Discussion of:

Double Adjusted Mutual Fund Performance

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Mutual Fund Performance

- In assessing manager performance, we don't want to give MF managers credit for "dumb"/mechanical strategies we could have implemented ourselves at zero (or very low) cost:
    - For example, if the manager's outperformance can be entirely attributed to their buying small high-momentum value stocks, they shouldn't get credit for this.
- The FF-Carhart (1997) ("FFC") view of the world is similar:
    - There are priced risk-factors other than the market. If the managers achieved higher return by loading on these risks and earning the corresponding risk-premia, they shouldn't get credit for this.

Factors Versus Characteristics

- Given the absence of arbitrage (or LOP):
  1. There exists a factor model that prices all assets perfectly.
  2. There exists a characteristics model that prices all assets perfectly.
- Thus, the rejection of a particular factor model (*e.g.*, the FFC model) doesn't imply that no correct factor model exists.
  - It just demonstrates that the mean variance efficient portfolio isn't spanned by the factors of the particular factor model considered.

Characteristics vs. Factor Models

- Given no-arbitrage (or LOP), and therefore the existence of an MVE portfolio:

$$\mathbb{E}[\tilde{R}_i] = \beta_{i,MVE} \cdot \mathbb{E}[\tilde{R}_{MVE}]$$

$$\mathbb{E}[\tilde{R}_i] = \underbrace{\beta_{i,MVE}}_{=\mathbf{b}'\boldsymbol{\theta}_i} \mathbb{E}[\tilde{R}_{MVE}]$$

  - As long as the MVE portfolio returns are in the span of a set of factor returns, that factor model will price every asset correctly.
- Similarly, if we define the vector of asset characteristics $\boldsymbol{\theta}_i$ appropriately, that characteristic model will also price each asset correctly.

Measuring Fund Performance

- Thus, what we need to make sure of in assessing fund performance is that there are no dumb/mechanical strategies that generate positive or negative alpha.
  - This suggests a benchmark problem, *i.e.*, a misspecified factor or characteristics model.

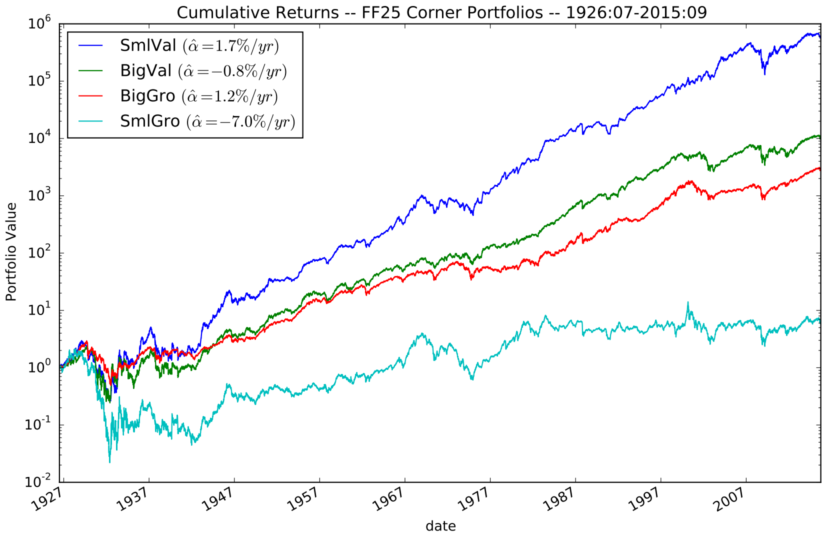
Double Adjusted Fund Performance

- In DGTW, we proposed using the characteristic-adjusted returns based on the evidence that, *after controlling for characteristics*, loadings on the FFC four-factors don't help to explain the cross-section of returns.
  - Specifically, DT(97) rejects the FF-3 factor model, but not the characteristics model.
- This paper argues that a better benchmark adjustment is achieved by double-adjusting.
  - Perhaps both the FFC factor model and the DGTW characteristics model are wrong.
- There could also be other really good reasons for double-adjusting:
  - e.g., obtaining more precise estimates of firm's alphas.

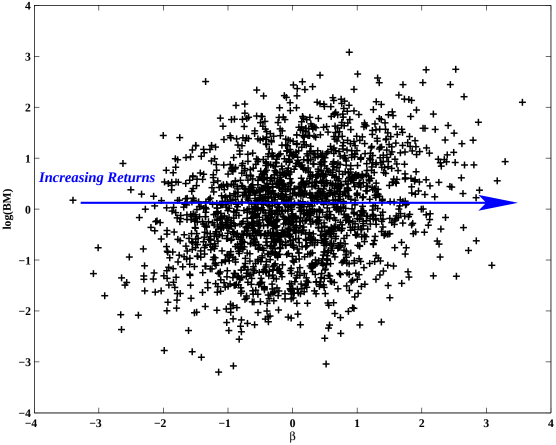
Model Misspecifications

- I want to quickly explore what we know about the misspecification of the FFC and the DGTW factor model on three dimensions:
  - Non-linearities
  - pricing of “risk” after controlling for characteristics.
  - Industry Effects

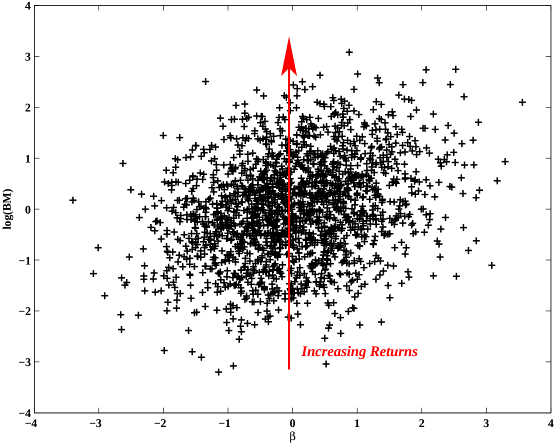
Size-Value Interactions (with FFC 4-factor alphas)



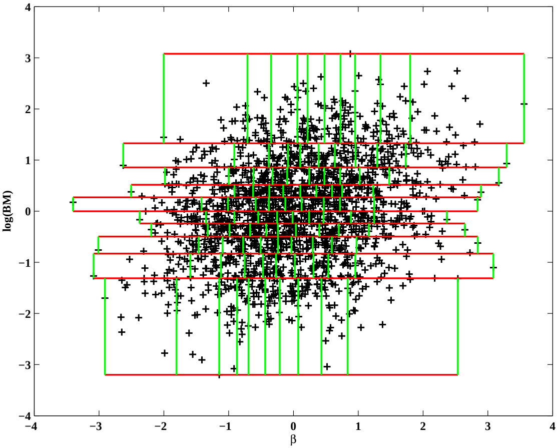
Factor Model Null Hypothesis



Characteristics Model Null Hypothesis



Loadings vs. Characteristics



Loadings vs. Characteristics

From Daniel, Mota, Rottke and Santos (2015):

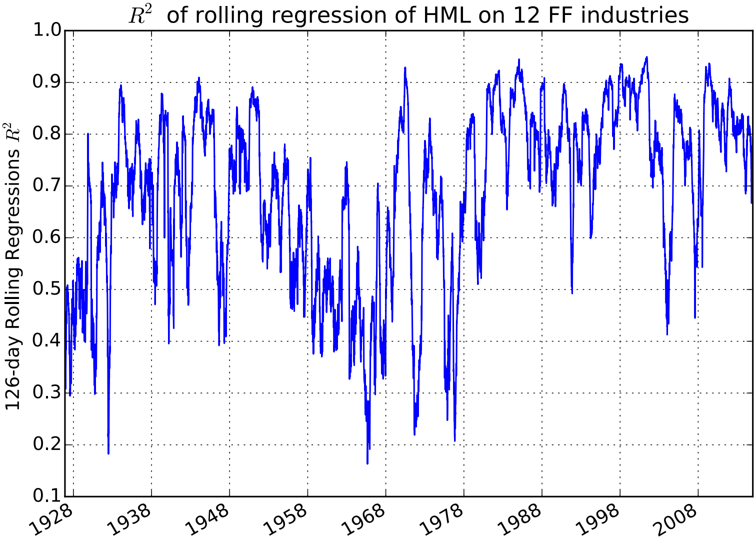
Sample Period: 1963:07-2014:12

Portfolio	ave	a	bMktRF	bSMB	bHML	bRMW	bCMA	R2
LbMHb	-0.09	0.16	-0.41	-0.40	-0.01	0.16	0.08	0.65
	(-0.71)	(2.00)	(-20.45)	(-13.99)	(-0.15)	(3.9)	(1.29)	
LsMHs	-0.18	-0.09	-0.16	-0.54	0.08	0.24	0.19	0.72
	(-1.64)	(-1.53)	(-10.75)	(-25.3)	(2.76)	(7.55)	(4.14)	
LhMHh	-0.11	0.17	-0.02	0.02	-0.91	-0.23	0.46	0.74
	(-1.0)	(2.92)	(-1.35)	(1.04)	(-33.66)	(-7.98)	(10.77)	
LrMHr	-0.15	0.17	0.03	-0.08	-0.28	-0.76	-0.03	0.70
	(-1.65)	(3.18)	(2.47)	(-4.42)	(-11.19)	(-27.55)	(-0.68)	
LcMHc	-0.04	0.19	-0.03	-0.02	0.31	-0.10	-1.14	0.54
	(-0.44)	(2.97)	(-1.71)	(-0.76)	(10.19)	(-2.94)	(-23.52)	
EW-Comb.1	-0.10	0.18	0.00	-0.03	-0.29	-0.36	-0.23	0.78
(h,r,c)	(-1.55)	(5.58)	(-0.58)	(-2.4)	(-19.73)	(-22.44)	(-9.88)	
EW-Comb.2	-0.10	0.17	-0.11	-0.12	-0.22	-0.23	-0.16	0.62
(b,h,r,c)	(-2.03)	(5.57)	(-13.83)	(-10.99)	(-15.17)	(-14.58)	(-6.7)	

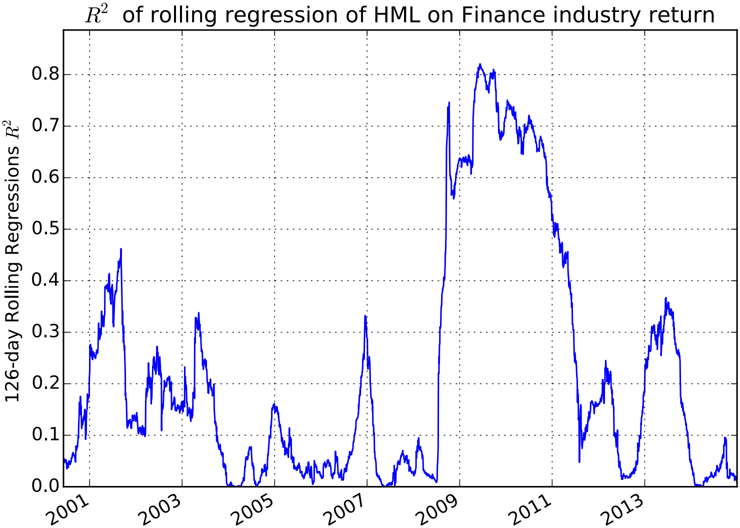
Industry Adjusted Valuation Metrics

- There is a big literature that shows that controlling for industry, particularly w.r.t. valuation metrics such as BM, produces more efficient portfolios.
- In addition, while the FFC factors may not have large *unconditional* loadings on industry factors, they do have large *conditional* loadings.
  - Thus, a high β_{HML}, for example, may not be a good indicator that a fund is really buying value stocks, but rather just an indicator that a fund currently holds stocks in a high-volatility industry that currently has low price-to-book multiples.

Industry Adjustment



Industry Adjustment



Short-Term Persistence Analysis

- This paper claims that the double-adjustment, and in particular the adjustment for factor loadings, identifies a persistent component of alpha.
- The short-term persistence analysis in particular shows really dramatic levels of persistence.
  - Far higher that the persistence levels documented in DGTW (97), Kosowski, Timmermann, Wermers, and White (2006) or Fama and French (2010).
- I'm concerned that there is a bias in the (post-ranking) alphas that may be driving this apparent persistence.

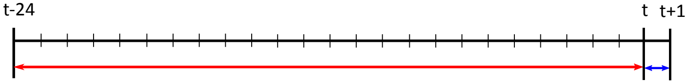
Short-Term Persistence Analysis

Table 4. Short-term Persistence Sorts

The table reports mean annualized post-ranking percentage four-factor alphas for funds sorted into deciles based on performance during a 24-month ranking period. The four-factor alpha in the post-ranking month is calculated as the difference between the realized fund return and the sum of the product of the factor betas estimated over the previous 24-month and the factor returns during the month. We compute *t*-statistics of the differences between the top and bottom deciles with Newey-West (1987) correction for time-series correlation with three lags. *, **, and *** indicate statistical significance at the ten, five, and one percent level respectively. The results reflect 392 individual monthly observations over a 1980m5-2012m12 sample period.

	Model					
		Double-adjusted		Characteristics		
Decile	Four-factor	Regression	Portfolio	Regression	Portfolio	DGTW CS
Bottom	-3.92	-3.58	-3.59	-0.93	-1.38	-1.54
2	-2.17	-2.68	-2.49	-0.71	-1.22	-1.06
3	-1.57	-1.64	-1.67	-0.85	-1.35	-1.09
4	-1.36	-1.45	-1.13	-1.06	-0.99	-0.99
5	-1.04	-1.05	-1.18	-0.80	-0.46	-0.71
6	-0.71	-0.43	-0.60	-1.00	-1.12	-0.77
7	-0.25	-0.19	-0.43	-0.95	-0.86	-0.82
8	-0.05	-0.01	0.20	-1.48	-0.74	-0.78
9	0.57	0.39	0.33	-0.39	-0.32	-0.38
Top	2.14	2.27	2.21	-0.16	0.13	0.28
Top-bottom	6.06***	5.85***	5.80***	0.77	1.51**	1.82***
t-statistic	(7.34)	(8.09)	(7.97)	(0.94)	(2.18)	(3.07)

Short-Term Persistence Analysis



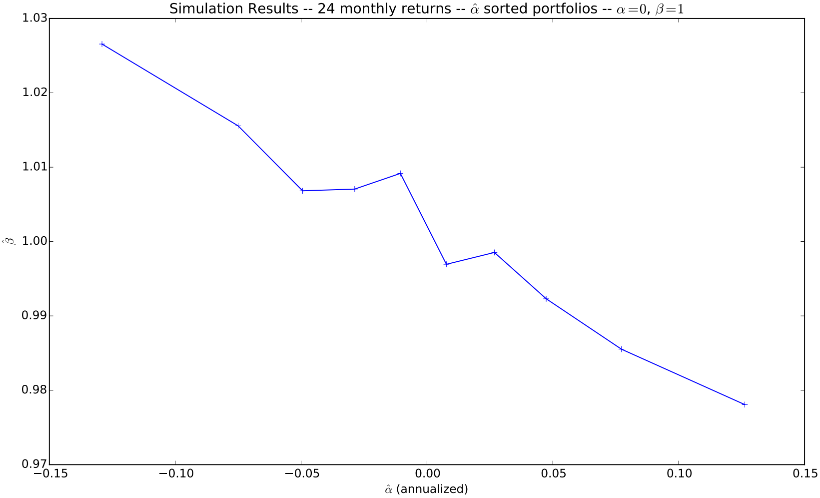
- Fund performance is estimated over the 24-month "ranking" period leading up to the rank date t (from $s = t-24, ..., t$, *e.g.*,

$$\tilde{r}_s = \alpha + \sum_k \beta_k \tilde{f}_s + \epsilon_s$$

- Funds are then sorted into decile portfolios based on the estimated abnormal performance.
- Finally post-ranking abnormal performance is measured as:

$$\hat{\alpha}_{t+1} = \tilde{r}_{t+1} - \sum_k \hat{\beta}_k \tilde{f}_{t+1}$$

Short-Term Persistence — Simulation



Identifying alpha

- This is a really interesting approach/methodology.
- It might be useful to attempt to formalize the arguments a bit more, along the lines laid out here.
- Even if risks is not priced, controlling for them may decrease residual risk (and s.e.($\hat{\alpha}$)), and make any true persistence easier to detect.
- Also, at this point, it would be useful to expand the factor and characteristics models to capture other characteristics that we now know forecast common equity returns.

References I

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