Classifying Hedge Fund Strategies with Large Language Models: Systematic vs. Discretionary Performance

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We Are Interested in

- Classify hedge funds into systematic or discretionary
  - Model-based "systematic" funds vs. human-based "discretionary" funds (Harvey et al., 2017)
    - Similar classifications: "quantitative" vs. "qualitative"("discretionary" ,"fundamental"), and "machine" vs. "man"(Chincarini,2014; Abis, 2018; Evans et al.,2018)
- Evaluate the performance of classified funds
  - Is fund performance due to authentic skills or sampling luck?
  - Do systematic funds (as a group) outperform discretionary funds?

This Paper

- A new approach to classifying funds
  - Textual analysis is applied to convert text of investment strategies into numeric data and extract "features" from such data.
  - Large Language Model is fine-tuning to classify the investment styles.
  - Our approach captures strategy similarities and avoids subjective judgement or choice of keywords (cf. Harvey et al., 2017; Abis 2018).
- Evaluating fund performance
  - Implementing a statistical test with a false discovery adjustment under two-pass asset pricing models.
  - 10% to 20% of funds exhibit significant positive alphas
  - Funds classified as Systematic yield higher factor-adjusted returns than their Discretionary counterparts, on average.

Related Researches

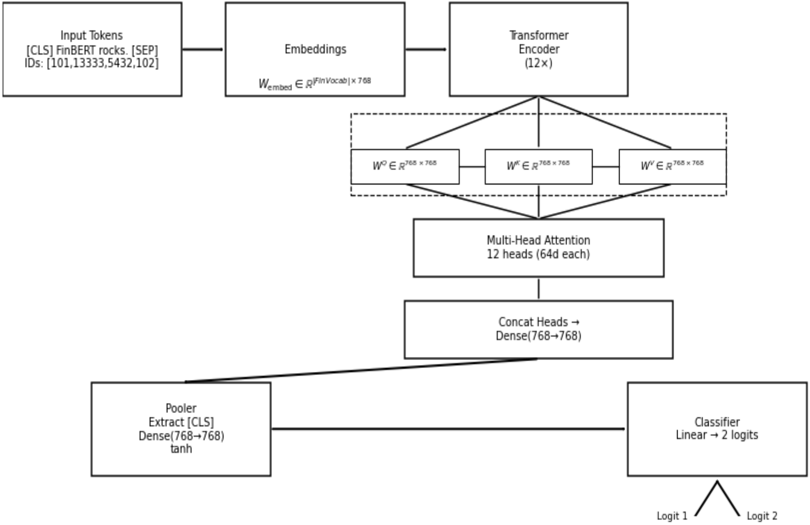
- Chincarini (2014)
  - word count: *algorithm, automate, econometric, mathematical, model, quantitative, statistic*
  - quantitative hedge funds have higher alphas than qualitative ones.
- Harvey et al. (2017)
  - word count approach. *algorithm, approx, computer, model, statistical,and system* are keywords used in their paper.
  - performances are similar.
- Abis (2018)
  - collected 2,607 mutual funds' "Principal Investment Strategies" in prospectuses from SEC.
  - classified manually a sub-sample of 200 prospectuses into two types.
  - apply machine learning (ML) methods to 200 (training sample) to classify the reaming funds (prediction sample).
  - compare stock picking/timing and holding performance and justify her empirical findings by a theoretical model.

Large Language Model: FinBERT

- BERT (Bidirectional Encoder Representations from Transformers), Devlin et al. (2019) pre-trained contextual information from both the left and right sides of a word on Wikipedia and BookCorpus.
- FinBERT, developed by Yang et al. (2020) and Huang et al. (2023), further trains BERT model on
  - SEC corporate filings (10-K and 10-Q),
  - financial analyst reports from Thomson Investext,
  - earnings call transcripts from SeekingAlpha.

  FinBERT captures contextual nuances in financial texts than the original BERT model.
- Domain-specific LLMs: science and biomedicine (Beltagy et al., 2019; Lee et al., 2020), legal studies (Chalkidis et al., 2020), ESG research (Huang et al., 2023; Webersinke et al., 2021), and innovation studies (Lee and Hsiang, 2020; Chuang et al., 2023)

Large Language Model: Fine-Tuning FinBERT



HFR Classification

- As Harvey et al. (2017), we only consider two main strategies (Equity Hedge and Macro) and their six sub-strategies in HFR.

Equity Hedge	Macro
Equity Market Neutral	Active Trading
Quantitative Directional	Commodity: Metals
Fundamental Growth	Commodity: Agriculture
Fundamental Value	Commodity: Energy
Sector: Energy/Basic Materials	Commodity: Multi
Sector: Healthcare	Currency: Discretionary
Sector: Technology	Currency: Systematic
Short Bias	Discretionary Thematic
Multi-Strategy	Systematic Diversified
	Multi-Strategy
Testing	Training

Classification: Training Sample

- Macro funds has natural candidate for training sample.
  - Systematic Diversified Macro funds: "investment processes that typically are functions of mathematical, algorithmic, and technical models, with little or no influence from individuals over the portfolio positioning."
  - Discretionary Thematic Macro funds: "primarily reliant on the evaluation of market data, relationships and influences, as interpreted by an individual or group of individuals who make decisions on portfolio positions."
- Training sample: Binary variable $y_i = 1$ if the i-th fund is a Systematic Diversified Macro fund and $y_i = 0$ if it is a Discretionary Thematic Macro fund; the feature matrix (explanatory variable matrix) of Macro funds as inputs to train classifiers.
- Our approach is free from subjective judgement of investment strategies/keywords.

Classification Performance

- In our training (on Macro funds) process:
  - Hold-out test set 15% (337 funds)
  - The remaining 85%, reserved 15% (286) for validation to monitor model performance
  - Leaving 1,619 funds for training

	Accuracy	AUC	Precision	F1	Recall
Training	93.14%	97.55%	92.38%	94.95%	97.66%
Validation	89.16%	93.47%	89.90%	91.99%	94.18%
Test	92.58%	96.16%	91.91%	94.53%	97.30%

- In our previous studies, we shown that the best performed ML algorithm (Random Forest among LDA, KNN, SVM, Classification Tree, and Gradient Boosting) achieved 86%, 82%, 86%, and 90% for accuracy, AUC, precision, and F1 score in the testing set respectively.

Classification: In sample performance

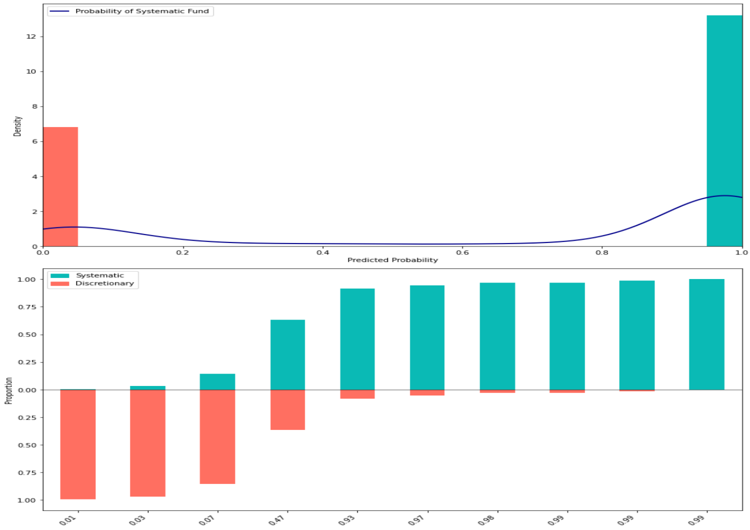


Figure 1: Equity Hedge: Discretionary

Figure 2: Equity Hedge: Systematic

Significant Performance under False Discovery Rate Control

Consider the following factor model:

$$E(r_i) = \alpha_i + \beta_i' \lambda, \quad i = 1, \cdots, N,$$

where r_i: excess return of fund i. α_i pricing error (alpha) of fund. β_i is a vector of risk exposures, and λ is the risk premia. We want to examine:

$$H_{0,i} : \alpha_i \leq 0, \quad i = 1, \cdots, N.$$

Rejecting the null hypothesis $H_{0,i}$ implies that the superior performance (positive alpha) of fund i is statistically significant and cannot merely be attributed to chance.

Significant Performance under False Discovery Rate Control

- We consider the following factor models
  - One factor: MKT
  - Three factors: MKT, SMB, HML
  - Five factors: PTFSBD, PTFSFX, PTFSCOM, PTFSIR, and PTFSSTK (returns from the long position of the lookback straddle of bonds, currencies, commodities, short-term interest rates, and stocks.)
  - Seven factors: MKT, SMB, CS (credit spread), Δ10Y, PTFSBD, PTFSFX, and PTFSCOM
  - Eleven factors: add HML, MOM, PTFSIR, and PTFSSTK to 7 factors

Fund Performance Comparison

Main Strategy	Style	Count	Mean	STD	Median	Mean Diff.
Seven-factor model (F7)						
Equity Hedge	Discretionary	2,728	8.24%	77.80%	15.29%	7.28%
	Systematic	1,177	15.52%	68.54%	15.82%	
Macro	Discretionary	338	10.20%	67.83%	7.52%	26.99%
	Systematic	791	37.19%	69.46%	33.57%	
Eleven-factor model (F11)						
Equity Hedge	Discretionary	2,728	11.35%	84.83%	17.10%	5.02%
	Systematic	1,177	16.37%	76.27%	17.40%	
Macro	Discretionary	338	13.86%	77.85%	15.59%	25.92%
	Systematic	791	39.79%	80.08%	39.39%	

Significant Performance under False Discovery Rate Control

- Giglio et al. (2021)'s test proceeds as follows:
  - First, they use observable risk factors to calculate risk exposures and residuals for each fund through time-series regression
  - Second, they employ matrix completion on the unbalanced residual matrix, Hastie et al. (2015), and use PCA to identify latent risk factors and exposures.
  - Third, they perform a cross-sectional regression of the mean excess return on the concatenated observed false and unobserved exposures to estimate risk premiums and fund alphas.
  - Finally, they apply the (adjusted) Benjamini-Hochberg False-discovery rate test to fund alphas to account for the data-snooping bias.
- We used the test from Giglio et al. (2021) to identify funds with positive alpha in each category without data-snooping bias and control for the false discovery rate at 5% level.

Significant Alphas by style across main strategies

Strategy Level	Style	F7	F11	F3+U4	F5+U2	U7
Panel A: All strategies						
	Discretionary	22.02%	19.57%	22.64%	23.39%	22.11%
	Systematic	18.70%	17.28%	21.39%	20.93%	19.21%
Panel B: Main strategies						
Equity Hedge	Discretionary	22.84%	20.16%	23.17%	24.05%	22.69%
	Systematic	24.55%	22.94%	24.38%	25.66%	23.53%
Macro	Discretionary	15.38%	14.79%	18.34%	18.05%	17.46%
	Systematic	9.99%	8.85%	16.94%	13.91%	12.77%

Conclusion

- This paper fine-tuned the FinBERT, a large language model (LLM) to mitigates the subjective judgment traditionally involved in categorizing investment strategies.
- Our classification performance exceeds most ML based approaches.
- We find that, on average, funds classified as Systematic yield higher factor-adjusted returns than their Discretionary counterparts.
- About 10% and 20% of funds exhibit statistically significant positive alphas in models combining observable and unobservable factors.

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