On the High Frequency Dynamics of Hedge Fund Risk Exposures

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June 2011

Hedge fund trading strategies are dynamic

- Hedge funds are a large and important segment of the money management industry.
  - Around $US 1.2 trillion under management (down from around $US 1.5 trillion).
  - Their use of leverage means their impact in markets is greater than their assets under management.
- Unlike traditional fund managers, little is known in detail about the strategies employed by hedge funds. Anecdotally,
  - Strategies are **dynamic**, with fast turnover.
  - Involve long and short positions.
  - Often use relatively illiquid assets.

Hedge fund risk exposures are also dynamic

- Hedge funds are significantly exposed to systematic risk, proxied by indices of equity, bond and options returns.
  - Agarwal and Naik (2004, *RFS*); Fung and Hsieh (1997, 2001, 2004); Jagannathan et al. (2010, *JF*); Bali, et al. (2011, *JFE*) many more.
- Growing interest in capturing how these risk exposures change through time and across market conditions:
  - Optimal changepoint regressions (Bollen and Whaley, 2009, *JF*).
  - Factor loadings modelled as latent variables (Bollen and Whaley, 2009, Mamaysky, Spiegel and Zhang, 2007, *RFS*).

Contributions of this paper: Method

1. We propose a new method for capturing **intra-monthly** variation in hedge fund risk exposures, exploiting information from relatively high frequency conditioning variables.
   - Baseline specification builds on the Ferson-Schadt (1996, *JF*) model, allows us to determine **which variables** drive movements in risk exposures
   - We consider a general modeling framework, and then explore in detail **three functional forms**.
   - Simulation results, and results based on daily hedge fund index data, confirm that the proposed method works well.

Contributions of this paper: Empirical

- We use data on 14,194 hedge funds and funds-of-funds from a consolidated hedge fund data set from 1994 to 2009.

1. Intra-monthly variation in risk exposures is important for hedge funds
   - Daily conditioning information roughly doubles the number of funds with significant time variation in exposures.
   - Interesting intra-monthly "seasonal" patterns in risk exposures.
2. Intra-monthly variation in risk exposures is much less important for mutual funds
   - Daily conditioning information adds little beyond monthly information
3. Using data from 13-F filings on long-short equity hedge funds, we find around 75% of variation in beta comes from changes in portfolio weights.

Outline of the talk

1. High frequency changes in hedge fund risk exposures
2. The accuracy of the approach
3. Results from a study of 14,000 individual hedge funds
    - And 32,000 individual mutual funds
4. Movements in weights or movements in underlying betas?
5. Performance measurement
6. Robustness checks and conclusions

A model with monthly changes in risk exposures

- A monthly model (Ferson and Schadt, 1996, *JF*):

$$\begin{aligned} r_{it} &= \alpha_i + \beta_{it} f_t + \varepsilon_{it} \\ \text{where} \quad \beta_{it} &= \beta_i + \gamma_i Z_{t-1} \end{aligned}$$

  Risk exposures are driven by the variable Z.

  - Which Z variables best describe hedge fund returns?

- Substituting second equation into first we obtain:

$$r_{it} = \alpha_i + \beta_i f_t + \gamma_i f_t Z_{t-1} + \varepsilon_{it}$$

  This basic interaction model can be estimated using OLS.

- But hedge fund factor exposures vary at higher frequencies, too...

Daily changes in risk exposures I

- Our hedge fund returns data are only available monthly, but consider the following model for *daily* hedge fund returns:

$$r^*_{id} = \alpha_i + \beta_{id} f^*_d + \varepsilon^*_{id}$$

- Let Z^*_d denote Z measured at the daily frequency, and Z_d at the monthly frequency. Then let

$$\beta_{id} = g(Z_{d-1}, Z^*_{d-1})$$

$$\begin{aligned} \text{eg} \quad \beta_{id} &= \beta_i + \gamma_i Z_{d-1} + \delta_i Z^*_{d-1} \\ \text{so} \quad r^*_{id} &= \alpha_i + \beta_i f^*_d + \gamma_i f^*_d Z_{d-1} + \delta_i f^*_d Z^*_{d-1} + \varepsilon^*_{id} \end{aligned}$$

- Next, we aggregate returns up to the monthly frequency:

$$r_{it} \equiv \sum_{d \in \mathcal{M}(t)} r^*_{id} = \alpha_i n_t + \beta_i f_t + \gamma_i f_t Z_{t-1} + \delta_i \sum_{d \in \mathcal{M}(t)} f^*_d Z^*_{d-1} + \varepsilon_{it}$$

Daily changes in risk exposures II

- The baseline linear model for monthly hedge fund returns:

$$r_{it} = \alpha_i n_t + \beta_i f_t + \gamma_i f_t Z_{t-1} + \delta_i \sum_{d \in \mathcal{M}(t)} f_d^* Z_{d-1}^* + \varepsilon_{it}$$

1. The first two terms are the usual constant-parameter factor model
2. The third term is the familiar Ferson-Schadt style term
3. The fourth term is new: it uses a monthly aggregate of daily returns to capture daily changes in hedge fund betas

- Assuming ε_{id} is serially uncorrelated and uncorrelated with the RHS variables in the daily model for all (d, s) we can estimate the model using standard OLS.
  - An important assumption, which we study.

Conditioning variables

- Variables (restricted to those with daily data)
  1. Change in the short-term interest rate (ΔLevel): to capture movements in costs of taking on **leverage**.
  2. Change in the TED spread (3-month LIBOR rate minus the 3-month T-bill rate): to capture **funding liquidity** (Garleanu and Pedersen (2009)).
  3. Innovation in VIX: to capture changes in **volatility**.
  4. Returns on the S&P 500: to capture changes in **benchmark returns**.

The accuracy of the proposed method

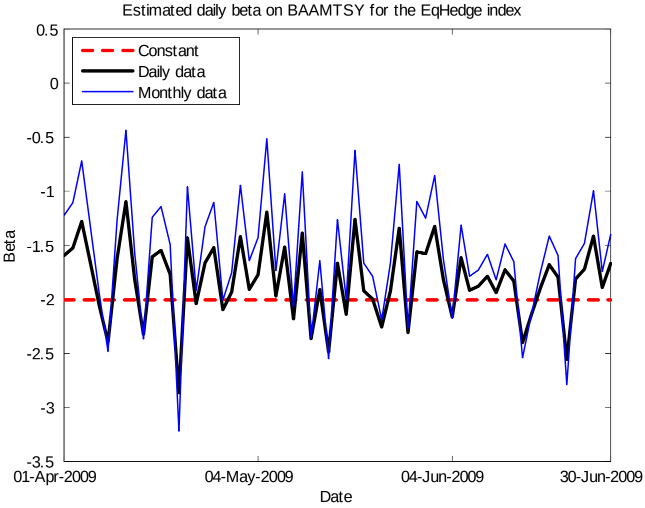
- Before estimating our proposed model, we first test whether it is likely to be accurate. We do so in two ways:

1. **Using daily hedge fund index returns:** a limited amount of *daily* data on hedge fund index returns is currently available – we use that to check how close our method (using only monthly returns) comes to what would be obtained using daily data.

2. **Using simulations:** we use a simulation study, calibrated to match our real data, to check the accuracy and sensitivity of the method to various parameters.

Daily betas for Equity Hedge Index

2009Q2, credit spread factor, SP500 conditioning variable



High frequency dynamics in hedge fund risk exposures

Proportion of 14,194 funds that reject null of constant risk exposures at 0.05 level

- Using daily conditioning information almost doubles the proportion of funds with significant variation

	Conditioning variable				
Model	dLevel	SP500	VIX	TED	Avg
Daily and Monthly	25.673	22.973	21.566	19.281	22.373
Monthly only	15.393	13.608	9.448	9.531	11.995
Daily given Monthly	23.018	21.399	23.056	20.870	22.086
Monthly given Daily	15.325	10.386	9.947	9.947	12.273

Results for mutual funds

Daily information matters much less for mutual funds than for hedge funds

Model	Conditioning variable: dLevel	SP500	VIX	TED	Avg
Equity Mutual Funds					
Daily and Monthly	17.685	18.733	7.340	19.537	15.824
Monthly only	17.492	13.894	9.684	18.228	14.824
Daily given Monthly	8.941	13.337	4.477	12.013	9.692
Monthly given Daily	16.633	10.234	5.757	17.720	12.586
Bond Mutual Funds					
Daily and Monthly	13.966	15.756	6.759	13.033	12.379
Monthly only	12.078	14.899	5.386	12.429	11.196
Daily given Monthly	10.422	9.719	5.667	10.539	9.087
Monthly given Daily	10.808	12.049	4.110	14.286	10.313

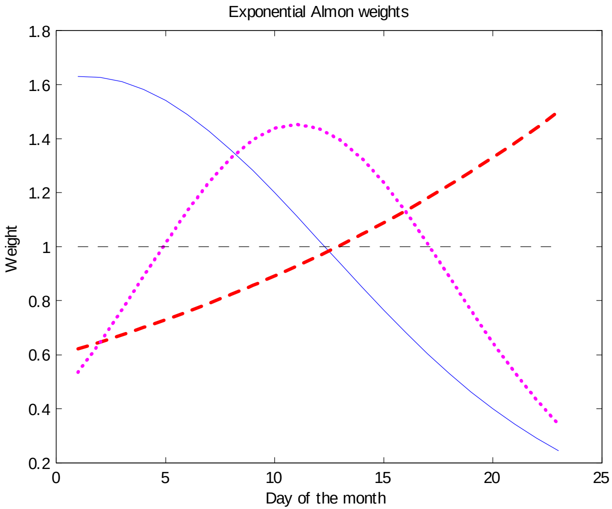
A model with day of the month effects

- We attempt to capture this variation with the following specification:

$$\beta_d = \bar{\beta}\lambda_d\left(\theta_\lambda\right) + \gamma Z_{d-1} + \delta Z^*_{d-1}$$

  - where $\lambda_d\left(\theta_\lambda\right)$ is a flexible parametric function of d/n_t: we use a MIDAS-style "Exponential Almon" model for this function
  - See Ghysels, et al. (2006, *JoE*) for more on MIDAS
- This model can capture variation in betas on specific days of the month.
- Do funds display seasonal patterns in intra-month risk-exposures?

Exponential Almon weight functions

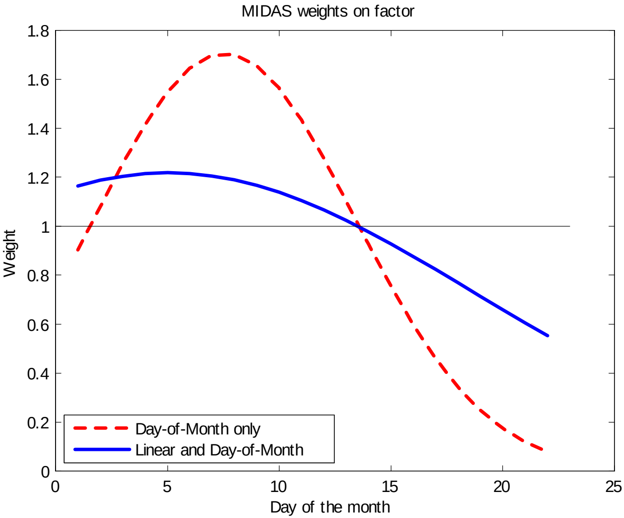


Performance of the day of the month model

Evidence of a significant day-of-the-month effect, even when controlling for other variables

Model	Conditioning variable				
	dLevel	SP500	VIX	TED	Avg
Linear	25.673	22.973	21.566	19.281	22.373
Day of month only	23.421	23.421	23.421	23.421	23.421
Day of month, given linear	32.188	31.328	28.994	31.294	30.951

Day of the month variation in risk exposures



A threshold model for daily risk exposure variation

- Next we consider a model where beta is *nonlinear* in the conditioning variable, based on a threshold model:

$$\beta_d = \begin{cases} \beta_{lo}, & Z^*_{d-1} \leq \bar{Z} \\ \beta_{hi}, & Z^*_{d-1} > \bar{Z} \end{cases}$$

- Here here consider variables, Z^*_d, that cumulate gains, losses or volatility through each month, and reset at the beginning of a new month.
  - Eg: beta is constant as long as the cumulated market return remains above some threshold; if the threshold is crossed then beta jumps to a new level.

Results from the threshold model

- Falling S/T int rates ⇒ shrink short positions in L/T bonds and credit
- Falling S&P 500 index ⇒ move out of small caps
- High S&P 500 volatility ⇒ shrink all positions towards zero
- Decreased liquidity ⇒ shrink all positions towards zero

		Signif	**SP500**	**SMB**	**TC10Y**	**BAATSY**
	Avg β		0.419	0.233	-1.780	-4.595
Cond var	*Quantile*		*% change relative to avg exposure*			
dLevel	<0.10	18.7	10.3	-19.7	88.2	45.7
SP500 ret	<0.10	15.5	-0.7	-126.2	-45.9	-35.9
SP500 vol	>0.90	35.0	-64.4	-16.7	72.7	107.6
TED	>0.90	33.4	-52.7	-98.7	77.2	10.4

What is driving changes in fund betas?

- Changes in risk exposures could come from fund portfolio re-balancing or from variation in underlying risk exposures of assets, or both.
- Consider the exposure of the fund to a single risk factor as a function of the exposures of its holdings:

$$\beta_t^f \equiv \sum_{i=1}^{n} \omega_{i,t-1}\beta_{i,t}$$

- Re-write the weights and stock betas in terms of deviations from their means: $\omega_{i,t-1} = \bar{\omega}_i + \tilde{\omega}_{i,t}$ and $\beta_{it} = \bar{\beta}_i + \tilde{\beta}_{it}$

$$\beta_t^f = \sum_{i=1}^{n} \bar{\beta}_i\bar{\omega}_i + \sum_{i=1}^{n} \bar{\beta}_i\tilde{\omega}_{i,t} + \sum_{i=1}^{n} \bar{\omega}_i\tilde{\beta}_{it} + \sum_{i=1}^{n} \tilde{\omega}_{i,t}\tilde{\beta}_{it}$$

- We next use 13-F filings to try to estimate the relative importance of these terms in driving changes in hedge fund risk exposures.

Using the 13-F data

- 13-F filings only contain (large) long equity positions, we focus on long/short equity funds.
- For each of these we matched all unique management companies filing 13-F reports, with 1,754 unique management companies for 2,790 long/short equity hedge funds in our data.
  - Yields 252 matches.
- For each stock, compute time-varying quarterly beta using the conditioning variables identified in the row headers below.
  - Fund's total beta applies reported stock-level weights from the 13-Fs to stock-level time-varying betas.

Source of beta variation, 13-F filings

Around 75% of variation in beta is due to changes in portfolio weights

	Pure weight	Pure beta	Weight ×beta	Cov terms
dLevel	59.963	33.014	17.013	-6.991
t-stat	33.107	20.577	20.702	-3.352
SP500	79.606	9.848	18.560	-8.014
t-stat	38.087	8.696	17.493	-4.046
VIX	81.516	8.260	9.963	0.262
t-stat	58.984	8.878	13.448	0.239
TED	72.902	15.321	18.221	-6.444
t-stat	41.099	7.677	13.863	-2.322
Average	**72.747**	**16.611**	**15.939**	**-5.297**

Performance measurement: Alphas from different models

Accounting for time-varying betas improves the risk-adjusted performance of hedge funds

- Like Ferson and Schadt (1996) for mutual funds, our use of $t-1$ interaction variables yields a managed strategy implementable with public information; can be used to benchmark the portfolio manager.

	Mean Alpha Static model (1)	Mean Alpha T-V beta model (2)	Difference	|Difference|
Linear model				
All funds	4.173	5.066	-0.893	3.170
t-stat	*40.683*	*46.089*	*-16.733*	*67.635*
Funds w/sig. variation	3.677	5.105	-1.428	3.497
t-stat	*28.905*	*35.398*	*-17.478*	*49.191*

Summary and conclusions

- We present a new method to model changes in hedge fund risk exposures, using information from variables measured at a higher frequency than hedge fund returns.
  - Simulations and daily index returns confirm that the proposed method works well.
  - We find significant evidence of higher-frequency changes in beta: around 25% of funds exhibit daily changes in beta (relative to 15% using only monthly data)
  - A set of robustness checks confirms these results
- Our approach may be useful for other managed investment performance evaluation applications (such as private equity) where "interim trading" is a concern.

Appendix: daily hedge fund index returns

- HFR indices are available at the daily frequency starting in April 2003, for 12 hedge fund styles.
- We estimate the *daily* version of our model on these returns.
- Then compare resulting estimates with those from our method applied to the monthly returns on these indices:

$$\begin{aligned}\text{Daily } r^*_{id} &= \alpha_i + \beta_{i1} f^*_{1d} + \beta_{i2} f^*_{2d} + \gamma_{i1} f^*_{1d} Z_{d-1} \\ &\quad + \gamma_{i2} f^*_{2d} Z_{d-1} + \delta_{i1} f^*_{1d} Z^*_{d-1} + \delta_{i2} f^*_{2d} Z^*_{d-1} + \varepsilon^*_{id},\end{aligned}$$

$$\begin{aligned}\text{Monthly } r_{it} &= \alpha_i n_t + \beta_{i1} f_{1t} + \beta_{i2} f_{2t} + \gamma_{i1} f_{1t} Z_{t-1} + \gamma_{i2} f_{2t} Z_{t-1} \\ &\quad + \delta_{i1} \sum_{d \in \mathcal{M}(t)} f^*_{1d} Z^*_{d-1} + \delta_{i2} \sum_{d \in \mathcal{M}(t)} f^*_{2d} Z^*_{d-1} + \varepsilon_{it}.\end{aligned}$$

Using daily index returns - parameter estimates

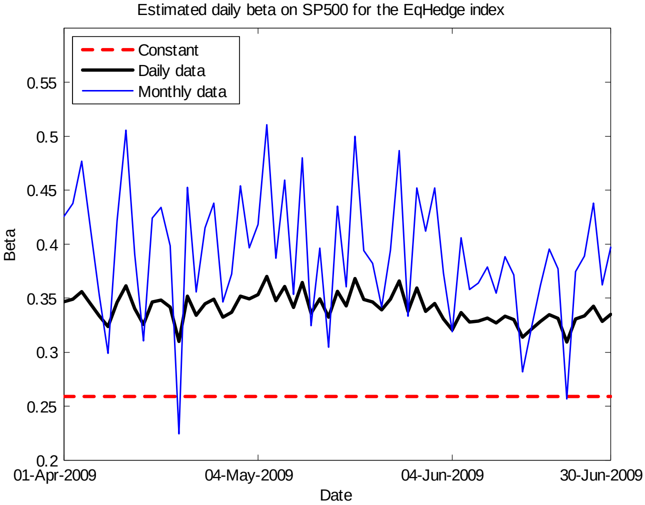
	Equity Hedge		Directional	
	Daily	Monthly	Daily	Monthly
Alpha	1.397	3.106	3.702	5.068
t-stat	0.643	1.508	1.113	1.613
Beta1	0.301	0.321	0.264	0.357
t-stat	38.426	6.374	29.344	3.940
Beta2	-1.832	-1.829	-2.590	-1.920
t-stat	-6.417	-2.613	-6.789	-1.468
Gamma1	0.006	0.009	0.086	0.272
t-stat	8.053	1.526	7.839	2.395
Gamma2	-0.007	0.025	-0.352	1.209
t-stat	-0.228	0.223	-0.759	0.641
Delta1	0.006	0.034	0.053	-0.164
t-stat	2.682	2.848	0.878	-0.570
Delta2	0.216	0.340	-14.831	-42.915
t-stat	3.053	0.444	-5.305	-1.961

Using daily index returns - model results

	Eq. Hedge	Macro	Dir. Traders	Merger Arb.	Rel. Value
Joint sig.(interactions)					
Boot p-val - daily	0.000	0.724	0.000	0.000	0.000
Boot p-val - monthly	0.010	0.692	0.044	0.633	0.004
Corr.(true,estimated)					
Corr $\left[\hat{\beta}_{1d}^{*}, \hat{\beta}_{1d}\right]$	0.887	-0.404	0.974	0.981	0.785
Corr $\left[\hat{\beta}_{2d}^{*}, \hat{\beta}_{2d}\right]$	0.936	-0.994	0.963	0.630	-0.770

Daily betas for Equity Hedge Index

2009Q2, SP500 factor, SP500 conditioning variable



A small simulation study: Design

- We next consider a small simulation study of the accuracy of the proposed method.

1. Assume that daily hedge fund returns are driven by a one-factor model, with time-varying factor loadings:

$$r_d^* = \alpha + \beta f_d^* + \gamma f_d^* Z_{d-1} + \delta f_d^* Z_{d-1}^* + \varepsilon_{R,d}^*, \quad d = 1, 2, ..., 22 \times T,$$

2. Assume that the conditioning variable follows an AR(1):

$$Z_d^* = \phi_Z Z_{d-1}^* + \varepsilon_{Z,d}^*$$

3. We also allow the factor return to be persistent:

$$f_d^* = \mu_F + \phi_F \left(f_{d-1}^* - \mu_F \right) + \varepsilon_{F,d}^*$$

A small simulation study: Parameter values

- We calibrate the parameters of the model to the results obtained from estimation using daily HFR equity hedge index returns:

$$\alpha = 2/(22 \times 12), \ \beta = 0.4, \ \gamma = 0.002, \ \delta = -0.004$$
$$\mu_F = 10/\left(22 \times 12\right), \ \sigma_F = 20/\sqrt{22 \times 12}, \ \sigma_Z = 10, \ \sigma_{\varepsilon R} = \sqrt{0.1}$$

- All innovations are normally distributed, with:

$$Corr\left[\varepsilon^*_{R,d}, \varepsilon^*_{Z,d}\right] = Corr\left[\varepsilon^*_{R,d}, \varepsilon^*_{F,d}\right] = 0$$
$$Corr\left[\varepsilon^*_{Z,d}, \varepsilon^*_{F,d}\right] \equiv \rho_{FZ} \in \{\ 0\ ,\ 0.5\ \}$$

- Key parameters:

$$\phi_Z \in \{\ 0\ ,\ 0.5\ ,\ 0.9\ \}$$
$$\phi_F \in \{\ -0.2\ ,\ 0\ ,\ 0.2\ \}$$
$$T \in \{\ 24\ ,\ 60\ ,\ 120\ \}$$

A small simulation study: Results

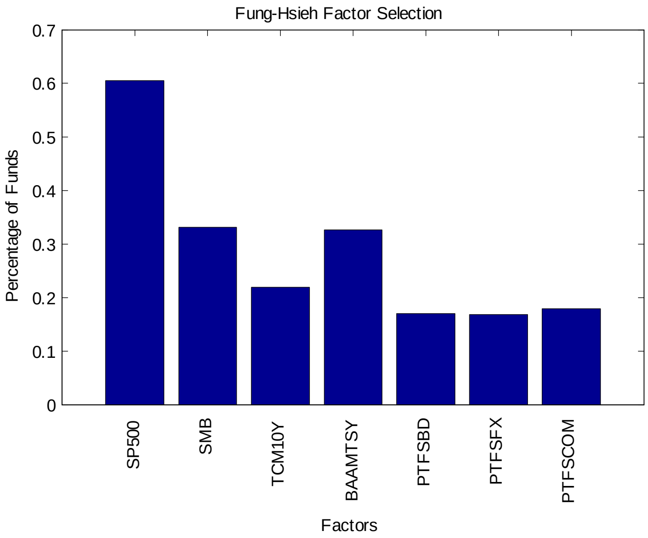
	True values	Base case	Short sample	High ϕ_Z	Corr ρ_{FZ}	ϕ_F ρ_{FZ}
T		60	24	60	60	60
ρ_{FZ}		0.0	0.0	0.0	0.5	0.5
ϕ_Z		0.5	0.5	0.9	0.5	0.5
ϕ_F		0.0	0.0	0.0	0.0	0.2
Mean α	0.76	0.72	0.83	0.77	0.81	0.72
Mean β	0.40	0.40	0.40	0.40	0.40	0.40
Mean γ	0.20	0.20	0.20	0.20	0.20	0.20
Mean δ	-0.40	-0.39	-0.40	-0.40	-0.41	-0.39
St dev α		0.09	0.15	0.09	0.19	0.19
St dev β		0.04	0.06	0.04	0.04	0.03
St dev γ		0.01	0.01	0.00	0.01	0.00
St dev δ		0.04	0.06	0.05	0.03	0.03

Summary statistics

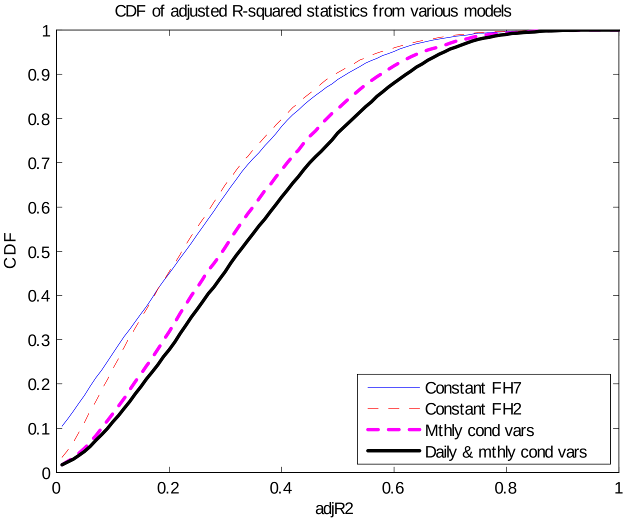
	Returns	Unsmoothed Returns	AUM ($MM)	Management Fee	Incentive Fee	Lockup (Days)	Redemption Notice (Days)
25th Prctile	-0.700	-0.841	9.400	1.000	10.000	0.000	10.000
50th Prctile	0.720	0.710	32.000	1.500	20.000	0.000	30.000
75th Prctile	2.230	2.363	106.756	2.000	20.000	90.000	45.000
Mean	0.845	0.847	166.714	1.484	15.162	94.176	33.913

	<36 Months	>=36 , <60	>=60
Length(Return History)	17.423	31.062	51.515

First-stage factor selection



Explanatory power of linear model



Significance, linear model, by strategy

Relative Value, FoF, and Multi-Process styles have highest signif; CTA and Macro styles have lowest.

Panel B: Daily given monthly

		Conditioning Variables				
Style	N(funds)	dLevel	SP500	VIX	TED	Avg
Security Selection	2942	18.101	15.551	17.641	16.082	16.844
Macro	885	11.200	9.467	11.867	11.200	10.933
Relative Value	146	18.382	26.471	20.588	23.529	22.243
Directional Traders	1813	19.493	16.394	18.085	19.268	18.310
Fund of Funds	3309	40.217	35.876	41.178	33.488	37.690
Multi-Process	1775	24.442	24.031	24.266	23.090	23.957
Emerging	478	13.978	15.914	17.204	13.763	15.215
Fixed Income	805	19.766	28.088	16.515	22.887	21.814
CTA	1981	9.145	8.355	10.263	8.421	9.046
Other	43	17.949	12.821	12.821	12.821	14.103

Robustness checks

- We considered a variety of robustness checks:
  1. Sub-samples: 1994-2001 vs. 2002-2009
  2. History length: $[24, 36]$, $(36, 60]$, $(60, 186]$ months of data
  3. Assets under management: low, mid and high terciles

- Our conclusions are generally robust to these variations
  - Our method works better in the latter sub-period, and better for larger funds.