Quantitative Asset Management

Bernard Herskovic

UCLA Anderson
SCHOOL of MANAGEMENT

Spring 2019

Outline

1. Persistence in Mutual Fund Performance
   Carhart (1997, JF)
2. Time-varying betas
   Ang and Kristensen (2012, JFE)
3. Time-varying prices of risk
   Adrian, Crump, and Moench (2015, JFE)

Mutual Fund Performance

- Is mutual fund performance persistent?
- How to measure persistence?

Mutual Fund Performance

- What can explain persistence in mutual fund performance?

Mutual Fund Performance Persistence

- Carhart investigated persistence mutual fund performance
- Persistence is the key!
- Does previous performance predict alpha next year?

  If it does not, then there is no point in chasing alpha!
- Sort mutual funds by performance in the past 12 months into 10 bins
  - Form equal-weighted portfolios of mutual funds
  - What should we calculate for each portfolio? Why?
  - What are the main findings?

Portfolios of Mutual Funds

Equal-weighted Portfolios sorted on lagged one-year returns from 1963-1993. Table III.

Portfolio	Returns	*CAPM* α	market	Carhart α	market	SMB	HML	MOM
1A	0.75	0.27	1.08	-0.11	0.91	0.72	-0.07	0.33
1B	0.67	0.22	1.00	-0.10	0.86	0.59	-0.05	0.27
1C	0.63	0.17	1.02	-0.15	0.89	0.56	-0.05	0.27
1	0.68	0.22	1.03	-0.12	0.88	0.62	-0.05	0.29
10	0.01	-0.45	1.02	-0.40	0.93	0.32	-0.08	-0.09
10A	0.25	-0.19	1.00	-0.19	0.91	0.33	-0.11	-0.02
10B	0.02	-0.42	1.00	-0.37	0.91	0.32	-0.09	-0.09
10C	-0.25	-0.74	1.05	-0.64	0.98	0.32	-0.04	-0.17

Persistence in Performance

- There is still unexplained persistence: nearly 30bps
- Most from worst performing funds
- What else can explain the remaining persistence?
- Managers' claim:

  > 'expense and turnover do not reduce performance, since investor are paying for the quality of the manager's information, and because managers trade only to increase expected returns net of transaction costs"

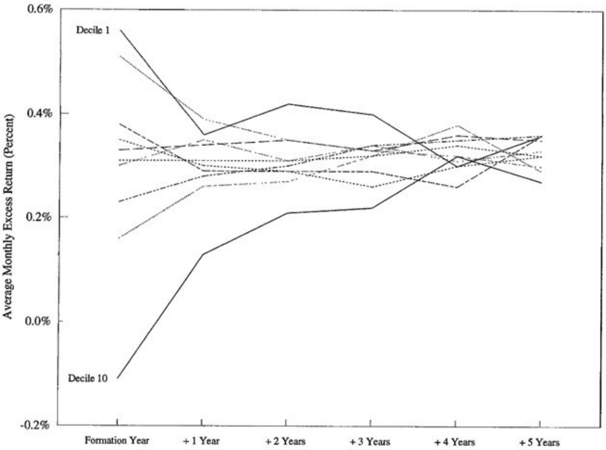
- Is this consist with the data according to Carhart (1997)?

Persistence in Performance

- Evidence for persistence in (out-)performance by mutual funds is not very compelling
- Once you remove the momentum effects, most of it gone
- There is strong evidence of persistent underperformance by some mutual funds:
  - True negative alpha is a also puzzle because you should not be able to consistently underperform the market, since another could short your strategy! (see Cochrane, 2013).

Persistence?

Figure 5



Post-formation portfolio returns. Source: Carhart (1997)

Momentum and mean-reversion in mutual funds

- Sort mutual funds by worst/best performing sectors
  - Past year
  - 3 years
  - 5 years
- Outperformance over the next year of the best funds
  - Momentum effect
- Underperformance over the next 5 years of the best funds
  - Mean-reversion effect
  - See e.g. The best, the worst and the ugly in The Economist (2012)


Place your bets
Average total returns* when selecting funds from best/worst-performing sector of previous years
1983-2012, %
Best-performing
Worst-performing
1-year return when selection based on performance over the past:
0
10
20
30
40
50
60
70
80
1 year
3 years
5 years
3-year return:
1 year
3 years
5-year return:
1 year
5 years
Source: Lipper
*British mutual funds

Looking for Skill by Bootstrapping

- An alternative to looking for persistence as evidence of skill is to compare the distribution of alpha in the data to the distribution we would see if true alpha is zero and all of the measured alpha is due to luck
  - Fama and French (2010, JF) simulate 10,000 bootstrap simulations for the cross-section of mutual funds under the null that true alpha is zero (same properties as actual fund returns except that alpha is set to zero)
- After fees (on net returns), the simulated data look a lot like the actual data: if there are managers skilled enough to cover costs, this gets completely undone by the mass of unskilled managers who can't cover costs

Time-varying betas

Time-varying betas

Ang and Kristensen (2012)

- Asset's expected return should be zero after controlling for asset's systematic factor exposure
- However, we typically assume constant loadings
- Betas change over time!
- We have done some time-vary betas:

  Remember Lecture 4 on volatility-based strategies?
- Ang and Kristensen (2012)
  - Methodology to estimate time-vary alphas and betas
  - Distinction between long-run and short-run estimates
  - Kernel-weighted ordinary least squares
  - Asymptotic distributions

Time-varying betas

Conditional Factor Model

Return of stock k at time t_i:

$$R_{k,i} = \alpha_k(t_i) + \beta_k(t_i)' f_i + \omega_{kk}(t_i) z_{k,i}$$

In matrix notation:

$$R_i = \alpha(t_i) + \beta(t_i)' f_i + \Omega^{1/2}(t_i) z_i$$

where

- R_i is M by 1
- $\alpha(t_i)$ is M by 1
- $\beta(t_i)$ is J by M
- f_i is J by 1
- $\Omega(t_i)$ is M by M
- z_i is M by 1: $\mathbb{E}_i[z_i] = 0$ and $\mathbb{E}_i[z_i z_i'] = I_M$

Time-varying betas

Conditional Factor Model

We want to estimate:

$$\alpha(t_i)$$

and

$$\beta(t_i)$$

Time-varying betas

Conditional Factor Model

Definition of long-run alphas and betas

$$\alpha_{LR,k} \equiv \lim_{n\to\infty} \frac{1}{n} \sum_{i=1}^{n} \alpha_k(t_i)$$

and

$$\beta_{LR,k} \equiv \lim_{n\to\infty} \frac{1}{n} \sum_{i=1}^{n} \beta_k(t_i)$$

Remember that: $0 < t_1 < t_2 < \ldots < t_n < T$

Time-varying betas

Conditional estimators

Definition of time-varying alphas an betas

$$\left[\alpha(t_i), \beta(t_i)'\right]' = \Lambda^{-1}(t_i)\mathbb{E}_i\left[X_i R_i'\right]$$

where

$$X_i = [1, f_i']'$$

and

$$\Lambda(t_i) = \mathbb{E}_i\left[X_i X_i'\right]$$

This is an OLS conditional on information available at time t_i

Time-varying betas

Conditional estimators

Local least squares estimator for any time $0 \leq t \leq T$:

$$\left[\hat{\alpha}(t), \hat{\beta}(t)'\right]' = \arg\min_{(\alpha,\beta)} \sum_{i=1}^{n} K_{h_k T}(t_i - t) \left(R_{k,i} - \alpha - \beta' f_i\right)^2$$

where

$$K_{h_k T}(z) = \frac{K\left(\frac{z}{h_k T}\right)}{h_k T}$$

$K(\cdot)$ is a kernel and $h_k > 0$ is a bandwidth

Intuition: kernel defines which obs. are more 'important'

- What happen is $K(z)$ higher around $z = 0$?
- What happen is h_k is large or too small?

Time-varying betas

Conditional estimators

Optimal kernel-weighted least squares:

$$\left[\hat{\alpha}(t), \hat{\beta}(t)'\right]' = \left[\sum_{i=1}^{n} K_{h_k T}(t_i - t) X_i X_i'\right]^{-1} \left[\sum_{i=1}^{n} K_{h_k T}(t_i - t) X_i R_{k,i}\right]$$

and they use a Gaussian density as kernel

$$K(z) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right)$$

How to optimally choose the bandwidth?

Time-varying betas

Data generating process

Let $\Delta = t_i - t_{i-1}$. Discrete version of continuous-time model:

$$\Delta s_i = \alpha(t_i) + \beta(t_i)'\Delta F_i + \Sigma^{1/2}(t_i)\sqrt{\Delta} z_i$$

where Δs_i is log change in prices excess of the risk-free asset

$$\Delta F_i = \mu_F(t_i)\Delta + \Lambda_{FF}^{1/2}\sqrt{\Delta} u_i$$

Estimators:

$$\mathbb{E}\left[\hat{\beta}(t)\right] \simeq \beta(t) + (hT)^2 \beta^{(2)}(t)$$

$$\mathrm{Var}\left(\hat{\beta}(t)\right) \simeq \frac{1}{nh}\kappa_2 \Lambda_{FF}^{-1}(t) \otimes \Sigma(t)$$

where h is a common bandwidth

- Trade-off between bias and variance

Time-varying betas

Theorem 1: betas

Asymptotics :

$$\sqrt{nh}\left(\hat{\beta}(t)-\beta(t)\right)\sim N\left(0,\kappa_2\Lambda_{FF}^{-1}(t)\otimes\Sigma(t)\right)$$

Sample equivalents:

$$\hat{\Lambda}_{FF}^{-1}(t) \text{ and } \hat{\Sigma}(t)$$

Time-varying betas

Alphas

Estimators:

$$\mathbb{E}\left[\hat{\alpha}(t)\right] \simeq \alpha(t) + (hT)^2 \alpha^{(2)}(t)$$

$$\text{Var}\left(\hat{\alpha}(t)\right) \simeq \frac{1}{Th} \kappa_2 \Sigma(t)$$

No Asymptotics! As $Th \to \infty$, the variance explodes..

- Informally:

$$\sqrt{nh}\left(\hat{\alpha}(t) - \alpha(t)\right) \sim N\left(0, \kappa_2 \Sigma(t)\right)$$

  in large samples

- Solution: normalization assumption

$$\alpha(t) = a(t/T) \text{ and } \Sigma(t) = S(t/T)$$

Time-varying betas

Long-run alphas and betas

Estimators:

$$\hat{\alpha}_{LR,k} = \frac{1}{n}\sum_{i=1}^{n} \hat{\alpha}_k(t_i)$$

$$\hat{\beta}_{LR,k} = \frac{1}{n}\sum_{i=1}^{n} \hat{\beta}_k(t_i)$$

Theorem 2:

$$\sqrt{T}\left(\hat{\alpha}_{LR} - \alpha_{LR}\right) \sim N(0, \Sigma_{LR,\alpha\alpha})$$

$$\sqrt{n}\left(\hat{\beta}_{LR} - \beta_{LR}\right) \sim N(0, \Sigma_{LR,\beta\beta})$$

Sample equivalents:

$$\hat{\Sigma}_{LR,\alpha\alpha} \text{ and } \hat{\Sigma}_{LR,\beta\beta}$$

Now we can test if alphas are zero!

Time-varying betas

Long-run alphas and betas

- We can test if long-run alphas are zero!

  Wald-type of test
- We can also test if alphas and betas are constant over time

  Theorem 3
- But we still need to choose the bandwidth..

Time-varying betas

Bandwidth

How to choose the optimal bandwidth?

$$h^*_{\beta,k} \qquad \text{and} \qquad h^*_{\alpha,k}$$

Two-step method proposed

- Step 1:
  - Assume variance-covariances matrices to be constant,
  - alphas and betas to be polynomials,
  - estimate polynomial parameters, and
  - compute the ‘optimal’ bandwidth
- Step 2
  - Use the bandwidth from step 1, and compute time-varying betas and alphas
  - Calculate another bandwidth: second-pass bandwidth
  - LR bandwidth is further scaled down

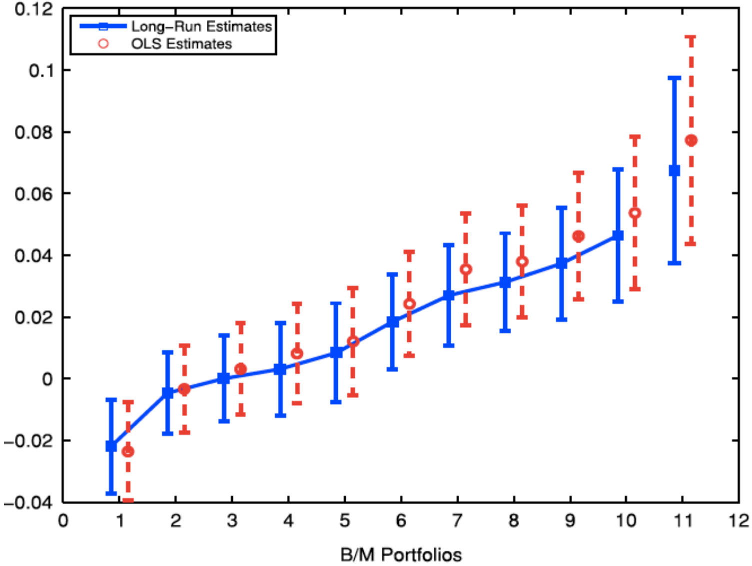
Time-varying betas

Data

- Look at BM sorted portfolios
- Alphas do not change much over time
- but Betas change over time

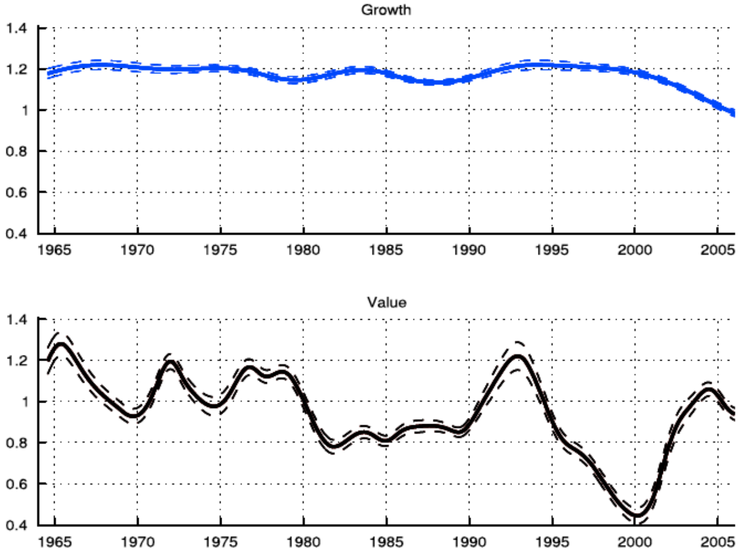
Time-varying betas

Fig 1: Long-run alphas vs. OLS alphas in BM-sorted portfolios



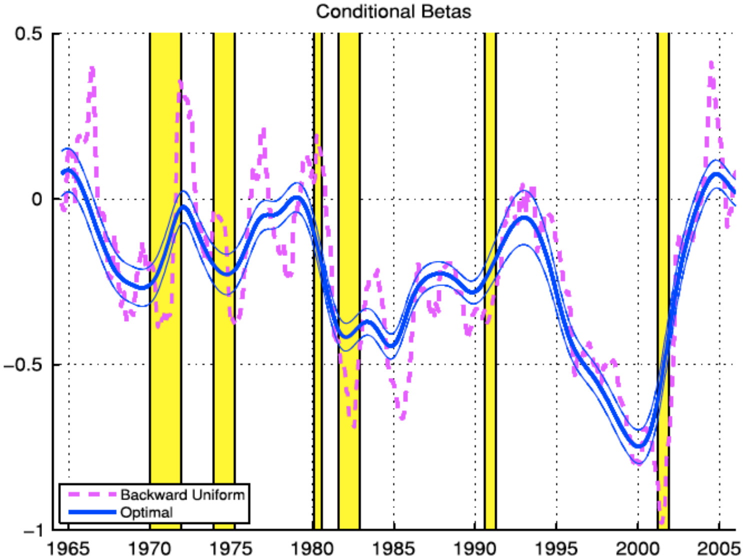
Time-varying betas

Fig 2: Time-varying betas for growth and value stocks



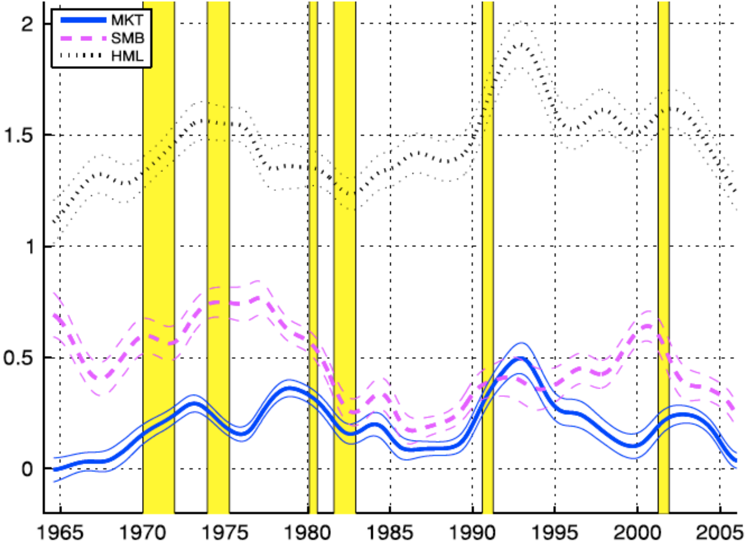
Time-varying betas

Fig 3: Time-varying betas for value strategy



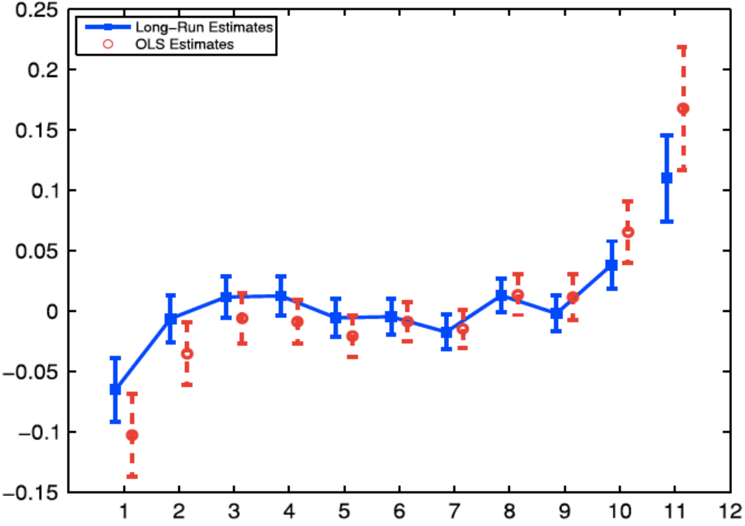
Time-varying betas

Fig 4: Time-varying FF loadings for value strategy



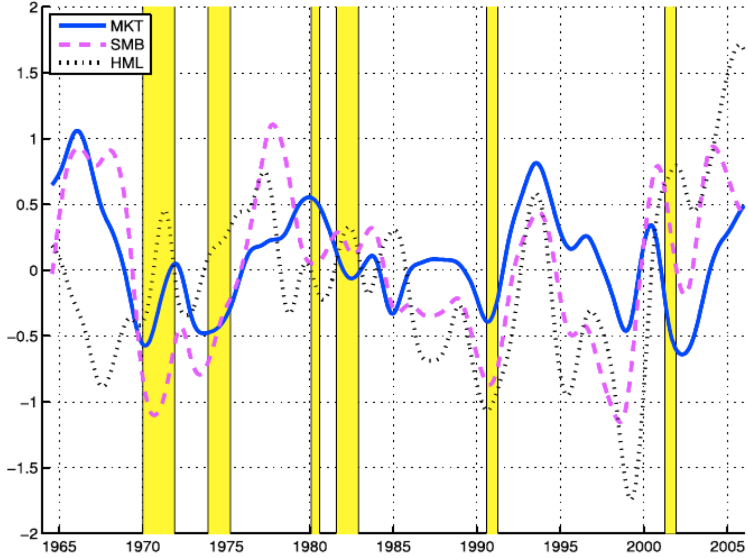
Time-varying betas

Fig 5: Long-run alphas vs. OLS alphas in momentum-sorted portfolios



Time-varying betas

Fig 6: Time-varying FF loadings for momentum strategy



Time-varying prices of risk

Time-varying prices of risk: Set-up

- K state variables following an vector autoregressive process

$$X_{t+1} = \mu + \Phi X_t + v_{t+1}, \quad t = 0, \ldots, T-1,$$

- Partition the state variables into three categories:
  - risk factor only: $X_{1,t}$
  - risk and price of risk factor: $X_{2,t}$
  - price of risk factor only: $X_{3,t}$

$$C_t = \begin{bmatrix} X_{1,t} \\ X_{2,t} \end{bmatrix}, \quad F_t = \begin{bmatrix} X_{2,t} \\ X_{3,t} \end{bmatrix}, \quad u_t = \begin{bmatrix} v_{1,t} \\ v_{2,t} \end{bmatrix}$$

- Assumptions:

$$\mathbb{E}\left[v_{t+1} \middle| \mathcal{F}_t\right] = 0, \quad \mathbb{V}\left[v_{t+1} \middle| \mathcal{F}_t\right] = \Sigma_{v,t}$$

Time-varying prices of risk: Set-up

- Using excess returns,
- Assume existence of a pricing kernel:

$$\mathbb{E}\left[M_{t+1}R_{i,t+1}\middle|\mathcal{F}_t\right] = 0$$

This is a very general assumption

see Cochrane's book (Asset Pricing, chapters 4 and 6)

- Assume linear pricing kernel:

$$\frac{M_{t+1} - \mathbb{E}\left[M_{t+1}\middle|\mathcal{F}_t\right]}{\mathbb{E}\left[M_{t+1}\middle|\mathcal{F}_t\right]} = -\lambda_t' \Sigma_{u,t}^{-1/2} u_{t+1}$$

- Assume affine prices of risk:

$$\lambda_t = \Sigma_{u,t}^{-1/2}\left(\lambda_0 + \Lambda_1 F_t\right)$$

Time-varying prices of risk: Set-up

- All this implies

$$\mathbb{E}\left[R_{i,t+1}\middle|\mathcal{F}_t\right] = -\frac{\mathbb{C}[M_{t+1}, R_{i,t+1}|\mathcal{F}_t]}{\mathbb{E}\left[M_{t+1}\middle|\mathcal{F}_t\right]}$$
$$= \lambda_t' \Sigma_{u,t}^{-1/2} \mathbb{C}\left[u_{t+1}, R_{i,t+1}|\mathcal{F}_t\right]$$
$$= (\lambda_0 + \Lambda_1 F_t)' \Sigma_{u,t}^{-1} \mathbb{C}\left[C_{t+1}, R_{i,t+1}|\mathcal{F}_t\right]$$

- Some re-writing

$$\mathbb{E}\left[R_{i,t+1}\middle|\mathcal{F}_t\right] = \beta_{i,t}'(\lambda_0 + \Lambda_1 F_t)$$

where

$$\beta_{i,t} = \Sigma_{u,t}^{-1} \mathbb{C}\left[C_{t+1}, R_{i,t+1}|\mathcal{F}_t\right]$$

Time-varying prices of risk: Set-up

- Hence, we can write realized returns as

$$R_{i,t+1} = \beta'_{i,t}(\lambda_0 + \Lambda_1 F_t) + (R_{i,t+1} - \mathbb{E}[R_{i,t+1}|\mathcal{F}_t])$$

  where returns can be decomposed as follows

$$R_{i,t+1} - \mathbb{E}[R_{i,t+1}|\mathcal{F}_t] = \gamma'_{i,t}(C_{t+1} - \mathbb{E}[C_{t+1}|\mathcal{F}_t]) + e_{i,t+1} = \gamma'_{i,t} u_{t+1} + e_{i,t+1}.$$

  $e_{i,t+1}$ is a cond. orthogonal to innovations in C_{t+1}, and

$$\gamma_{i,t} = \Sigma_{u,t}^{-1} \mathbb{C}[C_{t+1}, R_{i,t+1}|\mathcal{F}_t] = \beta_{i,t}$$

- Finally

$$R_{i,t+1} = \beta'_{i,t}(\lambda_0 + \Lambda_1 F_t) + \beta'_{i,t} u_{t+1} + e_{i,t+1}$$

Time-varying prices of risk: Constant betas

- Constant betas (matrix notation)

$$R = B\lambda_0 \iota_T' + B\Lambda_1 F_- + BU + E$$
$$X = \mu + \Phi X_- + V$$

- We can write more generally as

$$R = A_0 \iota_T' + A_1 F_- + BU + E = A\tilde{Z} + E,$$

where $\tilde{Z} = [\iota_T \mid F_-' \mid U']'$ and

$$A_0 = B\lambda_0, \quad A_1 = B\Lambda_1, \quad A = [A_0 \mid A_1 \mid B]$$

- For some positive definite weighting matrix, we have

$$\lambda_0 = (B'WB)^{-1} B'WA_0, \quad \Lambda_1 = (B'WB)^{-1} B'WA_1$$

and the regression counterpart is

$$\hat{\lambda}_{0,\text{ols}} = \left(\hat{B}_{\text{ols}}' \hat{B}_{\text{ols}}\right)^{-1} \hat{B}_{\text{ols}}' \hat{A}_{0,\text{ols}}, \quad \hat{\Lambda}_{1,\text{ols}} = \left(\hat{B}_{\text{ols}}' \hat{B}_{\text{ols}}\right)^{-1} \hat{B}_{\text{ols}}' \hat{A}_{1,\text{ols}}$$

Time-varying prices of risk: Constant betas

Theorem 1

- Asymptotic distribution (ols) at $T \to \infty$

$$\sqrt{T}\,\mathrm{vec}\left(\hat{\Lambda}_{\mathrm{ols}} - \Lambda\right) \xrightarrow{d} \mathcal{N}(0, \mathcal{V}_{\Lambda})$$

where

$$\mathcal{V}_{\Lambda} = \left(\Upsilon_{FF}^{-1} \otimes \Sigma_u\right) + \mathcal{H}_{\Lambda}(B, \Lambda)\mathcal{V}_{\mathrm{rob}}\mathcal{H}_{\Lambda}(B, \Lambda)',$$

$$\Upsilon_{FF} = \mathrm{p}\lim_{T \to \infty} \tilde{F}_{-}\tilde{F}'_{-}/(T-1),\ \tilde{F}_{-} = [\iota_T \,\vdots\, F'_{-}]',\ \textit{and}$$

$$\mathcal{H}_{\Lambda}(B, \Lambda) = \left[\left(I_{(K_F+1)} \otimes (B'B)^{-1}B'\right) \vdots -\left(\Lambda' \otimes (B'B)^{-1}B'\right)\right]$$

Time-varying prices of risk: empirical application

- Test assets:
  - Ten-size sorted portfolios
  - Seven Constant maturity treasury portfolios:

    1, 2, 5, 7, 10, 20, 30 years
- Risk factors (C):
  - Market portfolio (CRSP)
  - SMB factors
  - TSY10: constant maturity ten-year Treasury yield
- Prices of risk factors (F):
  - TSY10: constant maturity ten-year Treasury yield
  - TERM: term spread between ten-year vs. three-month Tbill
  - DY: dividend yield on the S&P 500

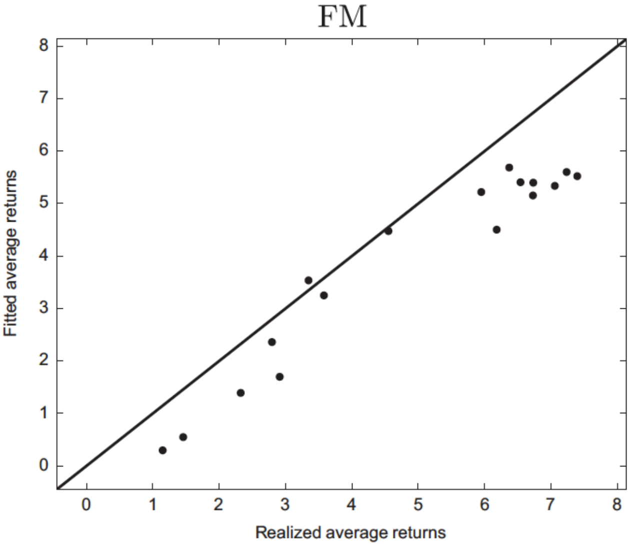
Time-varying prices of risk: empirical application

Table 2

	λ_0	TSY10	TERM	DY	$\bar{\lambda}$
Panel A: Time-varying betas					
MKT	0.062***	−0.184***	0.302***	0.014***	6.797**
	(0.017)	(0.058)	(0.088)	(0.004)	(2.785)
SMB	0.054***	−0.194***	0.099	0.011***	3.565
	(0.013)	(0.044)	(0.066)	(0.003)	(2.690)
TSY10	0.004***	−0.014***	−0.046***	0.001**	−0.359
	(0.001)	(0.005)	(0.007)	(0.000)	(0.229)
Panel B: Constant betas (OLS)					
MKT	0.063**	−0.187*	0.301**	0.014**	6.067***
	(0.028)	(0.098)	(0.147)	(0.006)	(1.487)
SMB	0.054**	−0.192***	0.093	0.011**	3.023
	(0.022)	(0.073)	(0.108)	(0.005)	(2.336)
TSY10	0.004	−0.013	−0.050***	0.001	−0.386***
	(0.002)	(0.008)	(0.012)	(0.001)	(0.085)

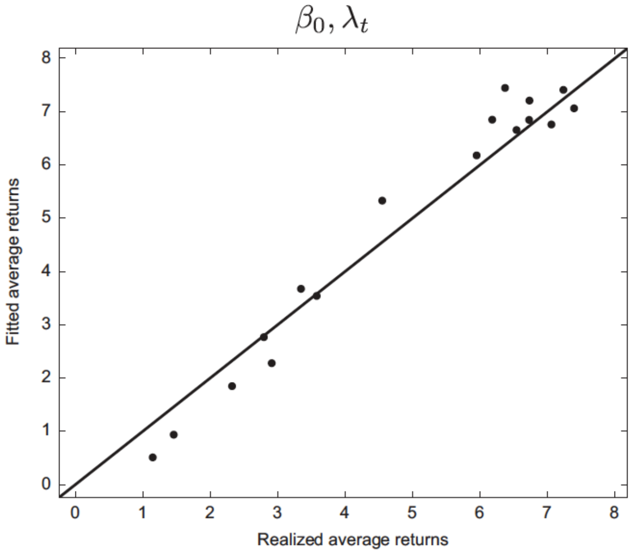
Time-varying prices of risk: empirical application

Figure 2



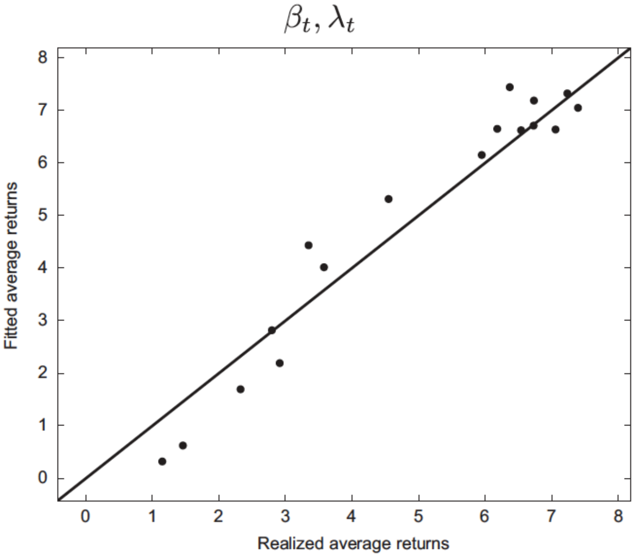
Time-varying prices of risk: empirical application

Figure 2



Time-varying prices of risk: empirical application

Figure 2



Annex

Hedge Fund Overview

Dichev and Yu (2011, JFE); Jurek and Stafford (2015, JF); Mitchell and Pulvino (2001, JF)

Hedge fund overview:

1. Overview of Hedge Fund Data
2. **Performance Measurement Challenges**
3. Persistence in Hedge Fund Performance
4. Performance Decomposition Challenges
5. Compensation and Incentives
6. Conclusion

Hedge Funds

- Hedge funds seem to deliver promising returns but there are huge measurement challenges we need to address
- Most of the high returns came early in the industry's development when it was still very small
- Most hedge funds seem to be in the business of delivering exotic beta (rather than true alpha)
- That's fine but the question is how much do we want to pay for all this?

Multi-factor world

- We live in a multi-factor world
- Lots of different sources of risk premia out there
  - Mutual funds are not well-positioned to package these risk premia and sell them (although some do, like DFA and AQR)
  - That's where hedge funds come in!

HFRI Data

- HFRI: series of benchmarks designed to reflect hedge fund industry performance by constructing equally weighted composites of constituent funds, as reported by the hedge fund managers listed within HFRI Database
  - Starts in January 1990
  - Weighting: equal-weighted
  - Reporting: net of all fees

Hedge Fund Returns

	HFRI all	S&P 500
average	7.38	5.24
Standard dev.	6.73	15.25
SR	1.08	0.34

Source: HFRI. Sample: 1990.1-2014.11. Monthly data. Annualized Returns

Market Timing

- To gauge market-timing ability, we compute the difference between the dollar-weighted and time-weighted geometric average return realized by mutual fund investors
- If the dollar-weighted return is lower than the time-weighted average return, that means investors have poor timing ability.

Buy-and-hold Returns

- The buy-and-hold geometric average return is simply given by

$$1 + r_{tw} = \left(\prod_{t=1}^{T} (1 + r_t) \right)^{\frac{1}{T}}$$

You start with 1 and you hold until T.

Dollar-weighted returns

- Capital flows can be computed from the Assets Under Management at the start of each period and the buy-and-hold rate of return for one period r:

$$CapFlows_t = AUM_t - AUM_{t-1}(1 + r_t)$$

- The dollar-weighted geometric average return is simply given by

$$\frac{AUM_T}{(1 + r_{dw})^T} = AUM_0 + \sum_{t=1}^{T} \frac{CapFlows_t}{(1 + r_{dw})^t}$$

U.S. Hedge Fund Returns

	Buy-and-hold	Dollar-weighted	difference
all	12.6	6	6.6
1980-1994	16.4	11.7	4.8
1995-2008	8.6	5.8	2.9

Source: Table 3 in Dichev and Yu (2011). Higher Risk, Lower Returns. 1980.1-2008.12

Dollar-weighted Returns

- Dollar-weighted returns may be lower in case of negative correlation between capital inflows at t and realized returns at t
- This could happen because
  1. Hedge fund investor capital chases past returns (Dumb Money)
  2. Hedge funds have trouble deploying new capital leading to lower future returns

Hedge Fund Strategy Classification

Equity Hedge
- Equity neutral
- Fundamental value

Event Driven
- Merger arbitrage
- Credit arbitrage

Macro
- currency
- commodity

Relative Value
- Fixed income corporate
- Fixed income sovereign

Low Vol but highly Illiquid

	Equity Hedge	Event-driven	Macro	Relative Value
average	9.12	3.50	8.87	7.95
stdev	8.89	2.98	12.54	6.64
SR	1.03	1.17	0.71	1.20
autocorrelation	0.21	0.08	0.19	0.37

Source: HFRI data. Annualized Monthly Excess Returns. 1990-2014.11

Split Sample

	Equity Hedge	Event-driven	Macro	Relative Value
average	4.42	1.94	4.46	5.70
stdev	9.07	2.85	11.86	6.48
SR	0.49	0.68	0.38	0.88
autocorrelation	0.19	-0.02	0.13	0.39

Source: HFRI data. Annualized Monthly Excess Returns. 2000-2014.11

Hedge fund overview:

1. Overview of Hedge Fund Data
2. **Performance Measurement Challenges**
3. Persistence in Hedge Fund Performance
4. Performance Decomposition Challenges
5. Compensation and Incentives
6. Conclusion

Backfill bias

- Mutual funds must report their periodic audited returns to regulators and investors
- Hedge fund managers provide information to databases only if they want to, for as long as they want to
  - Only the most favorable of the early results are then 'filled back' in the database together with current results
  - 7.31pps difference in estimated average returns!

  - Source: Malkiel at al (2005, Financial Analysts Journal)

	Backfilled	Not Backfilled	Difference
Mean	14.65%	7.34%	7.31%
Median	11.69%	5.95%	5.74%

Survivorship Bias

- Survivorship bias:
  - Databases available today tend to show the returns for hedge funds that are alive today
  - They tend not to include the returns from hedge funds that are no longer in existence
  - sign of bias:
    - Less successful hedge funds have trouble attracting assets
    - They tend to shut down

	Live	Defunct	Difference
Mean	13.74%	5.39%	8.35%
	Live	Live+Defunct	Difference
	13.74%	9.32%	4.42%

Source: Malkiel at al (2005, Financial Analysts Journal)

Self-reporting bias

- Some hedge funds may report performance despite being closed to new investors or when returning money to investors
- Some exiting hedge funds may impose constraints on withdrawals
- Search costs: experience a lot of search costs and due diligence costs to find the right HF for you
- One way around is to look at fund-of-fund returns: more precise representation of the actual returns earned
  - E.g. liquidation: HFs have an incentive to stop reporting before the actual liquidation
  - Funds of funds are more likely to survive the liquidation of one of the funds and hence returns will be more representative

Lecture 8

Hedge fund overview:

1. Overview of Hedge Fund Data
2. Performance Measurement Challenges
3. **Persistence in Hedge Fund Performance**
4. Performance Decomposition Challenges
5. Compensation and Incentives
6. Conclusion

Persistence in Hedge Fund Returns

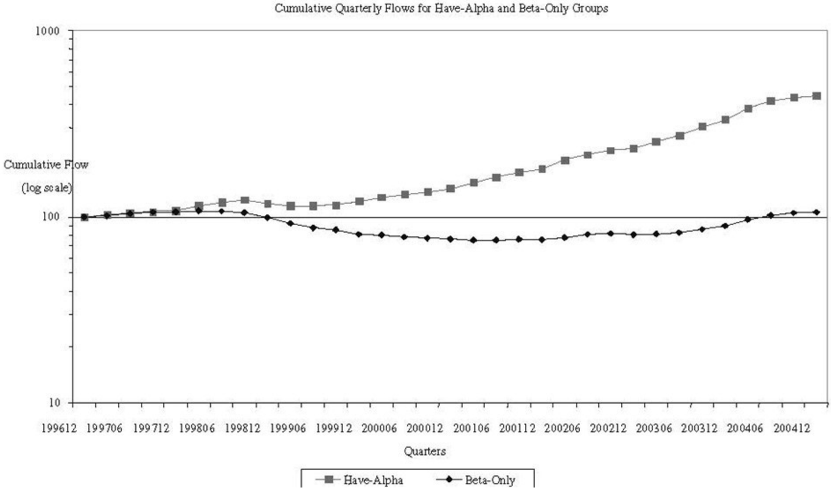
- When selecting individual hedge funds, we'd like to know whether we can pick winners on the basis of past performance
- Very important for hedge funds
  - because we're committing for a significant lock-up period
  - because the attrition rate among hedge funds is much higher than for mutual funds
- getting it wrong may be very costly

Persistence in Hedge Fund Returns

- When selecting individual hedge funds, we'd like to know whether we can pick winners on the basis of past performance
  - DEFINITION:
    - Winner is a fund with returns above the median
    - Loser is a fund with returns below the median
  - The probability of being a winner next year conditional on being a winner this year is 51.56
    - Might as well flip a coin
    - Source: Malkiel at al
- Lack of persistence at annual frequencies confirmed in other studies
- Some persistence at quarterly frequencies may be driven by stale valuations (see Agarwal and Naik, 2004 RFS)
- The lack of persistence is mainly due to decreasing returns to scale (see Berk and Green model)

Hedge Fund Inflows and Performance

- The alpha-producing funds are not as likely to liquidate as those that do not deliver alpha (see Fung, Hsieh, Naik and Ramadorai 2008 JF)
  - alpha-producing funds experience far greater and steadier capital inflows than their less fortunate counterparts.
- These capital inflows negatively impact the ability of the alpha producers to continue to deliver alpha in the future.



Source: Fung, Hsieh, Naik and Ramadorai 2008

Some Persistence in Performance

From/To	Have alpha	Beta only	Liquidated	Stop reporting
Have-alpha	**28%**	65%	4%	3%
Beta only	**14%**	69%	11%	6%

Transition Probabilities over 2-year period
Source: Fung, Hsieh, Naik and Ramadorai 2008

Flows and Alpha

Inflows	Have alpha	Have beta	liquidated	Stop reporting
Above median	***22%***	72%	3%	2%
Below median	***34%***	55%	5%	6%

Transition Probabilities over 2-year period for have alphas
Source: Fung, Hsieh, Naik and Ramadorai 2008

Lecture 8

1. Overview of Hedge Fund Data
2. Performance Measurement Challenges
3. Persistence in Hedge Fund Performance
4. **Performance Decomposition Challenges**
5. Compensation and Incentives
6. Conclusion

HF Returns Decomposition Challenges

1. Liquidity
2. Tail Risks
3. Linear Regression Methods Fall Short

Stale Prices

- If we're dealing with stale prices, then the standard performance attribution exercise won't work
  - See evidence from autocorrelations
- You may find a low market beta for a particular strategy and then conclude that this strategy has low market exposure
- But the only reason you found a low beta is because the prices are stale!

Lagged Factors

- Take the simple CAPM
- Instead of only including the contemp. Market return, we include lagged market returns as well:

$$R_t - R_f = \alpha + b_{M,1}(R_{t,M} - R_f) + b_{M,2}(R_{t-1,M} - R_f) + b_{M,3}(R_{t-2,M} - R_f) + e_t$$

- Stale prices in illiquid securities markets

Total Betas (including Lagged betas)

Style	β	β_{tot}	α	α_{tot}
Index	0.28	0.44	0.46	0.36
Event	0.22	0.37	0.46	0.38
Emerging Markets	0.58	0.69	0.00	-0.07
Global Macro	0.17	0.31	0.82	0.74

β_{tot} is the sum of beta and three lagged betas. α_{tot} is the resulting alpha. Monthly Returns. Source: Asness, Krail and Liew: Do Hedge Funds Hedge? Journal Of Portfolio Management. Fall 2001

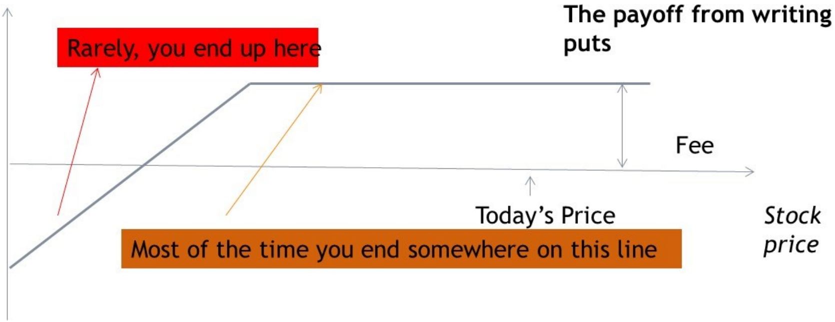
Writing OTM put options

- some of the hedge returns look like the returns you would get from writing deep OTM put options
  - you collect the fee as long as the market does not tank (which is most of the time)
  - and you make a little bit of money
  - occasionally, you lose a ton of money

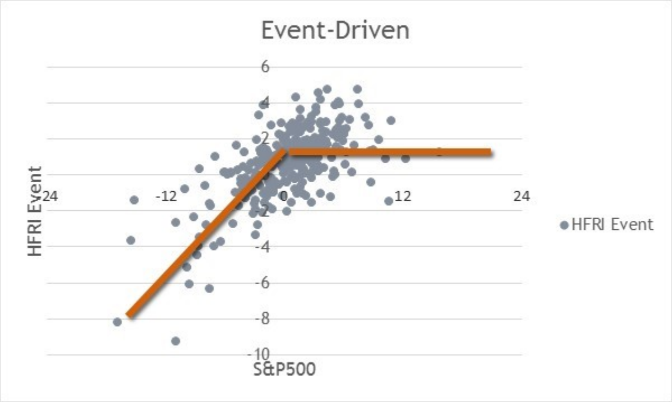
Merger Arbitrage

- Merger arbitrage is a great example
- Take-over or merger target is announced
  - If deal is consummated, then small return (with high prob.)
  - If deal is not consummated, then large negative return (with small prob)
- In typical market conditions, the probability of deal is not sensitive to market returns; hence, were mostly exposed to idiosyncratic risk
- But large declines in market substantially reduce prob. of actual merger or takeover happening..

Writing Puts



Put-option-like payoffs



Event-driven (Merger arbitrage)

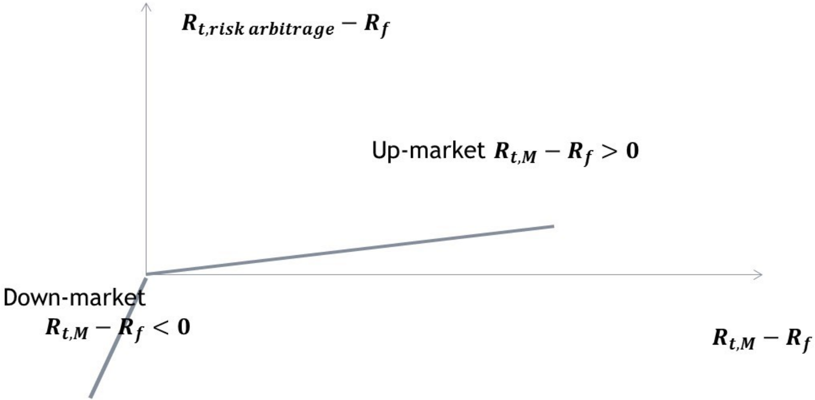
- Even though its an all-equity strategy (no option positions) dynamic trading gives an option-like payoff.
- Not necessarily a bad thing! Writing index puts earns a premium. It provides disaster insurance to the market.
- But no need to pay 2+20 to write index puts!
- How to evaluate performance in this case?

Piecewise linear CAPM

- In order to detect exposure to downside risk, we can run a linear regression with up and down market factors
- That delivers an up and down beta

$$R_t - R_f = \alpha + b_{M,up}(R_{t,M} - R_f > 0) + b_{M,down}(R_{t,M} - R_f < 0) + e_t$$

Piecewise linear CAPM



Option Returns

- We need returns on option-writing strategies in the benchmark
- If we're dealing with strategies that produce option-like returns, then we probably should include option returns as benchmarks

$$R_t - R_f = \alpha + b_M(R_{t,M} - R_f > 0) + b_{put,index}(R_{t,put} - R_f < 0) + e_t$$

Option-adjusted alpha

	β_{SPPo}	α
Event/Arbitrage	-0.92	0.04
Emerging Markets	-0.94	0.20

Monthly Returns
Source: Agarwal and Naik (RFS). SPPo is the return from rolling over Out-of-the-money put options

Linear Regression Methods

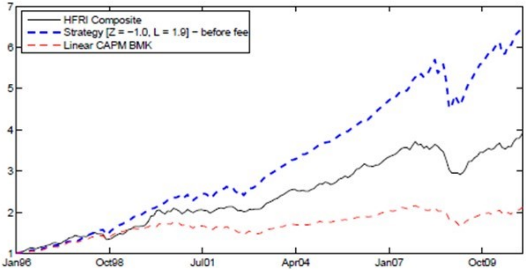
- Linear regression methods may not be sufficient
  - Betas change over time
  - Relation between market returns and hedge fund payoffs is non-linear
- Another approach is to figure out the right benchmark returns by developing on option-writing strategy that matches the hedge fund returns (see Jurek and Stafford, 2015)

Hedge Fund Performance

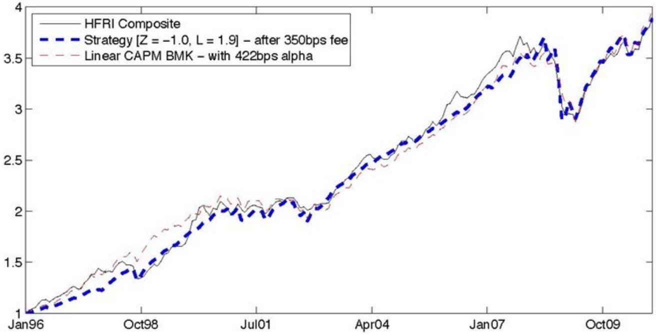
- Performance is rather impressive
- High returns but not as much market risk
- Seem to manufacture alpha, not beta
- The average hedge fund manager is very skilled, right?
- Well, let's consider another strategy (X) that is completely mechanical, does not involve any skill, and can easily be implemented

Data

- T-bill is the return on the one-month U.S. Treasury T-bill obtained from
- Ken French's website. S&P 500 is the total return on the S&P 500 index obtained from the CRSP database.
- HFRI Composite Index is the Hedge Fund Research Inc. Fund Weighted Composite Index. DJ/CS Broad
- Index is the Dow Jones Credit Suisse Broad Hedge Fund Index. HFRI Fund-of-Funds Index is the Hedge Fund
- Research Inc. Fund of Funds Composite Index.



The top panel plots the total return indices for X strategy, the HFRI Fund-Weighted Composite Index, and a linear benchmark comprised of a portfolio of 42% S&P 500 and 58% T-bills.



The bottom panel plots the total return index for X after deducting an 350bps annual fee to account for the all-in fees paid by direct hedge fund . The total return index for the linear benchmark is plotted after adding the in-sample estimate of CAPM alpha (422 bps).

Naked Put Writing

- X is a mechanical option trading strategy:
  - Each month, we write an out-of-the-money put option on the S&P500
  - These options expire seven weeks from trade initiation
  - The delta is chosen to match the beta and the drawdowns of the hedge fund returns

Investors in HFs do not cover cost of capital

- HFs have earned an annualized excess return of 6.3% between 1996 and 2010
- A simple derivative-based strategy, which accurately matches the risk profile of hedge funds, realizes an annualized excess return of 10.2% over this sample period, while providing monthly liquidity and complete transparency over its state-contingent payoffs.
- Linear clones based on popular factor models deliver annualized risk premia of 0-3% over the same period.

Take-away

- Hedge fund returns: seemingly generate lots of added value for investors
- Large alpha's left after accounting for fees
- But we have developed a simple out-of-the-money put writing strategy that delivers the same alpha and low beta produced by the hedge fund returns!
- The point is not that they're literally writing puts (though some may do that)

Conclusion

- The asset management industry is constantly developing new ways to increase returns without commensurate increases in standard market exposure
- Evaluating the value added by an active manager is actually very hard, especially when dealing with alternative investments
  - But it's essential to get this right
  - Asset owners (e.g., pension funds) constantly have to make these types of assessments

Lecture 8

1. Overview of Hedge Fund Data
2. Performance Measurement Challenges
3. Persistence in Hedge Fund Performance
4. Performance Decomposition Challenges
5. **Compensation and Incentives**
6. Conclusion

Fees

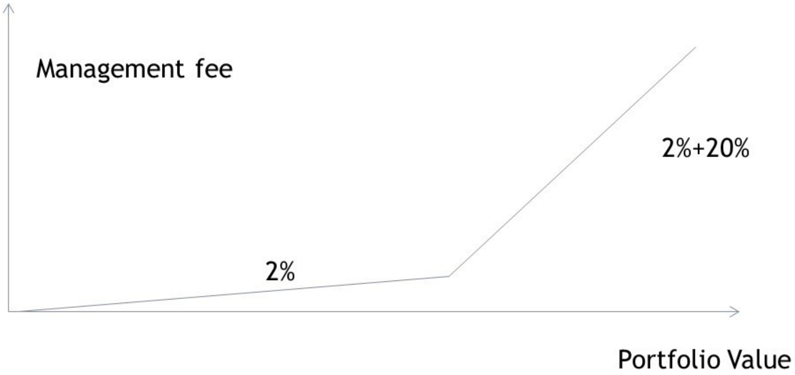
- 2% of asset value + 20% of gains
- That includes funds of funds (another layer of fees)
- More competition does not seem to help much in the HF industry
  - Lots of new entry
  - Fees do not seem to come down that much
  - Surprising!

Incentives

- A 2/20 contract gives you an option pay-off
- 2/20 contracts provide perverse incentives for taking on volatility by

1. Writing put options
2. Dynamically trade securities to replicate put option payoffs
3. Delivering Hidden betas

Fees, Incentives and Options



Example

- Option-like payoff creates incentives to take on value-destroying bets
- Suppose you are given \$1000
- You have three options
  1. Do nothing
  2. Fair Bet: \$500 : 50/50 bet
  3. Unfair Bet: Bet 99/1: 99% +\$1000, 1% -\$100,000

  Note: the last bet destroys \$10 on average

Source: Example taken from John Cochrane's slides on HF

Manager takes the unfair bet

1. Do nothing: \$20 fee
2. Bet \$500 on 50/50 bet: \$70 Fee

$$1/2 \times 0.02 \times \$500 + 1/2 \times (0.02 \times \$1500 + 0.20 \times \$500)$$

3. Bet 99/1: 99% +\$1000, 1% -\$100,000: \$238 Fee

$$0.99 \times (0.02 \times \$2000 + 0.20 \times \$1000) + 0.01 \times (0) = \$237.60$$

Solutions to Incentive Problems

- GPs invest large fractions of their own wealth
  - Huge loss of diversification to GP
  - Does not apply to HFs run by banks and large financial institutions
- High-water marks: option strike is reset whenever a new high-water mark is reached
  - Reduces incentive to take on too much volatility
- Reputation: GPs want to preserve their reputation, reduces incentive to take on too much volatility

Takeaway

- When dealing with hedge funds, we face a huge challenge in measuring added value by managers:
  - Need lots of factors: currency, momentum, size, value, credit, market, plus options on all these!
- Standard regression method strained: more right hand side variables than data points
- HF styles shift over time: betas change
- HF styles group are not all that meaningful
- Perhaps we've raised the bar too high
- If a HF delivers exposure to a factor that you cannot manufacture yourself, then maybe you do want to pay a 2/20 fee for that exposure
- Instead of focusing on measuring alpha, we should focus on alpha and beta you cannot manufacture yourself