation in results comes from style not selection."

(b) Puzzles, to me:

   i. Why are there so many styles, and these are so unrelated to any betas or sensible risks I've ever heard of? What does "growth and income" mean? Is this just marketing, so we can always have some type of fund that did well last year to tout?
   ii. If value/size is important, why are we arguing about performance relative to the Market/CAPM? Why do value funds not blow away the graph? FF answer: Most funds were not really following value. (Davis, Fama, French, below; h breakpoints are -0.08 and 0.3 in my graph above). OK, but why not? (New facts, p.51) If funds didn't know about the value premium, how can it be an equilibrium risk premium? (Their answer: "growth is where I can find alpha.")
   iii. For 40 years we have been railing about the wasted money on active management. From Jensen 1968 to Ken French 2009. Yet it persists. Everywhere else, free market economists say "if something persists, it must be serving a function," not "Active management persists because investors are dumb." We don't allow the "investors are dumb" story for price movements, how do we allow it for active management?
   iv. Put a different way, fees mean that active management is valuable – people are paying voluntarily. We just don't know for what!
   v. Related, Carhart's Table III shows that fees and turnover are bad for investors. Why? This makes no sense from a market-at-equilibrium perspective. Management wants you to think more fees pay for more research, which raises alpha, and they split that alpha with you. OK, a perfectly cynical competitive market perspective would say that returns to investors must always be the same, so fees raise alpha just enough to pay the fees. How in the world can fees hurt investors in a long-run (40 year) equilibrium? It's fun to be cynical but it doesn't make any sense.

(c) What are we asking here, really? Once upon a time, mutual fund performance was a test of "semi-strong form" efficiency – can you do better with public, but hard to get information? In this analysis, the *question* is, implicitly, do funds have "stock picking ability" to find "undervalued stocks," i.e. "inefficiencies," "information not reflected in market prices," and the alternative is "can I replicate fund returns by passive or mechanical portfolio formation strategies (without paying high fees)?"

Note, I think this *question* is really passé. The real issue for most active management is that the managers may understand multifactor betas you don't understand, a view you will see emerge over the next two weeks. But nobody knew multifactor betas existed in 1970, and old habits die hard.

5. Building up to Carhart: Reexamining the evidence, several authors did find "hot hands" – Last year's funds do better this year. (p. 57). We see this like momentum – by forming portfolios of last year's winners and noticing they do well. Why was it missed earlier? Well, it wasn't really. This is like my analysis of momentum; we're using a new telescope to make an old puzzle seem more important than it used to. There is still only a very small autocorrelation of individual fund returns.

   Suppose a winner is only 52% likely to win again, which is the old version of the facts. In the old days, you'd say "there's next to no skill; funds that went up last year are almost exactly as likely to go up as to go down next year." Like momentum, though the *same* fact has a much more dramatic-looking implication for a *portfolio of funds*. The portfolio of wining funds went up 100% last year, so only a 0.01 R^2 means a 10% mean return for this *portfolio* next year. The chance that the *portfolio* does better is much more than 52/48 because you diversify across fund risk. This is just like momentum in stocks – you don't have to buy just one stock! Recall how momentum is a way of magnifying a small return autocorrelation. Thus, by looking at portfolios, we confront the fact that Maybe that 52% is meaningful, and has important economic implications.

17.2 Carhart on funds – questions and answers

The introduction summarizes his conclusions:

1. Momentum in *stocks* accounts for momentum in *funds*. Funds that did well last year have stocks that went up and those stocks will keep rising a bit. It is *not*
   (a) Persistent skill, or
   (b) Good returns for momentum funds.
2. Momentum funds do poorly after transactions costs.
3. There is some persistent *under* performance
4. Survivor bias free data – includes funds that die. (Lots of hard work by Carhart, and another great CRSP dataset.) (p. 58)

We need to look for the facts! *Find the facts behind these assertions in the paper.*

Now *Questions for Class:*

1. On p.61 Carhart defends the four-factor model as a *performance attribution* model.
   (a) Why is it OK to use a "momentum factor" even if that is not a "state variable for investment opportunities?"
   (b) What *question* are we using the multifactor model to answer, and how is that question different from Fama and French's question?
   (c) Suppose you find, looking at very long samples, that $E(smb) = 0$. Might you still use sml for *performance attribution* in a shorter sample? If so, why?

   A: To measure *stock picking ability*, performance relative to mechanical portfolios is enough, whether or not it is a "true" multifactor model. What you want to know is whether you can replicate the fund's performance with (cheap) index or mechanical strategies, *not* whether the returns from such a strategy or "style" are justified from fundamental risk. Thus, Carhart's model is market, sml, hml, *momentum*, and we don't argue about whether momentum is a "real" factor or not. Anything that you could (and might have!) realistically programmed a computer to do on the right hand side goes here.

   SMB, for example. Yes for performance evaluation, as you would for an industry fund. Then in a period (5 years) where small stocks happened to do well, you could tell if a fund's good performance was due to skill, or due to the fact that they invest in small caps and small caps happened to go up. This is an instance of "style" vs. "selection."

   Even better see Fama and French p.1918 pp2 prose.
2. Does Carhart's "momentum factor" solve the return puzzles in Fama French's last table – does it account for returns in momentum-sorted stock portfolios? (No table here, but he does report some results)

   A: Yes, p.62.

3. (Hint: Table III is the most important. Spend most of your time to understand it.) How does Carhart form portfolios of mutual funds - -what are Portfolio 1A 1B...10C in column 1 of Table III?

   A: Re-formed once per year based on the previous year's performance.. Then look at monthly returns in the portfolios. Again, we have to form portfolios, then watch. *Keep in mind, all of Carhart's evidence is about* **portfolios** *of funds* (or average behavior of funds of a given type)*, not individual funds.*

4. Do funds that did well last year continue to do well next year? Point to numbers – is this serious or a tiny effect?.Is the phenomenon stronger among winners or among losers?

   A: Yes. See column 2 Table III Variation across portfolios of funds is 1% per month or 12% per year – a lot! Most of the action is in the losers. Most amazingly, 10C lose money in the following year!

5. Do the funds that went up last year always continue to go up? How much risk is there in this investment strategy? To quantify these questions, what is the chance that portfolio 1A will earn a positive return in a typical month of next year?

   A: For risk, std dev column. 1A is 0.75% with $\sigma = 5.45\%$. Thus, the chance of going up at all is $\Phi(0.75/5.45) = 55.47\%$. So this is still a 55 up / 45 down phenomenon, and that is among a group of funds in the highest 1/10 of performance for the previous year!

   And that's for the *portfolio* of funds – individual funds in the portfolio are even more volatile, so the chance of an individual winner fund doing well next year is even lower. Just a reminder that returns have a lot of risk with them! *Don't confuse alpha with arbitrage opportunity. Alpha means an average return, but not a good return every year.*

   Also, as with momentum, this is not a "new phenomoneon" it's a "new way of looking at something we knew all along." There is no conflict here with the conventional wisdom that funds who won last year are almost 50% likely to fall this year. If you can wrap your mind around that, you will have really understood the first column!

6. Perhaps the funds that do better in the test year continue to do well on average because they have high CAPM betas. What does Carhart say about that?

   A: Good point –E(R) is not a puzzle, only alpha is a puzzle. CAPM columns of TIII show that betas are all about 1, so ER variation is all alpha. These are single regression betas, so we are really using the CAPM. Anyway, what does it mean to use information to produce negative alpha?? (p.63)

7. How do the CAPM R^2 values compare to those for stocks you have seen before? What accounts for the difference?

   A: Especially in the middle, they're huge. Individual companies get about 40%; FF stock portfolios got about 65%, here we're seeing 98%. *Portfolios of active funds are almost exactly replicating the market index.* Note the R^2 tail off as we go up and down the table. *To be extreme, you have to stray far from the benchmark.* The 1 and 10 portfolios actually have very low R^2 meaning huge tracking errors, for funds.

8. Are all the alphas zero after the 4 factor model is done, or is there a puzzle? Who seems still to be outperforming and who is underperforming?

A: Alphas from -0.1% (1% / year, as before) to -0.2% (9). Then a big increase in the bottom end to an amazing $\alpha = -0.64\%$! Puzzle – how can you lose money in a diversified portfolio?? Efficient markets mean you can't do this either (or you and I short what they are long). Expenses? Coming up.

Note: negative alphas is not that surprising. The indices do not include transactions costs. Real-world performance is usually less than the index.

Note: FF4F have no transactions costs or short costs (hml is perpetually short small growth stocks, without any cost), and assume you buy at midpoint of b/a. Some negative alpha is natural.

9. Which factor's betas seems to account for the "hot hands" (spread in average returns)?

   A: A bit of SMB, mostly PR1YR. Point: get in the habit, as with FF, of looking at the beta pattern. (SMB: to get in the top 1/10 you have to take a big bet!)

10. What puzzle does Table IV address? What is its conclusion?

    A: Table IV wants to know how the bad funds can be so **bad**. In an efficient market, you can't get a negative alpha either! All you can do is hold too much σ (poor diversified). You can waste money in fees and trading, and that's what Carhart is trying to measure here. Is the remaining spread in alphas due to too much expenses and turnover (paying transactions costs)? Note *we're done with* **over***performance.* Turnover and expense ratios are a bit worse for 9,10, but not enough. p. 65 bottom.

11. Fund managers claim that fees and turnover do not reduce returns to investors. How could charging more money *not* reduce returns to investors? (Try to be a good salesperson for a high-turnover high-fee fund. Why should I give you my money? Then try to be a good supply-demand economist. What should the equilibrium relationship be between fees, expenses and returns to investors?)

    A: the claim is that fees pay for superior ability, and that turnover is losing dogs and buying good stocks so helps. Standard S=D ecomomics says we should see zero effect. It is a surprise to see any effect! .

12. (Table V. Make sure you understand how this table was created.How are Table IV and Table V different?) What does Carhart find about fees and turnover? How much does a 1% change in fees change returns to investors? How much does turnover – selling one stock and buying another – change returns to investors?

    A: Table V. and p. 67. Table V is based on individual funds, while Table IV looks at the portfolios of Table 1. Expenses and turnover are all bad. Expenses are more than 1-1 bad. Turnover corresponds to a 0.95bp/transaction cost. (Seems large; more than 1-1 as with expenses). I think this is a big puzzle, we should see zeros here in a market in equilibrium! You can't say "investors are dumb" in mutual funds but "investors are smart" in trading!

13. What are the two hypotheses that Carhart spends the rest of the paper distinguishing (see bottom of p. 70)

A: Read that carefully. Is the performance of funds due to the funds' stable strategy, or do funds just happen to own stocks that go up in a year?

14. What is the point of Figure 2? (Hint: what would it look like if the sort on one year performance indicated skill?)

    A: Skill shouldn't disappear, so the fact that returns seem to revert (2 year return is worse than 1 year return) suggests momentum in stocks (which does dissipate over time). If it were skill, the lines would be flat. This is the crucial evidence that it's momentum in underlying stocks, not skill. Also p. 71, 80% turnover in top funds each year.

15. What does Carhart say about momentum funds – funds that seem to follow a momentum strategy, as revealed by high loadings on the momentum factor? (Hint: no table, but text on p. 73)

    A: p.73. Momentum funds – sorted by PR1YR loadings – do not earn higher returns, let alone four-factor alphas. They lose it all in transactions costs. Hence, chance holders of the winners get a little boost. *This is his evidence that it's momentum in stocks, not momentum funds.* This also raises a strong suspicion about how easy it is to earn momentum returns in practice, once you account for trading costs.

16. *One* year lagged returns are probably mostly luck, not skill. What if you sort funds by the more common 5 year performance averages? (Hint: Figure 3)

    A: Figure 3. The initial expected return spread declines! 5 years is *less* revealing than one year! Other components stay the same. There is *less* effect in the 5 year sort.

17. Does Carhart suggest any trading strategies? (Hint. Look on p. 80 bottom)

    A: yes: p. 80-81. Buy winning funds for one year to get momentum strategy without trading costs, if you can get in at NAV. But you have to buy a fund of funds to do this, and many of Carhart's funds have loads too. Also, alas, you can't short funds.

18. Conclusion

    (a) 8% / year spread between 1 year winners and losers
    (b) 4.6% from factors, 0.7% from expenses, 1% from transactions costs. Most unexplained comes from 9-10 (worst two). "Cold hands."
    (c) Expenses, turnover, fees lower performance 1-1. Pre-load returns are 80bp lower in load funds!
    (d) Buy last year's winning fund gets you momentum for free (since you buy at NAV, not bid/ask). Funds are starting to charge fees to discourage this.

19. Comments/big take-away points:

    (a) Selection bias.

(b) Evaluating the average of a group, identified on ex-ante information, not "why is Warren Buffet rich?"

(c) Evaluate funds by regression of fund returns – how they *actually behave* not by word "style." The "portable alpha" problem – If you're a good bond fund you can become a good stock fund with a very small investment in index futures.

(d) A *Performance attribution* model – the question is only "can I replicate this performance with passive indices or a computer program, or do I need to pay for stock-picking (or style-picking) skill?"

(e) google shows lots of momentum funds, http://www.gobcafunds.com/portfolios/momentum.asp. Whatever it is, it's certainly not "overlooked."

17.3 Fama and French Mutual Fund Performance Q&A.

So far, we have been looking for “skill” by guessing some characteristic associated with skill – past returns, MBA by manager, etc. – and looking at the return of a sorted portfolio going forward. This paper tells us whether there is any skill at all, *without* us taking a stand on what characteristic can be used to find good funds. It answers the question “sure the average fund is mediocre, but there are some good funds.” Read 1916 top to understand why they're different than persistence tests – if there is skill, lagged returns are a very noisy measure of that skill.

1. What do Fama and French mean by “Equilibrium Accounting? (p. 1915 top)

   A: The average investor must hold the market. Anything else is a zero sum game. (p. 1915)

2. Table 2 tells us about the performance of mutual funds as a whole – it studies the portfolio of all mutual funds. What does it tell us? Do mutual funds as a whole outperform benchmarks? What kinds of indices are most similar to the performance of all mutual funds? Do mutual funds as a whole generate alpha, before or after fees?

   A: Mutual funds as a whole are delivering the market index, with no style deviation towards small or value. The gross returns might have a slight positive alpha – but mostly in small funds – though that is insignificant. Net returns have negative alpha. As a whole they're just swallowing fees.

3. Fama and French focus on the alpha t statistic. Why not look at alphas or information ratios?

   A: Short lived funds are more likely to deliver big alphas. (1924)

4. Why don't FF just use the t distribution, to judge how many funds should have alpha t statistics above a certain cutoff? Explain the bootstrap procedure. (Hint, p. 1924)

   A: Well, read the two paragraphs. They're doing a very careful derivation of the actual distribution of the t statistic in this dataset. When statisticians say “here is the distribution of the t statistic” they are making a lot of assumptoins.

5. Explain the numbers in Table 3.

   (a) What does the 95 row, first two columns (95 1.68 1.54) mean? (Hint: At what number x is the probability that a $N(0, 1)$ is larger than x is 5%? Ask norminv)

   (b) What would they look like if all funds had zero true alpha, but the pattern of luck fully conformed to the assumptions of the t distribution (normal, independent, etc.)?

   (c) What would they look like if there were some funds with +5% alpha and other funds with -5% alpha, so that the average fund was not skilled but some were good and some were bad?

   (d) Why is the probability of a t greater than 2 or less than -2 not the usual 5% value that we expect for a t statistic?

   (e) What does the ”% t<act” column mean?

   A: Table 3 shows you how many funds would have (say) 2.0 alpha t statistic if there really were no alpha but some got lucky. We don't know the degrees of freedom, but for large T t becomes normal, and the 5% probability point for a normal is 1.64. Thus, the “sim” 1.68 tells us that the actual distribution of alpha t statistics, is just a little bit wider than normal. 1.68 means "if there were no alpha then 5% of funds would have alpha t statistics greater than 1.68" 1.54 means "5% of the actual funds have alpha t statistics greater than 1.54" which is *less* than what should happen due to chance if there were any skill. Overall, that's very much what we see. *If there were "good" and "bad" funds, the distribution of alphas would be much more spread out than the simulated distribution* For example, if half the funds were truly +5% and half truly -5%, then we would see a distribution with two humps, and a lot more funds with t>2 or $t < -2$ than the roughly 5% in these tables. See also the figures which make the point visually.

The "% t < act" column. In a single simulation, Fama and French have a distribution of many fund returns, and so get a distribution of alpha t statistics across funds. But this *distribution* changes as the market return and other common factors are different across the different draws. So, look, say at a row in which the "%t<act" is about 50, the t statistic is 2, and the percentile is 95. That means that the "actual" distribution – resulting from the one sample we see – has, say, about 5% of funds with alpha t statistic greater than 2. It also means that *averaged across all the 1000 simulations*, 5% of funds have a t statistic greater than 2. But in some simulations, 8% of funds might have t stat greater than 2, and in other simulations 2% of funds might have that t statistic. So, FF report 50%. It is, if you will, a sense of a standard error on the comparison of t statistics. What chance is there that the difference between the first two rows occurs simply by chance of one sample?

6. The distributions are wider than zero alpha generates. How much "true alpha" do Fama and French find is necessary to explain the fat tails of sample alphas?

   A: p. 1935, Table IV. About $\sigma(\alpha)$ (standard deviation of true alpha across funds) of 1-1.5% per year. See my notes on a better way they could have done it, and recovered the distribution of true alpha.

7. Why can't we explain fat tails of estimated alphas by fat tails of the return distribution?

   A: That's the point of using the simulation / bootstrap rather than a t statistic. Large results from big outliers are repeated in the sampling experiments.

8. Do funds look better using only the CAPM in Table AI? IF so, what to FF say about it? How does this reconcile with the finding in Table II that funds don't load much on non-market factors?

   A: Yes, substantially. There are more good – and more bad – funds. The answer is, the good ones loaded on value (hml) and the bad ones on growth, since smb generated no premium and the funds weren't loading on momentum. Value is alpha to the capm, and there is a spread in value loadings across funds. The average fund does not load on value, but there are value and growth funds.

   A (!) This leads to an obvious answer to the question "why are there good and bad funds" in the main table, especially "why are there bad funds?" There are additional factors such as industry. It is likely that the "good" and "bad" funds in the main tables were just lucky with respect to additional factor bets. That view helps me to understand what negative alpha – before fees – means.

For comparison with FF, here is Pct and the normal distribution cutoffs. Compare to the numbers in Table III

```
>> x = [1 2 3 4 5 10 20 30 40 50 60 70 80 95 96 97 98 99]';
>> fprintf( '%6.0i %6.2f \n',[x norminv(x/100)]')
     Pct  Normal
     1  -2.33
     2  -2.05
     3  -1.88
     4  -1.75
     5  -1.64
    10  -1.28
    20  -0.84
    30  -0.52
    40  -0.25
    50   0.00
    60   0.25
    70   0.52
    80   0.84
    95   1.64
    96   1.75
    97   1.88
    98   2.05
    99   2.33
```

Questions

- What the heck is negative alpha – gross, before fees?
- Is it really a mistake to call hml "not alpha" – before people knew about it?

17.3.1 Fama and French Basics – see detailed notes below

- The average fund earns the market, but are there good ones and bad ones? So far, we had to guess a characteristic (past returns) to select them. This paper avoids that step
- You observe funds, some with good returns, some with bad returns. *If nobody had any skill at all, how many funds would we see with positive alphas?* If we see more than this number, there is some alpha out there. (And some "negative alpha" whatever that is)
- A simple version: Each fund generates returns

  $$R_t^i = \alpha_i + \varepsilon_t^i$$

  The sample alphas for a given fund will be

  $$\hat{\alpha}_i = E\left(R_t^i\right) = \alpha_i + \frac{1}{T}\sum_{t=1}^{T}\varepsilon_t^i$$

  Thus, the estimated alpha has a distribution

  $$\hat{\alpha}_i \tilde{\ } \alpha_i + N(0, \sigma_\varepsilon^2/T),$$

and the alpha t statistic has a t distribution

$$\frac{\hat{\alpha}_i}{\sigma(\varepsilon^i)/\sqrt{T}} \sim t$$

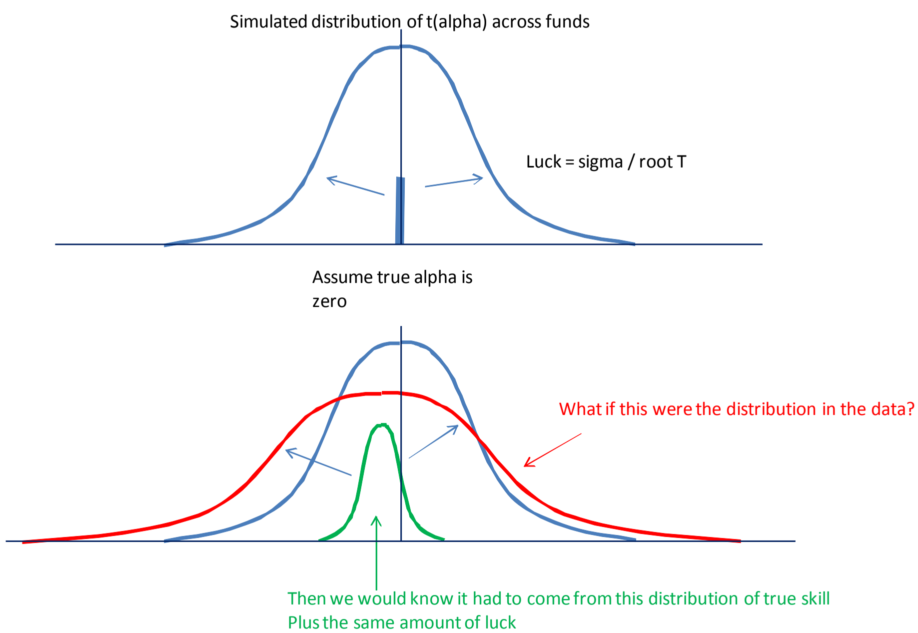
The t distribution is just a bit wider than normal and corrects for the fact that $\sigma(\varepsilon)$ is also estimated. *This is the good old t distribution.*

- Assume the ε^i have the same variance for each fund and are uncorrelated across funds. Then the distribution of alpha t statistics *across funds* should follow a t distribution. Looking across funds is then like "looking across universes," and we do get to see more than one draw of $\hat{\alpha}$.

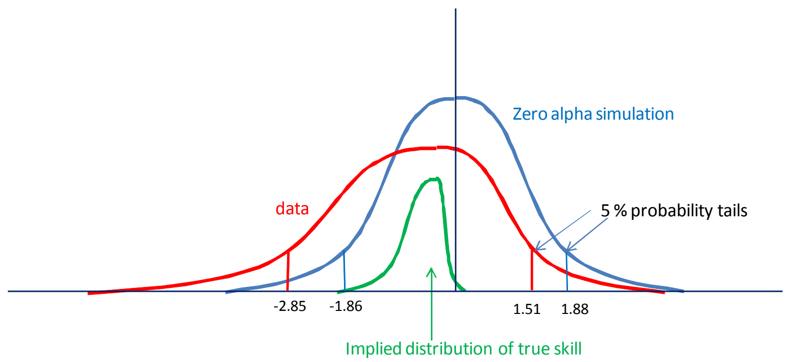
- *If true alphas are all zero, we should see no more than 5% of the funds with alpha t statistics greater than two or less than -two.*

- Fama and French: What if the ε *are* correlated across funds, funds follow styles too, and returns are not normal? Answer: do a big simulation. But it's just a fancy version of the distribution of a t statistic and doesn't really change things a lot. Notice the 5% cutoffs are pretty near 2.

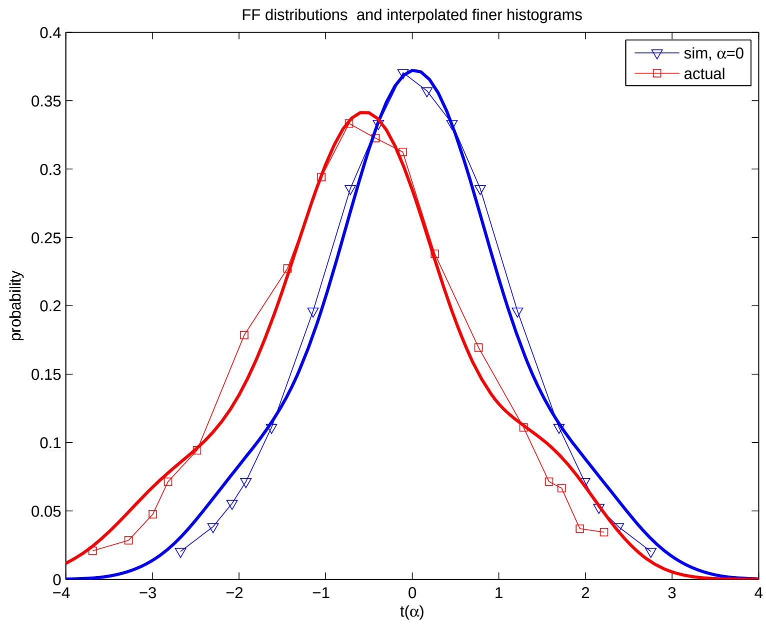
- Fama and French result: the actual distribution is shifted to the left and just a tiny bit wider than the t distribution centered around zero. That means the average alpha is a bit negative (?) But there are some funds with more or less skill.



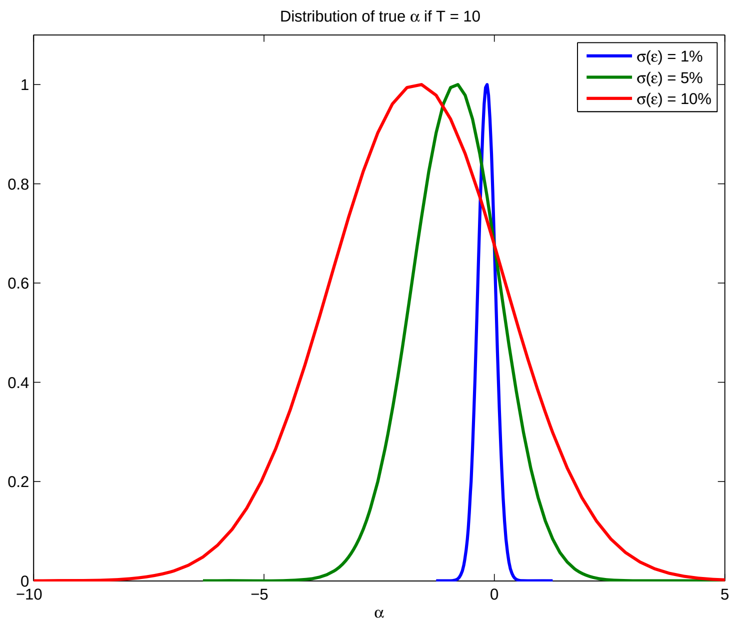
- JC: we can back out the distribution of "true" skill from how much wider the alpha t distribution is than the simulation.



- Fama French in graphical form



- It looks grim - the actual looks just like simulation shifted to the left. But look hard, the actual is just a bit wider – there is some skill out there!
- But unwinding t distributions to actual alphas looks better: I have to assume fund age and tracking error



17.4 Berk Q&A

1. What happens to future returns and flows, according to Berk, if a manager does have some skill?

   A: Berk's central idea: If someone has skill, he can earn better returns. Investors flow in, but all trading strategies have limited scale. The first investors make some alpha, but soon the alpha is driven down to zero. All that happens is that the fund has gotten bigger.

2. Berk says, unlike FF, that managers do have some skill even though alphas are all zero. How can that be?

   A: In the equilibrium above, skill implies larger funds, but no alpha.

3. Berk says that when investors chase past returns, investing in funds that have done well in the past, they are not being irrational, even though future returns are no better than average. How can this be?

   A: Past returns indicate skill. Then investors flow in as above. This drives the future returns back to normal. But it's not irrational.

4. Berk says that even though skill is permanent, returns will not be persistent. Why not?

   A: Same story. The "true" skill is persistent, but actual returns get eaten up.

17.4.1 Berk Comments

- Facts:

  1. Performance at best persists a year (Carhart)

2. Investors not only choose active managment, but they chase past returns. (Chevalier and Ellison)
3. Managers are paid a lot, in a competitive market.

- Instead of saying "folly" let's try to explain this as a normal competitive market
- 5 Hypotheses that we have taken for granted p. 2.

1. Returns (alpha) to investors measure skill
2. Average returns (alpha) do not beat the market so the average manager is not skilled
3. If a manger has skill, returns (alpha) should persist.
4. Since returns don't persist, investors who follow past returns are irrational.
5. Compenastion based on assets under management doesn't reward performance. (JC: This is pretty obvious)

- Paper in a nutshell: Suppose the mangager has skill,with 6% alpha and can run \$10m. Above that, the manager has to index because the strategy can only work at a \$10m scale. The fund charges 1% of AUM

1. Year 1: Fund has \$10m AUM, earns 6%, returns 5% to investors.
   - Fund earns \$600k. Manager gets \$100k, investors get \$500k
2. Investors see the good return and flock in. Year 2 Fund has \$20m AUM and earn 6% α on first \$10m, 0% α on the second \$10m. Thus overall the fund earns 3% α, charges 1%, returns 2% to invstors.
   - The fund still earns \$600k, gives the manager \$200k, returns \$400k to investors.
3. More investors join. Where does this stop? Year 3. The fund has \$60m AUM, *still earns 6%* α on the first \$10m, indexing the remaining \$50m. The fund charges *1% of \$60m.* Investors now get 0% α (The index). Still, there is no reason for them to leave. If any do, returns rise again, drawing them back in.
   - Equilibrium: Fund earns \$600k; Manager gets \$600k, investors get 0 – fees balance α.

- What do we see in this example

1. Skill lasts forever
2. Alpha to investors dies out after 2 years. (weeks?)
3. In equilibrium, fund alpha is uncorrelated with skill.
4. Skillful managers get paid a lot.
5. Investors are perfectly rational to chase past performance.
6. The manager is able to "raise his fee" to 5%, even though the stated fee is always 1%.

- Quibbles. Note it depends on the fixed 1% fee. Why not charge a higher fee? Answer: become a hedge fund! Why don't investors block new investors?

- Berk Vs. Fama and French: FF: Berk's model means we should see substantial alpha before fees, and zero alpha after fees. Berk: No, as that alpha gets swamped by the indexing. In my example, the 6% alpha before fees gets diluted with all the indexing until it's 1% alpha. I think that still means Berk says zero alpha after fees, not negative, but it's closer than the prediction of 6% alpha before fees.

17.5 Optional papers

17.5.1 Berk and van Binsbergen

Berk, Jonathan and Jules H. van Binsbergen, 2013, "Measuring Managerial Skill in the Mutual Fund Industry" . A retort to Fama and French.

- They measure skill by *dollars* not rate of return. "Value added" = gross return alpha *times assets under management.* 1 bp alpha on $1 billion is a lot. (p. 9)
- The use tradeable benchmarks, and also use only benchmarks available at the time in Vanguard funds. HML is alpha until Vanguard lets you buy it.

Voila': lots of skill.

1) FF factors do better than available Vanguard benchmarks

2) $140k - $270k/month depending on weighting. Total? The median fund still loses BTW.

3) Performance persists up to 10 years!

	MKT	SMB	HML	UMD
Alpha (b.p./month)	2	22	35	70
t-Statistic	0.83	2.80	3.37	3.38
Adjusted R^2	99%	74%	52%	15%

Table 2: **Net Alpha of FFC Portfolios:** We regress each FFC factor portfolio on the Vanguard Benchmark portfolios. The table lists the estimate (in b.p./month) and t-statistic of the constant term (Alpha) of each regression, as well as the R^2 of each regression.

Numbers are $1M/month, so 0.14 = $140,000 per month. Average *fund* is negative, but big funds have more alpha, so the average of all funds is positive. Weighted mean is the total profit over the years, not per month, so weights funds that are in business longer. (Weighted mean is total profit over time)

	Vanguard Benchmark	FFC Risk Measure
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%
Cross-Sectional Weighted Mean	0.27	0.25
Standard Error of the Weighted Mean	0.05	0.06
t-Statistic	5.74	3.94
No. of Funds	5974	6054

Table 3: **Value Added ($\hat{S}_i$):** For every fund in our database, we estimate the monthly value added, $\hat{S}_i$. The *Cross-Sectional* mean, standard error, 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 and t-statistic are computed by weighting by the number of periods the fund exists, that is, they are the statistical properties of $\bar{S}_W$ defined by (9). The numbers are reported in Y2000 $ millions per month.

These are portfolios sorted on past skill (dollars). What is the vertical axis? I'm not sure, but more is better

Panel B: FFC Risk Adjustment

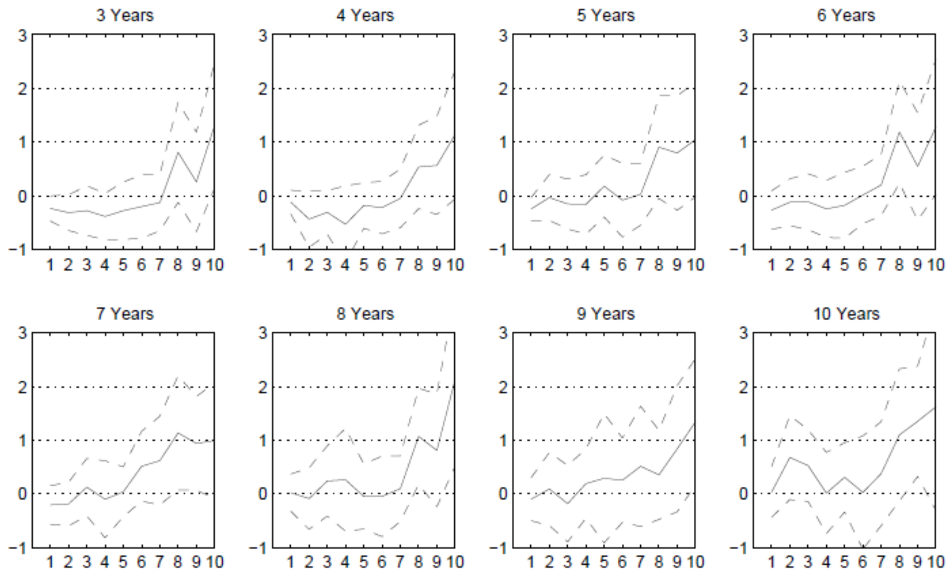


Figure 2: **Out-of-Sample Value Added**
Each graph displays average out-of-sample value added, $\hat{S}_i$ (in Y2000 \$ million/month), of funds sorted into deciles on the Skill Ratio, over the future horizon indicated. The solid line indicates the performance of each decile and the dashed lines indicated the two standard error bounds. Panel A shows the results when value added is computed using Vanguard index funds as benchmark portfolios and Panel B shows the results using the FFC risk adjustment.

17.5.2 Chevalier and Ellison, "Risk Taking by Mutual Funds"

- Background for Berk
- Figure 1 1177 for young funds, and Figure 2 for old funds. Doing well brings money in. Interestingly, you lose fewer customers by doing poorly. As in Carhart, there seem to be some awful funds that keep their customers.
- They see the convexity as an incentive to gamble.
- JC: Is this real? If so, funds would grow forever as luck bounces them from one to the other category.

RISK TAKING BY MUTAL FUNDS 1177

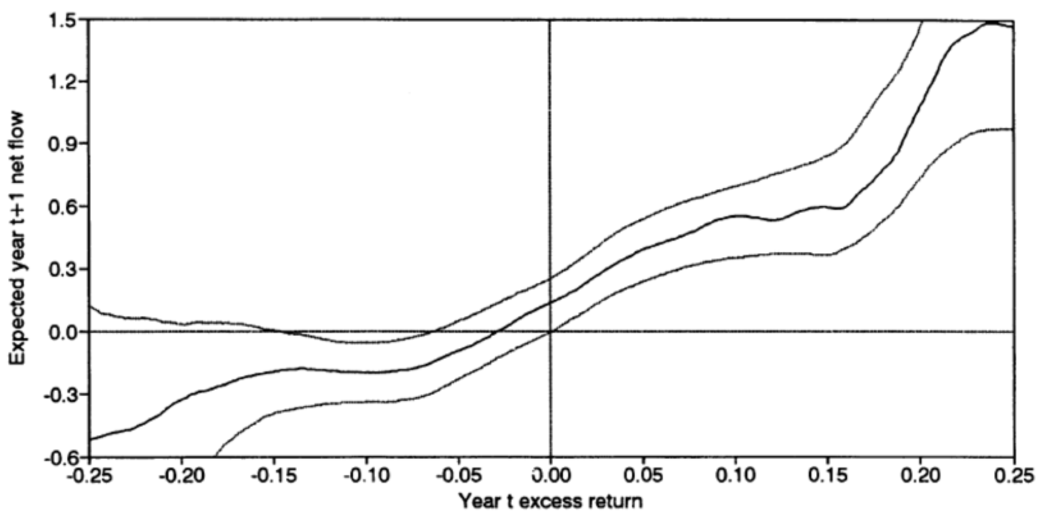


FIG. 1.—Flow-performance relationship $\hat{f}$ for young funds (age 2) with 90 percent confidence bands.

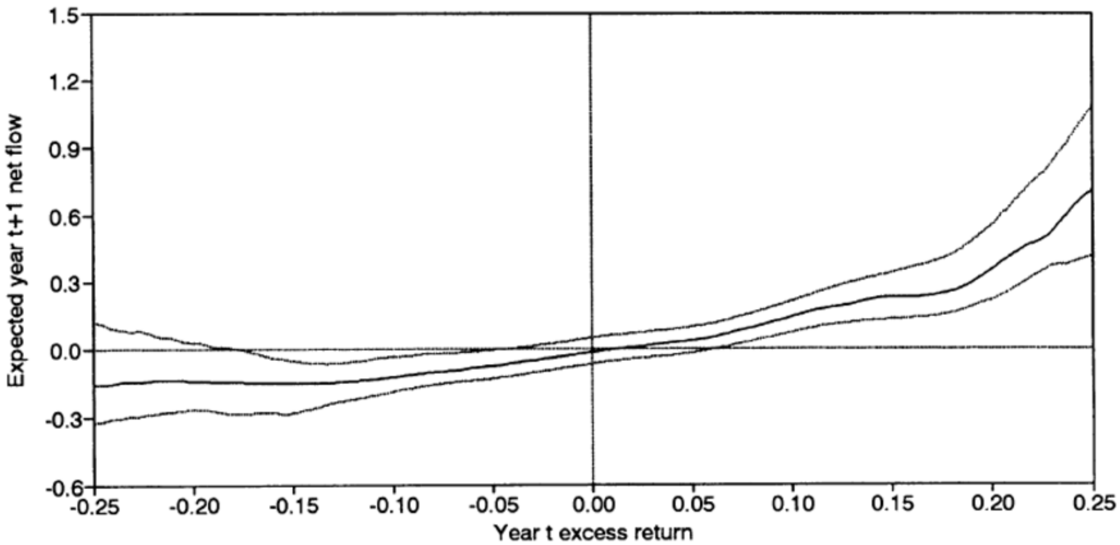


FIG. 2.—Flow-performance relationship $\hat{f}$ for old funds (age > 10) with 90 percent confidence bands.

17.5.3 Davis, Fama and French.

1. Most funds tilt towards small and growth. Even the 1/10 deep value funds aren't that value
2. Post ranking betas are a lotless disperesed than pre-ranking betas. Betas are harder to measure than you think.
3. A positive alpha at last, and almost significant! 13 bp per month, in the (pretty small) growth portfolio! (Since small growth underperforms the FF3F model, this is even better than a "characteristic adjustment" would suggest.)

Table 1. Three-Factor Results for Deciles of Mutual Funds Formed from *HML* Sorts, 1965–98
(*t*-statistics in parentheses)

HML Decile	Intercept	$R_m - R_f$	*SMB*	*HML*	R^2
A. Preformation averages by decile					
1	0.17	0.83	0.46	–0.81	
2	0.08	0.90	0.31	–0.43	
3	0.07	0.90	0.24	–0.29	
4	0.03	0.91	0.22	–0.18	
5	0.02	0.89	0.17	–0.09	
6	–0.01	0.89	0.14	–0.01	
7	–0.05	0.85	0.16	0.07	
8	–0.05	0.87	0.16	0.16	
9	–0.07	0.85	0.18	0.28	
10	–0.30	0.91	0.28	0.75	Notice lower post-formation betas
	Positive alpha at last!				
B. Postformation regression coefficients					
1	0.13	1.03	0.45	–0.45	0.94
	(1.76)	(56.59)	(17.43)	(–15.08)	
2	0.04	0.98	0.29	–0.31	0.96
	(0.80)	(71.18)	(14.61)	(–13.59)	
3	0.04	0.95	0.23	–0.25	0.97
	(0.86)	(91.22)	(15.71)	(–14.64)	
4	0.03	0.94	0.23	–0.16	0.97
	(0.76)	(95.99)	(16.11)	(–10.17)	
5	–0.05	0.92	0.17	–0.10	0.97
	(–1.41)	(96.97)	(12.93)	(–6.73)	
6	–0.04	0.93	0.16	–0.05	0.98
	(–1.03)	(109.39)	(13.43)	(–3.49)	
7	–0.03	0.87	0.17	0.02	0.97
	(–0.89)	(90.30)	(12.55)	(1.54)	
8	0.01	0.87	0.20	0.04	0.96
	(0.35)	(84.34)	(13.60)	(2.59)	
9	–0.04	0.86	0.22	0.15	0.97
	(–1.12)	(93.76)	(17.05)	(9.94)	
10	–0.23	0.83	0.40	0.20	0.86
	(–2.75)	(40.20)	(13.52)	(5.95)	

Even these aren't very deep value

17.5.4 Chevalier and Ellison, "Are some managers better than others?"

1. We've sorted on past return. How about sorting on who the managers are – MBA, SAT?
2. Table II p. 882. Yahoo! MBA = 63bp (p. 881) But is it style or skill? And of course the R^2 is pretty low.
3. Table III. Being smart and having an MBA means you have higher beta, lower turnover, lower fees!
4. Table IV, first two columns. Having an MBA raises your returns... Oh well, not your alpha – you get higher returns just because you took higher beta. SAT still has a small effect. Maybe

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Table II

Mutual Fund Performance and Manager Characteristics

The dependent variable, calendar year simple excess return is regressed on a set of manager characteristics, including the average SAT score of matriculants at the manager's undergraduate institution (divided by 100), a dummy variable that takes the value of one if the manager has an MBA degree and of zero otherwise, the manager's age, and the manager's tenure with the fund. A dummy variable is also included that takes the value of one if the fund is a growth and income fund and the value of zero if the fund is a growth fund. The observations are fund-years. Heteroskedasticity robust standard errors are in parentheses.

Independent Variables	Coefficients
Constant	−1.704 (1.756)
Manager college SAT	0.463 (0.136)
Manager MBA	0.631 (0.391)
Manager age	−0.086 (0.022)
Manager tenure	0.005 (0.046)
Growth-income dummy	−1.836 (0.351)
R^2	0.031
No. of observations	2029

Table III

Fund Characteristics and Manager Characteristics

Characteristics of and actions taken by mutual funds are regressed on characteristics of the funds' managers. The manager characteristics variables include the average SAT of matriculants at the manager's undergraduate institution (divided by 100), a dummy variable that takes the value of one if the manager has an MBA degree and zero otherwise, the manager's age, and the manager's tenure. The observations are fund-years. Newey-West standard errors are in parentheses.

	Dependent Variables			
Independent Variables	Beta	Log of Assets	Expense Ratio (%)	Turnover Ratio (%)
Constant	0.788	4.257	1.911	143.61
	(0.069)	(0.661)	(0.225)	(25.80)
Manager college SAT	0.011	0.063	−0.055	−5.09
	(0.005)	(0.054)	(0.029)	(2.19)
Manager MBA	0.067	0.393	−0.083	−1.88
	(0.016)	(0.149)	(0.054)	(5.18)
Manager age	0.0020	−0.0261	0.0211	−0.027
	(0.0009)	(0.0085)	(0.0076)	(0.351)
Manager tenure	−0.0055	0.054	0.023	−0.26
	(0.0020)	(0.019)	(0.017)	(0.58)
Growth-income dummy	−0.131	0.268	−0.006	−14.47
	(0.015)	(0.162)	(0.083)	(5.35)
Log of assets			−0.206	
			(0.031)	
R^2	0.102	0.036	0.238	0.020
No. of observations	2029	1907	1895	1885

Table IV

More Performance Regressions

Column 1 regresses simple excess return on manager and fund characteristics; columns 2–5 regress risk-adjusted excess returns on manager and fund characteristics. In columns 3–5, instrumental variable estimation is used, treating fund expenses and turnover as endogenous variables. Column 4 displays the same regression as column 3 utilizing only the reduced survivorship bias subsample of the data. Column 5 displays the same specification again, except the full dataset is used and a Heckman-like procedure is used to correct for survivorship biases. Finally, columns 6 and 7 show the same specifications as columns 4 and 5, replacing the dependent variable with the excess returns from a four-factor model. The regressors are manager and fund characteristics. The included manager characteristics are the average SAT score of matriculants at the manager's undergraduate institution (divided by 100), a dummy variable that takes the value of one if the manager has an MBA degree and zero otherwise, and the manager's age. A dummy variable that takes the value of one for growth and income funds and zero for growth funds is also included as a regressor. Columns 3 through 7 also include the fund's log of assets, expense ratio (%), and turnover ratio (%) as regressors. In all cases, the observations are fund-years and heteroskedasticity-robust standard errors are shown in parentheses.

	Excess Return Measure / Sample / Estimation Technique						
Independent Variables	Simple/Full/ OLS	Alpha/Full/ OLS	Alpha/Full/ IV	Alpha/RSB/ IV	Alpha/Full/ Heck-IV	Alpha4/RSB/ IV	Alpha4/Full/ Heck-IV
Constant	−1.730	−0.882	−0.237	−2.134	−1.007	−0.540	1.149
	(1.787)	(1.658)	(1.988)	(2.401)	(1.753)	(1.959)	(1.492)
Manager college SAT	0.462	0.376	0.306	0.253	0.291	0.248	0.363
	(0.135)	(0.127)	(0.133)	(0.160)	(0.120)	(0.143)	(0.102)
Manager MBA	0.630	0.042	−0.254	0.056	−0.279	0.437	0.417
	(0.390)	(0.363)	(0.388)	(0.494)	(0.346)	(0.415)	(0.295)
Manager age	−0.084	−0.082	−0.042	−0.015	−0.029	−0.043	−0.043
	(0.022)	(0.021)	(0.021)	(0.025)	(0.019)	(0.020)	(0.017)
Growth-income dummy	−1.835	−0.766	−0.512	0.888	−0.431	0.416	−0.788
	(0.351)	(0.331)	(0.356)	(0.460)	(0.336)	(0.388)	(0.288)
Expense ratio			−1.524	−1.579	−1.504	−1.949	−2.251
			(0.325)	(0.491)	(0.350)	(0.298)	(0.292)
Log of assets			−0.061	0.138	−0.018	0.206	−0.267
			(0.124)	(0.179)	(0.116)	(0.142)	(0.098)
Turnover ratio			0.014	0.013	0.013	−0.003	0.003
			(0.005)	(0.005)	(0.004)	(0.005)	(0.003)
R^2	0.03	0.02	0.05	0.05	0.05	0.16	0.10
No. of observations	2029	2029	1705	872	1705	872	1705

17.5.5 Cohen, Frazzini and Malloy "Small world"

1. Table III. Divide stocks held by a mutual fund into those where the fund manager and company CEO went to school together vs the others. Surprise, they do better in the stocks of their friends!

Value-weighted annual return		Panel A Connected holdings versus non-connected holdings						Panel B Connected minus connected not held		
	% of Assets	Raw return		DGTW-adjusted		4-factor alpha		Raw return	DGTW-adjusted	4-factor alpha
All holdings	100.00	12.77 (2.90)		0.22 (0.36)		-0.40 -(0.76)				
Not connected holdings	93.72	12.69 (2.89)		0.22 (0.37)		-0.47 -(0.87)				
		Connected holdings	L/S	Connected holdings	L/S	Connected holdings	L/S	L/S	L/S	L/S
CONNECTED1 *Same School*	6.28	15.33 (3.22)	2.64 (2.60)	1.82 (1.89)	1.61 (1.92)	2.01 (2.26)	2.49 (3.06)	1.77 (1.81)	1.08 (1.71)	0.98 (1.24)
CONNECTED2 *Same School, same degree*	2.86	15.49 (3.28)	2.80 (2.62)	1.89 (2.01)	1.67 (1.97)	2.07 (2.24)	2.54 (2.97)	2.05 (2.17)	1.17 (1.60)	1.13 (1.32)
CONNECTED3 *Same School, year overlap*	0.46	18.37 (3.71)	5.69 (3.74)	4.21 (2.52)	4.00 (2.74)	5.39 (3.28)	5.87 (3.74)	4.64 (2.95)	3.30 (2.40)	4.06 (2.43)
CONNECTED4 *Same School, same degree, year overlap*	0.22	20.53 (4.26)	7.84 (4.07)	5.91 (2.83)	5.69 (2.92)	8.00 (3.51)	8.47 (3.83)	6.84 (3.46)	4.95 (2.70)	6.59 (2.85)

This table shows calendar time portfolio returns. At the beginning of every calendar quarter, stocks in each mutual fund portfolio (based on the most recent SEC filing) are assigned to one of two portfolios (connected and non-connected). Connected companies are defined as firms where at least a senior official (CEO, CFO or Chairman) received any degree from the same institution as the fund's portfolio manager (CONNECTED1), received the same degree from the same institution as the fund's portfolio manager (CONNECTED2), received any degree from the same institution as the fund's portfolio manager and overlapped with the portfolio manager during the pursuit of the degree (CONNECTED3) or received the same degree from the same institution as the fund's portfolio manager, and overlapped with the portfolio manager during the pursuit of the degree (CONNECTED4). We compute monthly returns on connected and non-connected holdings between reports based on the assumption that funds did not change their holding between reports. Portfolios are rebalanced every calendar quarter and within a given fund portfolio, stocks are value weighted by the fund's dollar holdings. Finally, we compute value weighted calendar time portfolios by averaging across funds, weighting individual fund portfolios by the fund's total net asset value at the end of the previous quarter. This table includes all available stocks and all available funds. We report average returns, DGTW-adjusted returns and 4-factor alphas in the period 1990 to 2006. DGTW characteristic-adjusted returns are defined as raw returns minus the returns on a value weighted portfolio of all CRSP firms in the same size, market-book, and one year momentum quintile. Alpha is the intercept on a regression of monthly portfolio excess returns. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios and Carhart (1997) momentum factor. Panel A reports returns on connected stocks held by the mutual fund managers compared to their non connected holdings. Panel B reports returns on connected stocks held by mutual fund managers compared to the connected stocks they choose not to hold. Returns and alphas are in annual percent. L/S is the annual average return of a zero cost portfolio that holds the portfolio of connected stocks and sells short the portfolio of non-connected stocks (in Panel A) or the portfolio of connected but not held stocks (in Panel B). "% of Assets" is the average fraction of fund assets (in percent) invested in each group of stocks. t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

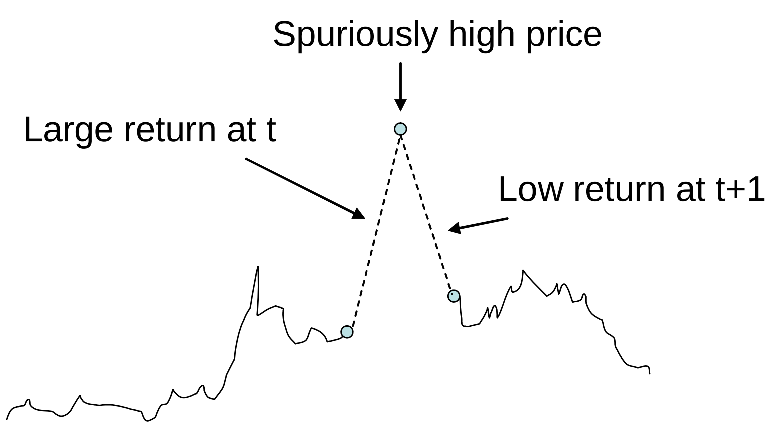
17.5.6 Carhart, "Leaning for the tape"

1. Table 1. Fund returns on last day of the year/ first day of the next year.

$+ \delta_4(YBEG_t + QBEG_t + MBEG_t) + \varepsilon_t.$

	Small-cap	Mid-cap	Large-cap
Panel A: Turn of the Year, *YEND/YBEG* Coefficients			
Value	141**/−30	120**/−34*	25**/−17**
Core	153**/−53**	155**/−73**	30**/−20**
Growth	174**/−96**	157**/−78**	37**/−33**

2. The effect is strongest in small cap growth.
3. The next day return being lower suggests it's not just luck, year end effects.
4. Figure 2 p. 667 the effect is strongest for funds near the top
5. Carhart interpretation: funds mark aggressively, and also buy their own holdings at the very end of the day to push up NAV of the stuff they already have



17.5.7 David Blitz, Joop Hui

"Another Look at the Performance of Actively Managed Equity Mutual Funds "

The Fama French factors don't have transactions costs, etc. Real passive benchmarks don't do as well, so FF alphas are too low.

Table 2: Performance of passive index funds

This table examines the performance of the passive index funds in our sample: the Vanguard 500 Index Investor fund (VFINX), the Vanguard Small Cap Index fund (NAESX), the Vanguard Value Index fund (VIVAX) and the Vanguard Growth Index fund (VIGRX). In addition we show the performance of a momentum strategy based on these funds, where at the end of every month we assume that the portfolio is fully invested in the Vanguard fund with the highest return over the preceding 12 months. We show the raw excess returns over the risk-free rate of return, as well as 1-, 3- and 4-factor alphas, estimated using data from French (2010), over our sample period April 1993 to March 2010.

	Vanguard 500 Index Investor (VFINX)	Vanguard Small Cap Index (NAESX)	Vanguard Value Index (VIVAX)	Vanguard Growth Index (VIGRX)	Synthetic momentum strategy
Panel A: Raw return					
Excess return %	5.28	7.38	5.44	5.48	6.90
Sharpe	0.35	0.38	0.35	0.34	0.40
Panel B: 1-factor model					
Alpha %	-0.14	0.86	0.23	-0.17	0.96
Alpha-t	-0.18	0.38	0.15	-0.14	0.52
Beta Market-Rf	0.94	1.10	0.90	0.98	1.01
R-square	96%	78%	85%	90%	82%
Panel C: 3-factor model					
Alpha %	0.11	-1.71	-1.14	1.59	0.44
Alpha-t	0.25	-2.23	-1.24	1.66	0.26
Beta Market-Rf	0.98	1.02	1.00	0.97	0.97
Beta SMB	-0.20	0.75	-0.17	-0.22	0.27
Beta HML	0.02	0.25	0.32	-0.27	0.01
R-square	99%	98%	94%	94%	85%
Panel D: 4-factor model					
Alpha %	0.32	-1.57	-0.34	1.32	-1.04
Alpha-t	0.78	-2.02	-0.40	1.36	-0.74
Beta Market-Rf	0.97	1.01	0.96	0.98	1.03
Beta SMB	-0.20	0.75	-0.16	-0.22	0.21
Beta HML	0.01	0.24	0.29	-0.26	0.06
Beta WML	-0.02	-0.01	-0.08	0.03	0.14
R-square	99%	98%	95%	95%	87%

"the SMB factor significantly overestimates the size premium that can be captured in reality by investing in a passive fund such as the Vanguard Small Cap Index fund"