EFM-EDHEC Symposium Risk and Asset Management

UK Mutual Fund Performance: Skill or Luck ?

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Introduction

- Study examines the abnormal (risk adjusted) performance of the UK equity unit trust industry between April 1975 – Dec 2002.
- Evaluates whether funds possess ‘genuine’ stock picking ability, controlling for sampling variability in performance (chance).
- Bootstrap simulations generate a distribution under the null at each point in the cross-section distribution of performance.
- Kosowski at al (2006), JoF.

Data

- Sample period: Monthly returns April 1975 – December 2002
- Data set of 1,620 funds (Unit Trusts and OEICs)
- 842 ‘Independent’ funds (excl 2nd units and trackers)
- Investment Objectives classified by IMA:
  - Equity Income (162)
  - General Equity (553)
  - Smaller Companies (127)
- 626 surviving funds, 216 nonsurviving funds
- 662 onshore, 180 offshore

Performance Measurement: Model Selection

Unconditional Three-Factor Model

$$R_{i,t} = \alpha_i + \beta_1 (R_{m,t}) + \beta_2 (SMB)_t + \beta_3 (HML)_t + U_t$$

Model Selection

Conditional Beta Model

$$R_{i,t+1} = \alpha_i + \beta_{it}(R_{m,t+1}), \qquad \beta_{it} = b_{i,0} + B'_i(z_t)$$

$$R_{i,t+1} = \alpha_i + b_{i,0}(R_{m,t+1}) + B_i^{'}(z_t.R_{m,t+1}) + U_{t+1}$$

Z (in deviations): market dividend yield, short term rate, gilt:equity yield ratio, term spread, credit spread

Model Selected based on SIC

$$R_{i,t+1} = \alpha_i + \beta_1(Rm)_{t+1} + \beta_2(SMB)_{t+1} + \beta_3(HML)_{t+1} + \beta_4[(R_{m,t+1})*(z_t)] + U_{t+1}$$

where z_t = dividend yield

Model Selection

Conditional Alpha-Beta Models

$$r_{j,t+1} = \alpha_j + \beta_j^{'}(F_{t+1}) + U_{j,t+1} \qquad R_{i,t+1} = \sum_{j=1}^{N} W_{j,t+1}.r_{j,t+1} \qquad W_{j,t+1} = W_{j,0} + W_j^{'}(z_t)$$

$$R_{i,t+1} = \sum_{j=1}^{N}[(W_{j,0} + W_j^{'}z_t).(\alpha_j + \beta_j^{'}F_{t+1} + U_{j,t+1})]$$

$$= \sum_{j=1}^{N} W_{j,0}.\alpha_j + \sum_{j=1}^{N} W_j^{'}\alpha_j z_t + \sum_{j=1}^{N} W_{j,0}B_j^{'}F_{t+1} + \sum_{j=1}^{N} W_j^{'}z_t B_j^{'}F_{t+1}$$

$$+[\sum_{j=1}^{N} W_{j,0}.U_{j,t+1} + \sum_{j=1}^{N} W_j^{'}z_t U_{j,t+1}]$$

$$R_{i,t+1} = \left[\alpha_{i,0} + A_i^{'}(z_t)\right] + b_{i,0}^{'}(F_{t+1}) + B_i^{'}(z_t.F_{t+1}) + U_{i,t+1}$$

Model Selected (based on SIC):

$$R_{i,t+1} = \alpha_i + A_1(z_t) + \beta_1(R_{m,t+1}) + \beta_2(SMB)_{t+1} + \beta_3(HML)_{t+1} + \delta_1(R_{m,t+1}.z_t) + \delta_2(SMB_{t+1}.z_t) + \delta_3(HML_{t+1}.z_t) + U_{t+1}$$

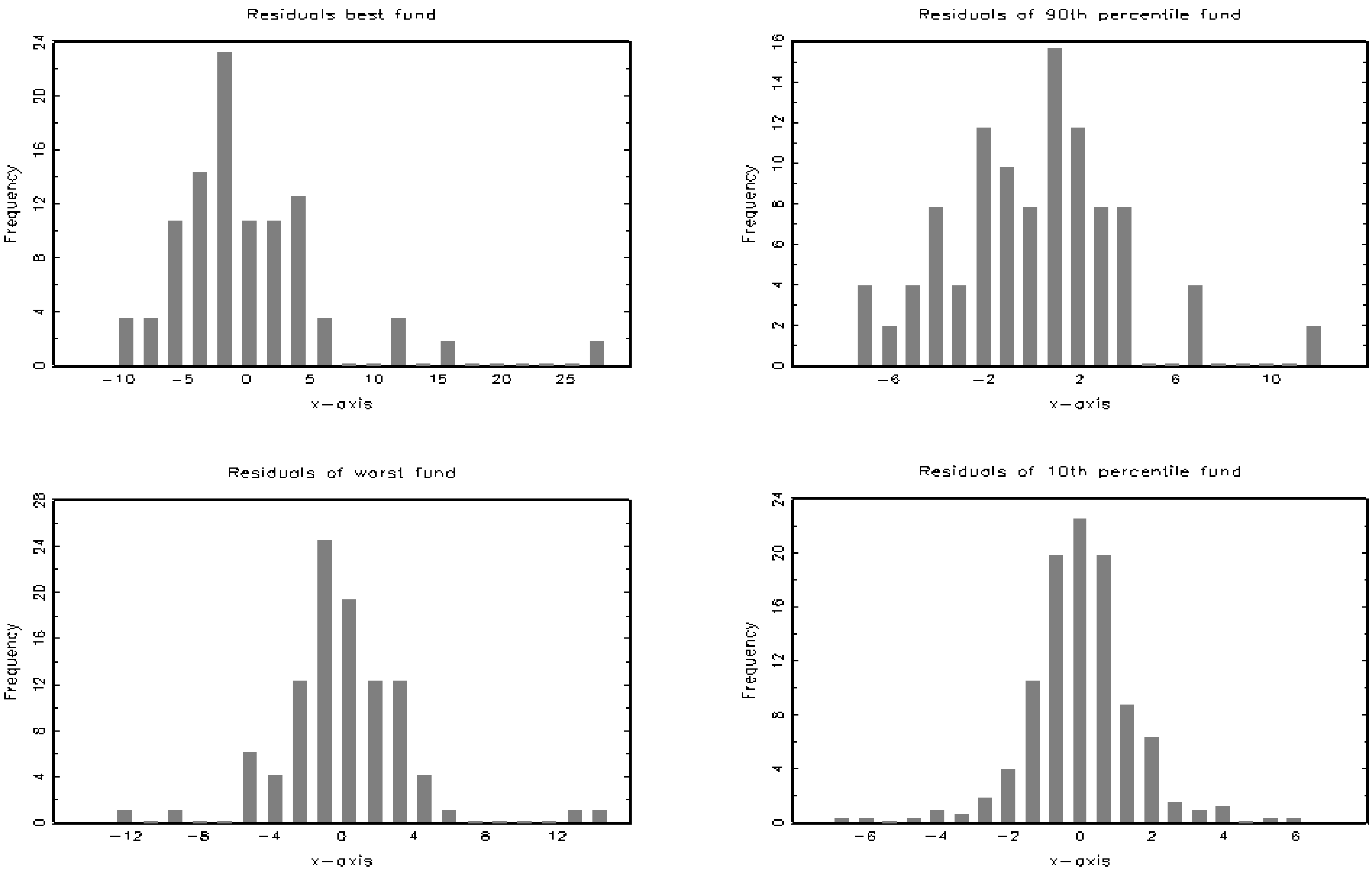
where z_t = dividend yield

Model Inferences

- A total of 54 models were estimated
- Alpha measures abnormal (risk adjusted) performance
- Standard inference tests require normality for validity
- Given large number of funds some will appear to do well/badly by chance – need to establish the role of luck
- Investors are more interested in funds in the tails of the performance distribution

Problem: non-normal ‘luck’

Residuals (Fama-French 3Factor)



Methodology

- Why Bootstrap?
  - Bootstrap is nonparametric: makes no assumption about ‘true’ shape of the distribution
  - Procedure establishes the nonparametric distribution at *each* point/percentile of performance.

Methodology

- Cross-sectional bootstrap procedure:
  - Estimate model, save coefficients and residuals

$$R_{i,t+1} = \hat{\alpha}_i + \hat{\beta}_1(R_{m,t+1}) + \hat{\beta}_2(SMB)_{t+1} + \hat{\beta}_3(HML)_{t+1} + \hat{\varepsilon}_{i,t+1}$$

  - Bootstrap simulation (with replacement) for fund *i* under the null hypthesis of zero abnormal performance, i.e. $\alpha_i = 0$.
  - Construct $\tilde{R}_{i,t}$ and estimate $\tilde{\alpha}_i$
  - Perform for B =1,2..1000 simulations on *each* fund *i* = 1,2...N, N = 675.
  - Within each simulation across funds, sort $\tilde{\alpha}_i$ from high to low
  - This provides an estimate of the distribution of abnormal performance (under the null of no abnormal performance) at ***each*** point in the performance distribution, i.e. an estimate of random sampling variation.
  - Here, luck distributions capture the valuable information (standard deviation) in *all* funds – not just fund by fund.
  - Each distribution of $\tilde{\alpha}_i$ is a function of $var(\hat{\varepsilon}_{i,t}) \forall i = 1,2 \ldots N$

‘Luck’ Distributions, bootstrap alphas and p-values

$$\tilde{\alpha}_1^{b,1}, \tilde{\alpha}_1^{b,2}, \ldots\ldots \tilde{\alpha}_1^{b,B}$$

$$\tilde{\alpha}_2^{b,1}, \tilde{\alpha}_2^{b,2}, \ldots\ldots \tilde{\alpha}_2^{b,B}$$

.

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$$\tilde{\alpha}_N^{b,1}, \tilde{\alpha}_N^{b,2}, \ldots\ldots \tilde{\alpha}_N^{b,B}$$

$$f(\alpha_{max}) : \tilde{\alpha}_H^{b,1}, \tilde{\alpha}_H^{b,2}, \ldots\ldots \tilde{\alpha}_H^{b,B}$$

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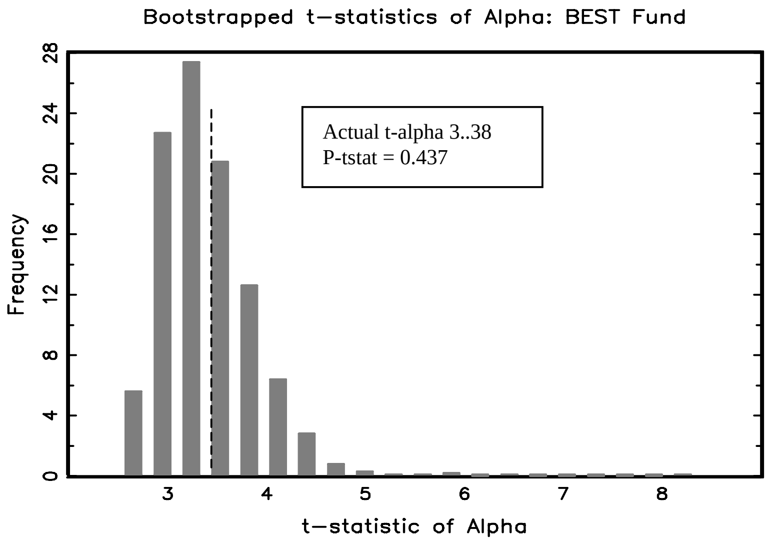
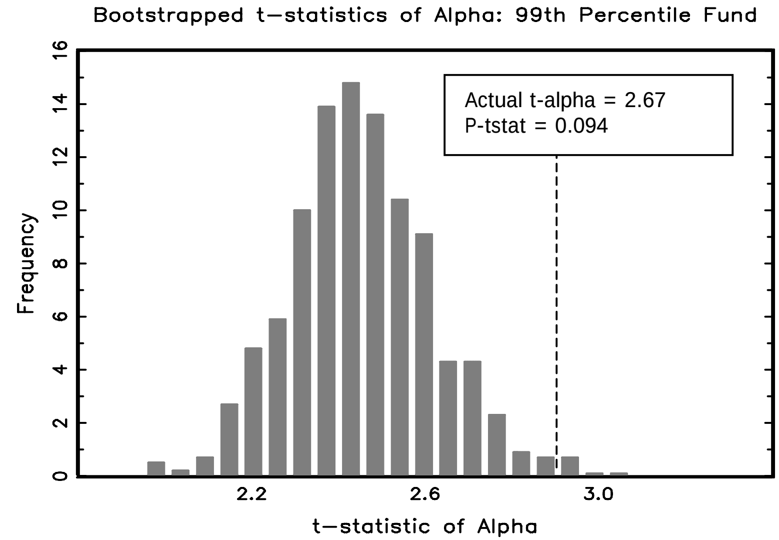
$$f(\alpha_{min}) : \tilde{\alpha}_L^{b,1}, \tilde{\alpha}_L^{b,2}, \ldots\ldots \tilde{\alpha}_L^{b,B}$$

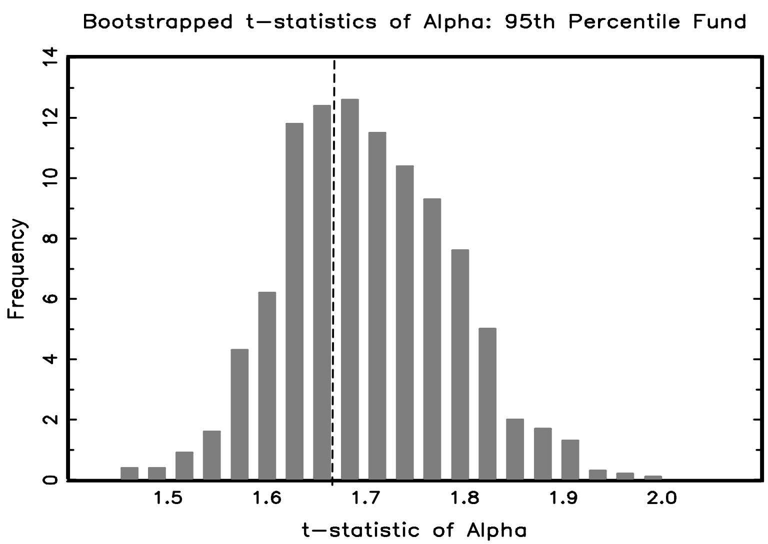
Methodology

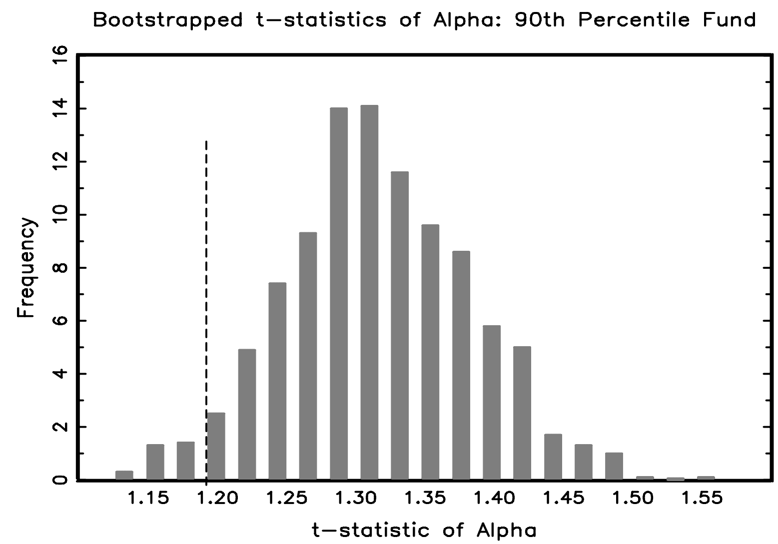
- We use the t-stat of alpha as the performance measure to (i) scale by precision and (ii) get more relaible estimates of tail performance
- Bootstrap p value:
  - Best funds: proportion of bootstrap t-alphas > actual t-alpha at each point/percentile
  - Worst funds: proportion of bootstrap t-alphas < actual t-alpha at each point/percentile
- Impose min 36 observations restriction, N = 675.
  - Shorter-lived funds => high Var(α) => these funds may disproportionately occupy the tails of both bootstrap and actual distributions
  - We check if results are robust due to look-ahead bias

Bootstrap Results : Best Funds – t-alpha

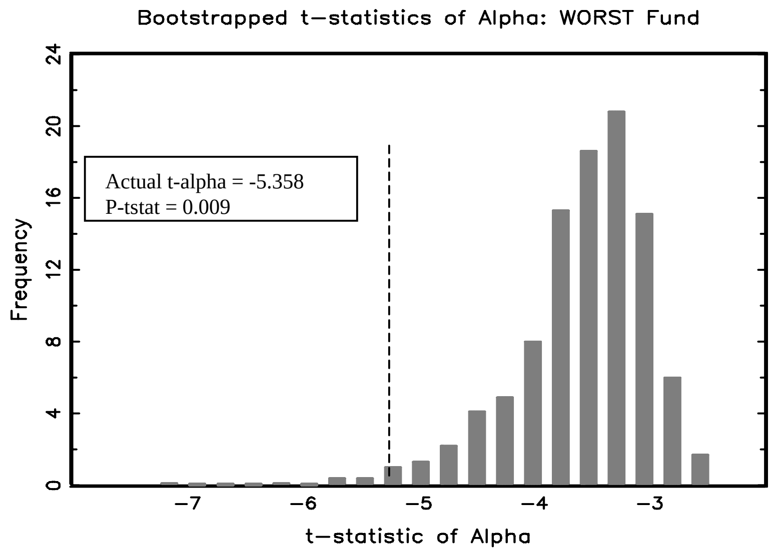


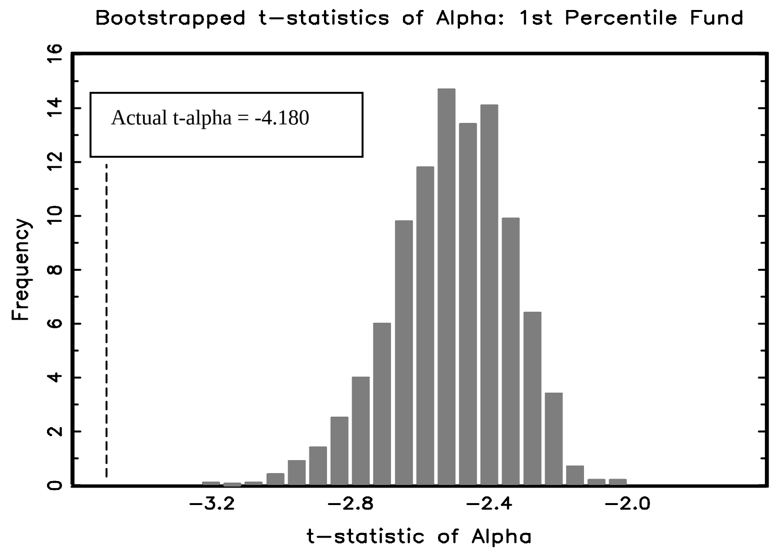


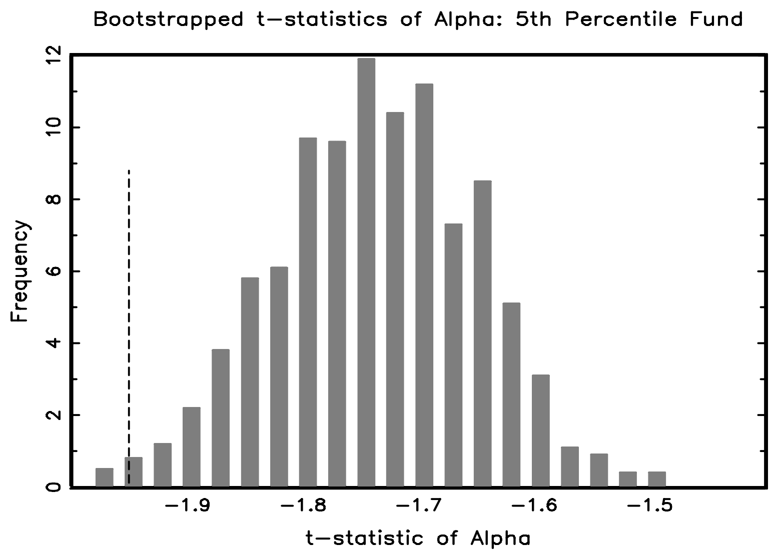


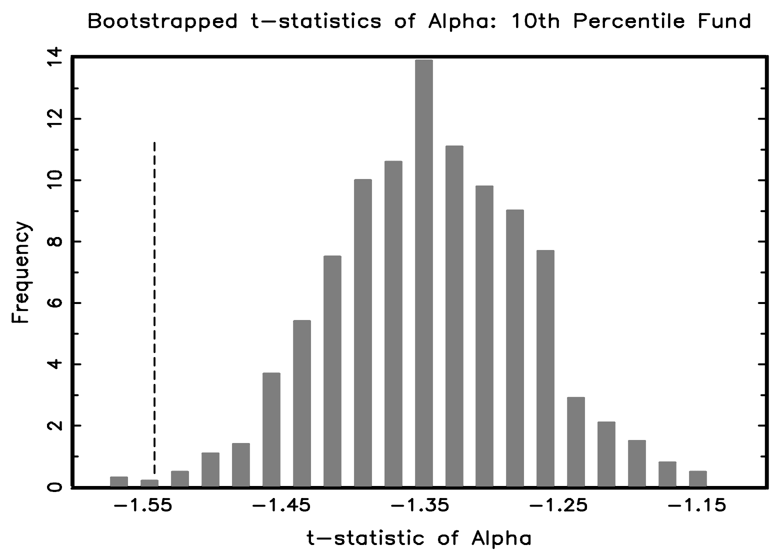


Bootstrapped Results : Worst Funds (t-alpha)









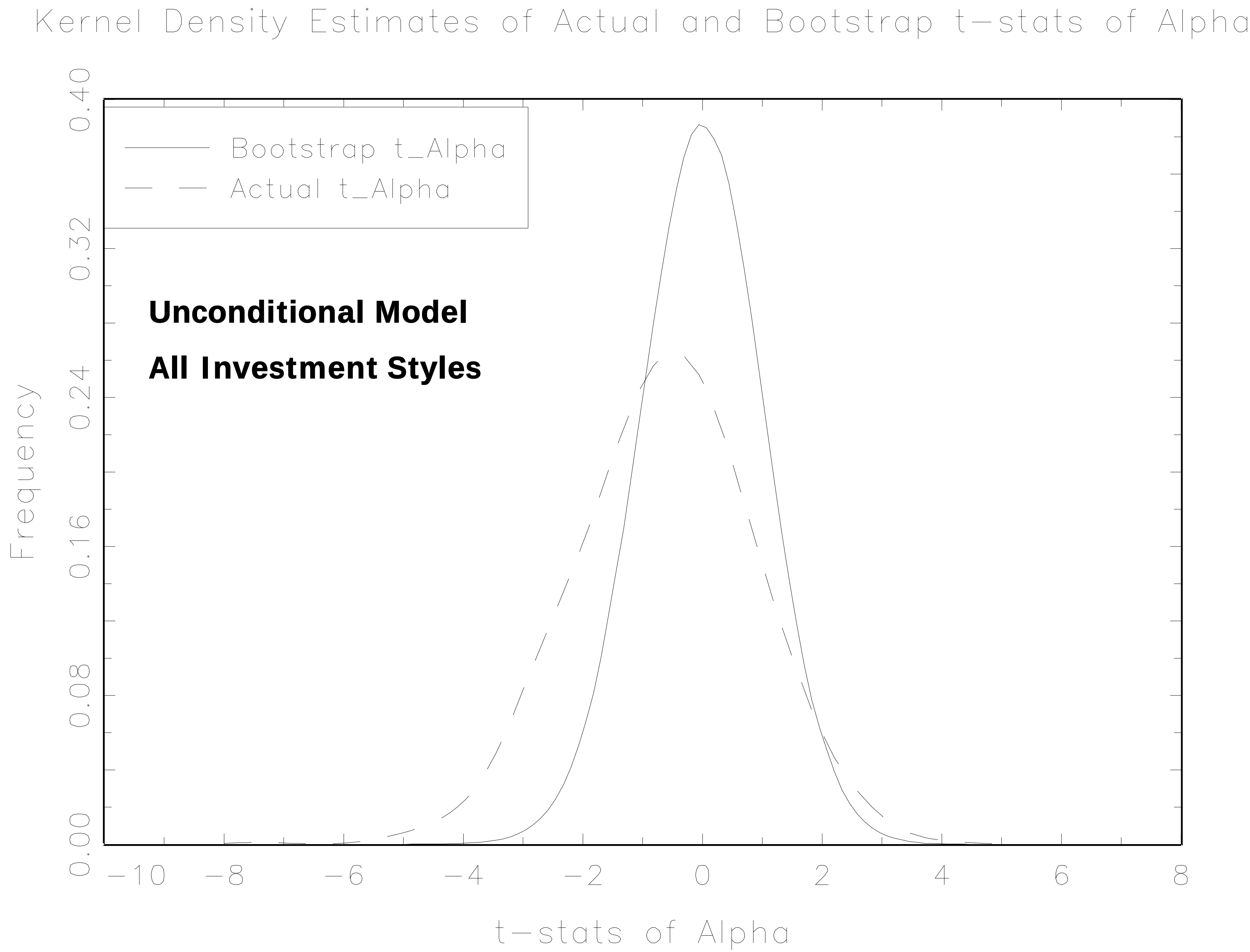
Bootstrap Statistics: p values of t-stats, BEST Funds

$R_{i,t+1} = \alpha_i + \beta_1 (R_{m,t+1}) + \beta_2 (SMB)_{t+1} + \beta_3 (HML)_{t+1} + U_{t+1}$					
Ranked Fund	Ranked Alpha	Ranked t-stats	Significant	p-value t-stats	Stock Picking
1	2.235	3.389	Sign.	0.437	'luck'
3	0.757	2.991	Sign.	0.232	'luck'
5	0.716	2.777	Sign.	0.157	'luck'
10	0.617	2.545	Sign.	0.038	'skill'
12	0.593	2.501	Sign.	0.020	'skill'
15	0.543	2.282	Sign.	0.070	'luck'

- $T\text{-stat}_{max}$ = 3.389 (significant), p value = 0.437 (insignificant). This contradiction is due to the highly non-normal idiosyncratic risk among top funds
- We cannot state that a fund is lucky but we cannot reject this hypothesis. We can state that a fund is skillful

Bootstrap Statistics: p values of t-stats, WORST Funds

$R_{i,t+1} = \alpha_i + \beta_1 (R_{m,t+1}) + \beta_2 (SMB)_{t+1} + \beta_3 (HML)_{t+1} + U_{t+1}$					
Ranked Fund	Ranked Alpha	Ranked t-stats	Significant	p-value t-stats	Stock Picking
Min	-0.901	-5.358	Sign.	0.009	Truly Bad
5. min	-0.661	-4.278	Sign.	0.000	Truly Bad
Min. 5%	-0.427	-3.045	Sign.	0.000	Truly Bad
Min 10%	-0.350	-2.509	Sign.	0.000	Truly Bad
Min 40%	-0.122	-0.873	Not Sign.	0.000	Truly Bad



Kernel Density Estimates of Actual and Bootstrap t-stats of Alpha
Bootstrap t_Alpha
Actual t_Alpha
Unconditional Model
All Investment Styles
Frequency
0.00
0.08
0.16
0.24
0.32
0.40
-10
-8
-6
-4
-2
0
2
4
6
8
t-stats of Alpha

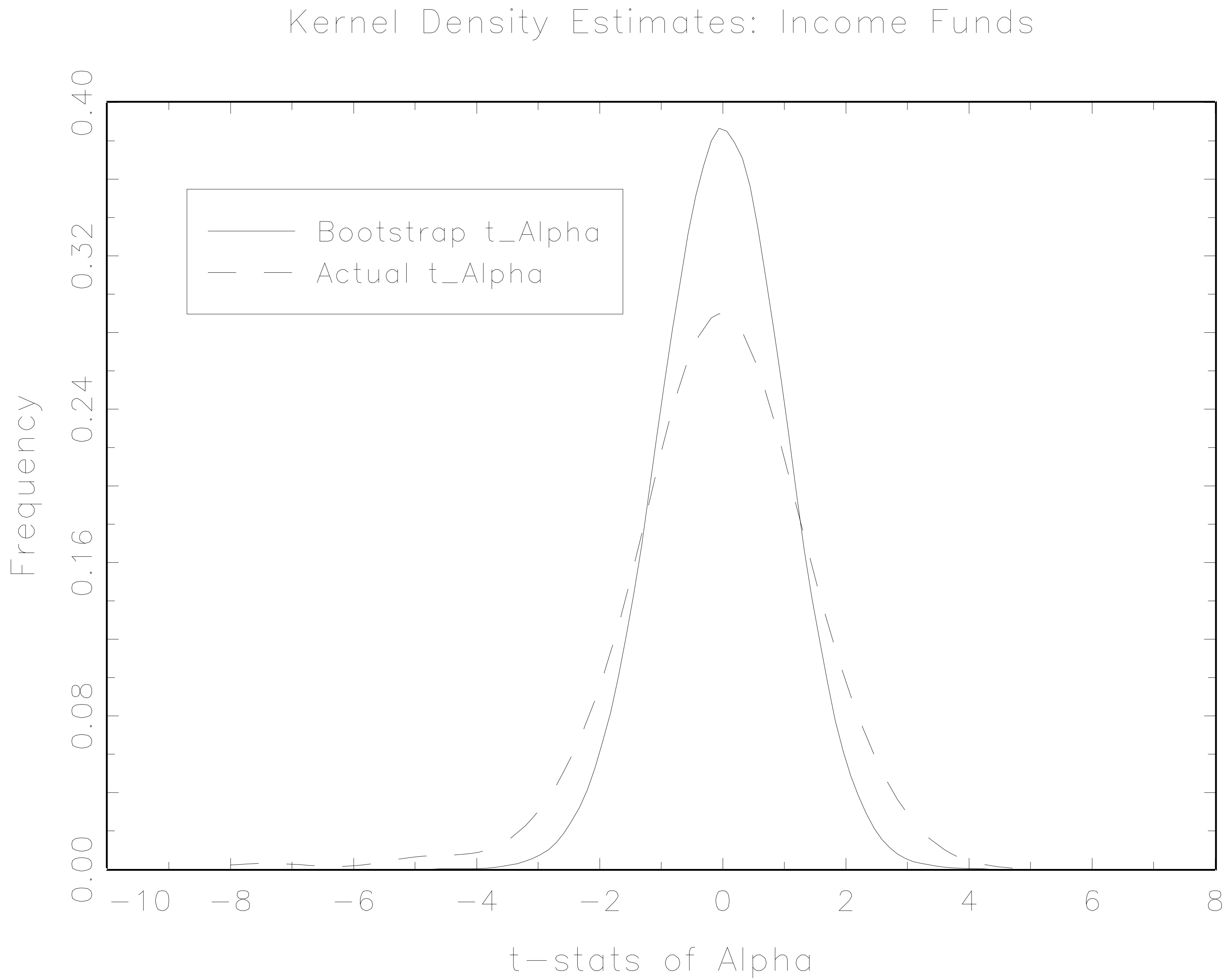
Performance and Investment Styles

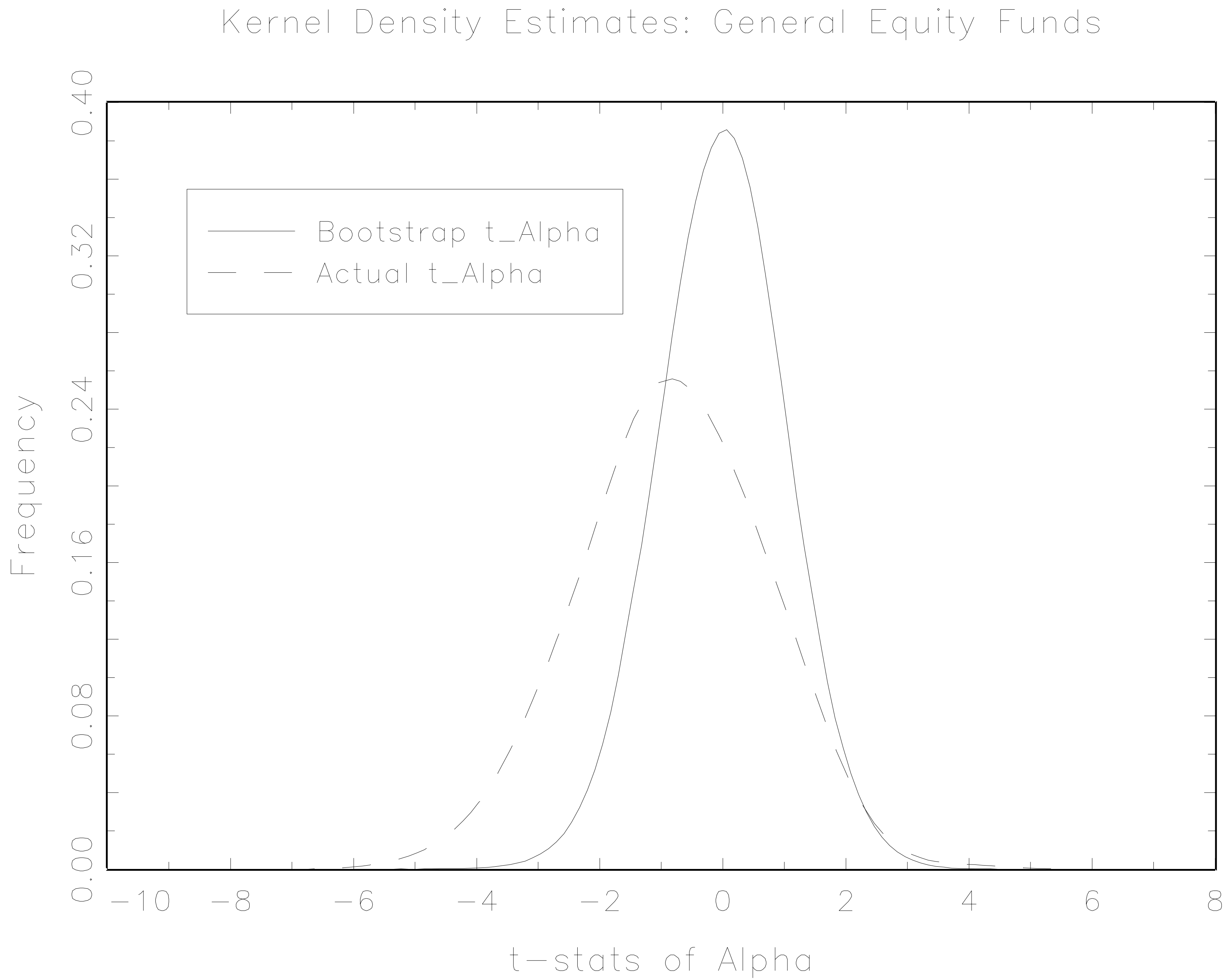
- Does stock picking ability vary with investment objective:
  - Self-declared objectives (monitored by IMA)
  - Income, General Equity, Small Co. stocks
  - In U.S., some evidence growth funds outperform
  - Is the market for small stocks less efficient ?

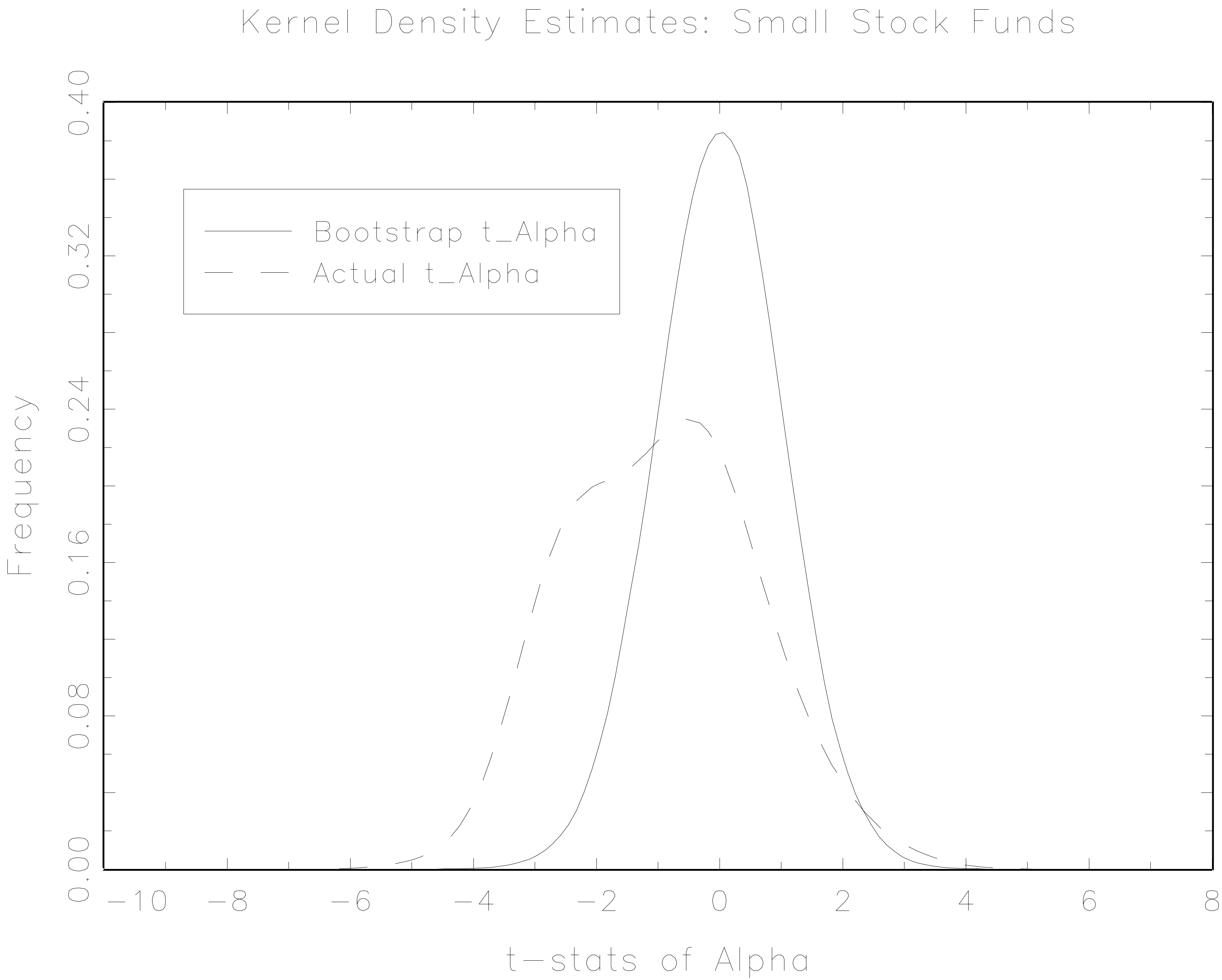
- Procedure controls for investment style risk characteristics which may not be captured by performance model

Performance and Investment Style

	Min	5 min	min 5%	max 20%	max 10%	10max	7 max	5 max	3 max	2 max	Max
Equity Income											
T-alpha	-2.95	-2.166	-1.863	0.977	1.667	1.740	2.245	2.50	2.545	2.634	2.777
Alpha	-0.33	-0.204	-0.314	0.470	0.184	0.275	0.229	0.302	0.431	0.279	0.478
P-tstat	0.33	0.165	0.179	0.171	0.007	0.107	0.008	0.005	0.067	0.181	0.415
UK All Companies											
T-alpha	-5.36	-4.190	-3.118	0.509	1.045	2.023	2.282	2.672	2.776	2.965	3.389
Alpha	-0.26	-0.355	-0.226	0.063	0.414	0.447	0.386	0.543	0.507	0.479	0.412
P-tstat	0.01	0.001	0.001	1.00	1.00	0.643	0.422	0.083	0.285	0.296	0.301
Smaller Companies											
T-alpha	-4.95	-3.117	-3.095	0.397	1.286	1.356	1.610	1.742	2.226	2.991	3.365
Alpha	-0.35	-0.360	-0.479	0.092	0.253	0.472	0.318	0.716	2.235	0.686	1.447
P-tstat	0.00	0.001	0.001	1.00	0.647	0.624	0.490	0.579	0.256	0.040	0.096


Kernel Density Estimates: Income Funds
Bootstrap t_Alpha
Actual t_Alpha
Frequency
0.00
0.08
0.16
0.24
0.32
0.40
−10
−8
−6
−4
−2
0
2
4
6
8
t−stats of Alpha


Kernel Density Estimates: General Equity Funds
Bootstrap t_Alpha
Actual t_Alpha
Frequency
0.00
0.08
0.16
0.24
0.32
0.40
−10
−8
−6
−4
−2
0
2
4
6
8
t−stats of Alpha


Kernel Density Estimates: Small Stock Funds
Bootstrap t_Alpha
Actual t_Alpha
Frequency
0.00
0.08
0.16
0.24
0.32
0.40
−10
−8
−6
−4
−2
0
2
4
6
8
t−stats of Alpha

Performance and Fund Location

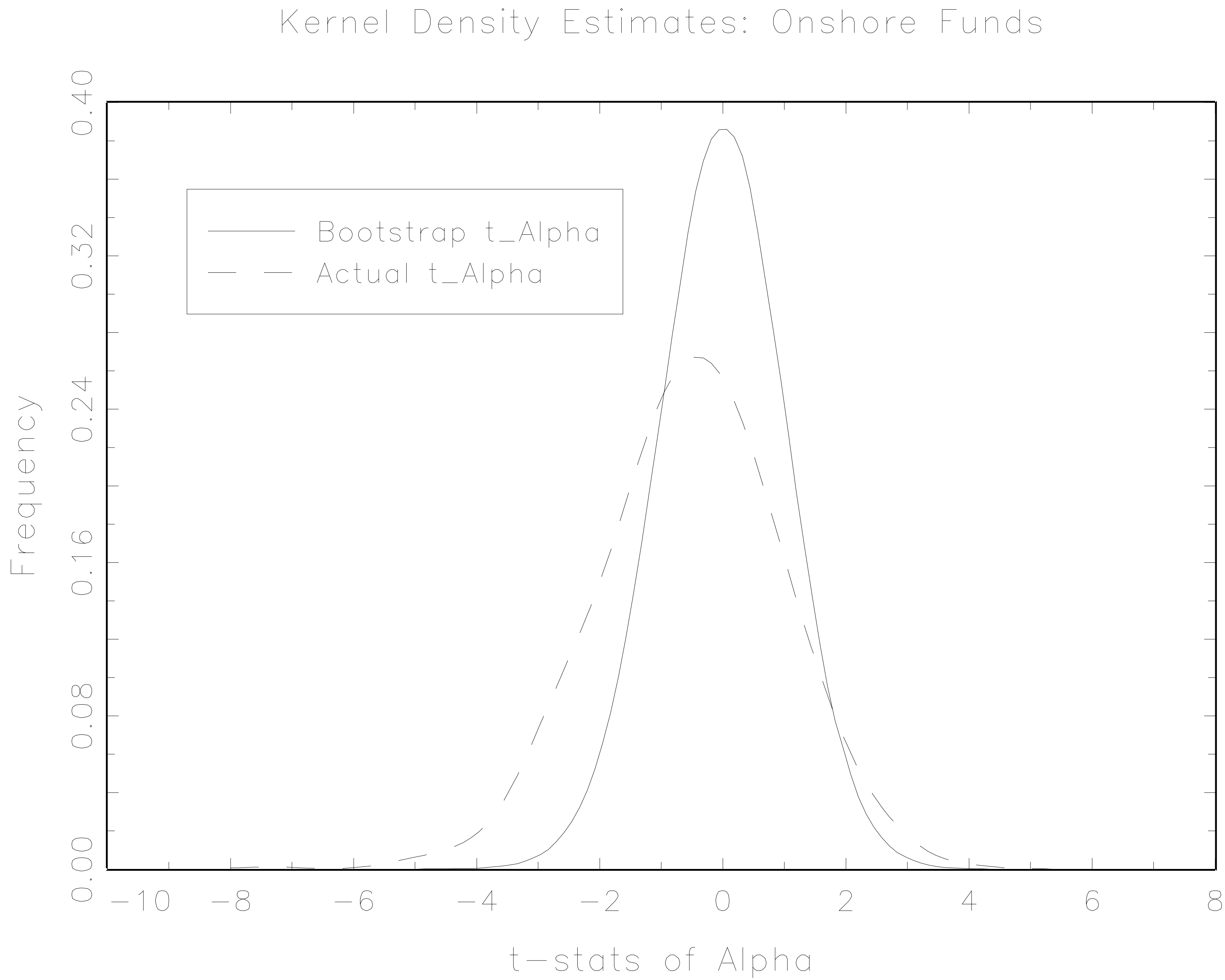
- All funds are UK equity funds
- Onshore UK: 662 funds
- Offshore: 180 funds
  - Dublin, Luxembourg, Channel Islands, Denmark, Other European locations

- Informational Asymmetry ?
- Differences in Skill ?

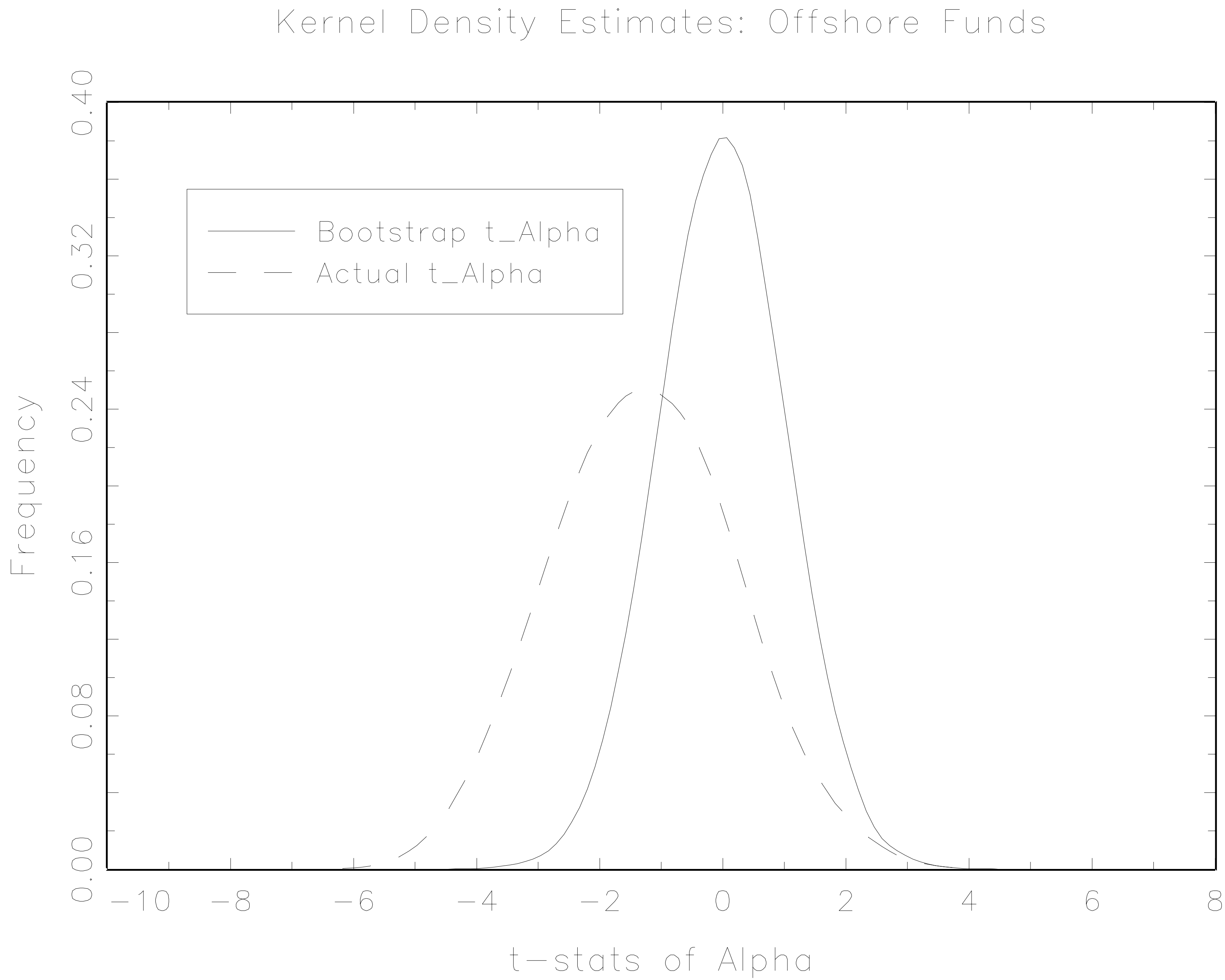
- Evidence of true outperformance among Onshore funds
- Not for Offshore funds

Performance and Fund Location

	Min	5 min	min 5%	max 20%	max 10%	20max	10max	5 max	3 max	2 max	Max
Onshore UK Funds											
T-alpha	-5.36	-4.119	-2.915	0.755	1.287	2.023	2.545	2.777	2.991	3.365	3.389
Alpha	-0.26	-0.321	-0.510	0.158	0.130	0.447	0.431	0.478	0.686	1.447	0.412
P-tstat	0.01	0.001	0.001	0.970	0.615	0.057	0.006	0.073	0.107	0.063	0.306
Offshore Funds											
T-alpha	-4.28	-3.751	-3.521	0.008	0.489	0.067	0.881	1.101	1.390	1.450	1.948
Alpha	-0.40	-0.414	-0.310	0.004	0.075	0.006	0.355	0.588	0.284	0.593	0.487
P-tstat	0.01	0.001	0.001	1.000	1.000	1.000	1.000	1.000	0.998	1.000	0.985



Kernel Density Estimates: Onshore Funds
Bootstrap t_Alpha
Actual t_Alpha
Frequency
0.00
0.08
0.16
0.24
0.32
0.40
−10
−8
−6
−4
−2
0
2
4
6
8
t−stats of Alpha


Kernel Density Estimates: Offshore Funds
Bootstrap t_Alpha
Actual t_Alpha
Frequency
0.00
0.08
0.16
0.24
0.32
0.40
−10
−8
−6
−4
−2
0
2
4
6
8
t−stats of Alpha

Survivorship Bias and Fund Histories

- Type 1. Survivor bias
  - Analysis includes nonsurviving funds 216 (25% of sample)

- Type 2. Look-ahead bias
  - A restriction of a minimum of 36 observations is imposed
  - This improves the precision of alpha (and factor loadings) estimates
  - Shorter-lived funds => high Var(α) => these funds may disproportionately occupy the tails of both bootstrap and actual distributions
  - Using bootstrap p values of t-stats mitigates.
  - However, the restriction may introduce look-ahead bias
  - We compare performance with $T_i \geq 36$ imposed
  - Alternative minimum fund histories: 18, 36, 60, 120 obs.
  - Survivor/Nonsurvivor comparison over last 24 months

Sensitivity Analysis & Bootstrap Extensions

- Serial correlation and block bootstrapping
  - Residual re-sampling and the *iid* assumption
  - Residual serial correlation may incorporate valuable information as to 'true' sampling mechanism.
  - Re-sampling in blocks more closely mimics underlying return generating process.
  - Cross-sectional bootstrap procedure

- Newey-West heteroscedasticity and autocorrelation adjustments

- Alternative bootstrap procedures
  - Residual-only resampling
  - Factor-residual independent resampling
  - Factor-residual pairwise resampling (heteroscedasticity)

End of Presentation