

# Discussion: Machine Learning Mutual Fund Flows

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# Summary

**Background:** Understanding flows allows fund managers to better manage liquidity, and researchers to better differentiate skill.

**Question:** Can ML improve on mutual fund flow predictions?

**Answer:** Yes.  $R^2$ : 22.8% (RF) vs. 18.2% (OLS) OOS (+25%)

**Insight:**

- Morningstar ratings dominating factor alphas.

## Overall Assessment

- Solid methodology with REFORMS checklist (Kapoor et al., 2024)
- Interpretable ML: SHAP values reveal interesting information.
- First systematic ML application to flow prediction (vs. alpha prediction)
- Fun and intriguing read!
- My comments will focus on interpretation and mechanism.

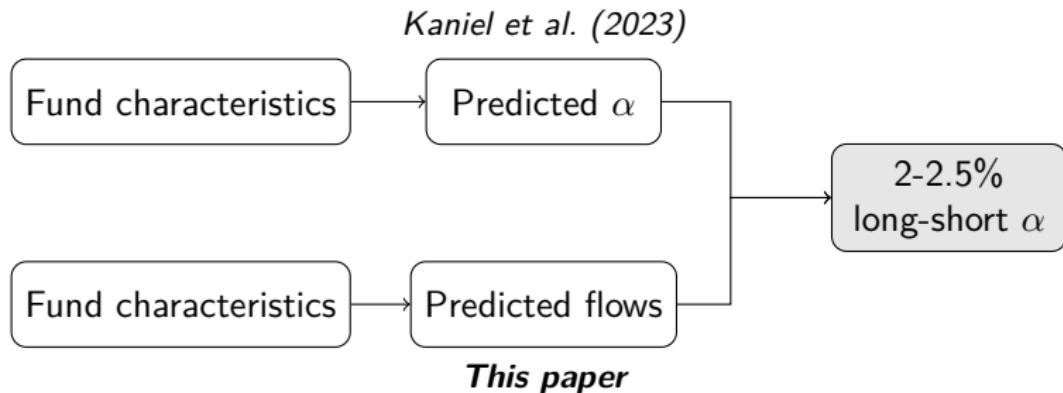
## Comment 1: Morningstar puzzle

- Puzzle: Morningstar ratings predict more than performance.
- Ben-David et al. (2022) investors chase stars.
- **This paper:** Rating is  $2\times$  more important than best  $\alpha$  (SHAP).

What's driving this?

- ① **Information:** Nonlinear risk-adjustment captures something alphas miss.  
→ *Add higher moments of returns; does rating importance drop?*
- ② **Behavioral:** Investors see stars, not factor regressions.  
→ *Rating × alpha interaction: ignored when stars are high?*
- ③ **Mechanical:** Categorical variable more ML-friendly than continuous alpha.  
→ *Discretize alpha into quintiles; does importance rise?*

## Comment 2: Flows vs $\alpha$



### Do flows add information beyond direct $\alpha$ prediction?

- Horse race: double sort on predicted flows  $\times$  predicted  $\alpha$ .
- Mechanism: temporary (price pressure) vs. permanent (smart money)?

## Comment 3: Prediction and performance

**Finding:** ML improvement over historical mean  $\uparrow$  Performance  $\downarrow$

**Interpretation:** Poor prediction  $\rightarrow$  Poor liquidity management  $\rightarrow$  Poor performance.

### Alternative explanations:

- Reverse: Poor performance  $\rightarrow$  Erratic behavior  $\rightarrow$  Poor prediction.
- Benchmark: historical mean. Is it fund's most likely used method?
- Strong assumption: funds not using ML in the sample period.

## Comment 4: Is the OLS benchmark the right comparison?

**Standard flow regressions in the literature include:**

- Fund fixed effects → capture time-invariant characteristics.
- Time fixed effects → capture aggregate shocks.

**This paper instead uses:**

- Lagged flows as proxy for fund FE.
- 9 macro variables as proxy for time FE.

**Suggestion:**

- How does OLS *with* fund + time FE perform as a benchmark?

## Minor comments

### Data and variables:

- Text data (prospectuses, shareholder letters) + NLP could capture soft information.
- Holdings data: portfolio-level characteristics (concentration, active share).

### Robustness and extensions:

- Crisis subsamples (2008, 2020): Does predictability collapse or strengthen?
- Heterogeneity: Does ML help more for small/young/high-turnover funds?
- International evidence: Do results generalize outside US?
- Time-varying expense ratio deserves more prominence.
- Imputing holdings for more granular prediction comparison (data if available).

# Conclusion

- Fun and suggestive paper!
- Mixes methodological novelties with an important question.
- Relevant both for academics and practitioners.

# Thank You!