

Machine-Learning the Skill of Mutual Fund Managers

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Summary of the Paper

The paper is forthcoming in JFE. My discussion focuses on

- ▶ Analyzing in detail the main insights of the paper
- ▶ Posing more questions related to the paper's insights

Main Insights of the Paper:

1. Model abnormal returns $\tilde{R}_{it} = (R_{it} - \sum_k \hat{\beta}_{ik} f_{kt})$, rather than excess returns $(R_{it} - R_f)$ for better detecting the skill of mutual fund managers. Why?
 - ▶ Because abnormal returns are less noisier
2. Abnormal returns are modeled using Neural Networks
 - ▶ Predictors are fund char, fund-family char, char of stocks that funds hold
 - ▶ Fund momentum, fund flow $\implies \tilde{R}_{it}$, but stock-chars $\not\Rightarrow \tilde{R}_{it}$
3. Long-short portfolios of funds with extreme abnormal returns yield high returns
 - ▶ Prediction-weighted long-short portfolios: Overweight funds in the extreme deciles with higher abnormal return forecasts

Discussion on Modeling Abnormal Returns

Why does modeling abnormal returns yield better inferences?

A GLS interpretation:

- ▶ Consider $r_{it} = g(z_{it-1}, \theta) + \epsilon_{it}$, where $\epsilon_{it} = \sum_k \beta_{ik} f_{kt} + \eta_i t$
- ▶ $\hat{\theta}_{OLS}$ delivers less precise forecasts than $\hat{\theta}_{GLS}$
- ▶ $\hat{\theta}_{GLS} \equiv$ implementing OLS on abnormal returns $r_{it} - \sum_k \beta_{ik} f_{kt}$
- ▶ Thus, targeting abnormal returns (rather than returns) is useful

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Related Questions:

- ▶ The paper sorts funds into deciles based on their abnormal return forecasts, and then it takes long (short) positions on the top (bottom) decile of funds
- ▶ If any, this long-short portfolio should deliver large **abnormal returns**
- ▶ But the paper documents that it delivers large **returns**. Why?
- ▶ Note that $\text{ret} = \text{abn ret} + \text{factor risk premia } (\beta_{ik} f_{kt})$.
- ▶ So, long-short abr port need not deliver large returns
- ▶ Does the paper implicitly assumes factor means to be zero? If yes, wouldn't α estimates be biased?

Discussion on Prediction-Weighted Portfolios

The paper uses prediction-weighted long-short strategies (PWS)

- ▶ These portfolios are in the spirit of Allena (2020, 2023 RFS *R&R*) which introduced precision-weighted long-short strategies

What are prediction-weighted strategies? Are they universally applicable?

- ▶ PWS first sort funds into deciles based on abnormal return forecasts
- ▶ Take prediction-weighted long (short) positions on top (bottom) decile funds

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Do prediction-weighted strategies always outperform? Need not always be

- ▶ return forecast = $E(\text{ret}) + \text{measurement error}$; forecast $\uparrow \implies E(r) \uparrow$ or *error* \uparrow
- ▶ Thus, by overweighting funds with high return forecast, one may be overweighting on the noise!
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One way to track noise is to look at **forecast variances**. Put more weights on forecasts with low forecast variances (Allena (2020, 2023))

- ▶ Fortunately, for Neural Networks, forecasts and forecast variances are correlated. Thus, prediction-weighted strategies outperform
- ▶ But for linear models, prediction-weighted strategies underperform

Discussion on Empirical Findings

Stock chars do not impact abnormal fund returns

Question: Is this result driven by the fact that stock chars are aggregated linearly whereas returns are modeled non-linearly?

- ▶ Consider two stocks with $r_{it} = a + bc_{i,t-1}^2 + \epsilon_{it}$, $i = 1, 2$
- ▶ Consider a fund that assigns equal weights on both stocks
- ▶ Then the expected abnormal return of the fund $E(R_F) = a + b \frac{c_{1,t-1}^2 + c_{2,t-1}^2}{2}$
- ▶ However, when the chars are first linearly aggregated to the fund-level, as in the paper, abnormal returns will be modeled using

$$r_{i,t+1} = f\left(\frac{c_{1,t-1} + c_{2,t-1}}{2}\right) + \epsilon_{it}$$

- ▶ $f\left(\frac{c_{1,t-1} + c_{2,t-1}}{2}\right) \neq E(R_F)$, and it may result in biased inferences
- ▶ Thus, linear aggregation of characteristics may not be suitable for non-linear modeling of fund returns

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Thought for future research: How to aggregate stock-level chars to the fund-level for modeling fund returns non-linearly?

Great paper! Main takeaways are

- ▶ Abnormal fund returns are predictable and are persistent
- ▶ Modeling abnormal returns is important
- ▶ Allowing for a non-linear relation between abnormal fund returns and fund chars is important