Which Variables Predict Future Active Mutual Fund Performance? New Insights From Academic Research

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Who am I?

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Topic of this presentation

Which variabes predict future active mutual fund performance?

or, in other words:

How can we apply academic research for manager selection?

Academic research papers:

- Focus: Actively-managed equity mutual funds
- Market: USA
- Performance measurement:

  Net-of-fees

  Risk-adjusted performance measures (Sharpe ratio, Treynor ratio, Sortino ratio)

  Benchmark-adjusted performance measures (alphas to different factor models)
- Variables: Fund-, fund firm-, and fund manager characteristics (all quantitatively measured)

Why is it so hard to predict fund performance? (I)

1. **Arithmetic of active investment** (Sharpe, 1991)

   Before costs, benchmark-adjusted performance among active traders is a zero-sum game; after costs, performance of the average active investor will be lower than the performance of the average passive investor.

2. **Efficient market hypothesis** (Fama, 1970)

   Asset prices reflect all publicly available information. $\Rightarrow$ It is difficult to cosistently earn superior (benchmark-adjusted) performance.

3. **Asset pricing anomalies disappear after their public disclosure** (McLean and Pontiff, 2016)

   Profitability of asset pricing anomalies (such as value, momentum, reversal, earning announcement drift) decreases after their existence has been published in a scientifc journal.

Why is it so hard to predict fund performance? (II)

4. **Performance chasing of investors**

   Disproportionally large inflows to well-performing funds can hinder fund managers to implement their best investment ideas (decreasing returns to scale).

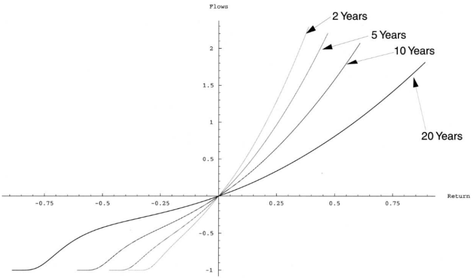

Figure: Berk and Green (2004)

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How to empirically investigate fund performance predictors

Data:

Historical data on fund returns and characteristics is obtained from commercial databases (CRSP, Morningstar, Factset, Lipper) and other sources.

Notation:

X_t^i: Characteristic related to fund i in month t
α_{t+1}^i: Performance of fund i in month $t+1$

Methodology 1: Portfolio Sorts

- In month t, form quintile portfolios by sorting funds based on X_t^i.
- Compute portfolio alphas over month $t+1$. Evaluate the spread in alphas between portfolio 5 (funds with high X) and portfolio 1 (funds with low X).

Methodology 2: Regression Analysis

- Run:

$$\alpha_{t+1}^i = \lambda + \beta \cdot X_t^i + \text{Controls} + \epsilon_{t+1}^i$$

- Check the sign of the coefficient estimate $\hat{\beta}$ and examine whether it is statistically significantly different from zero.

Fund predictors: Past performance and costs

Predictor	Paper	Data Source	Empirical Effect on Future Performance	Rationale
Past Performance	Grinblatt, Titman (1992) Hendricks et al. (1993) Carhart (1997)	Fund returns	Positive (*but controversal*)	Manager skill is (partly) persistent.
Morningstar's Rating	Blake, Morey (2000)	Fund returns Morningstar ratings	Positive (*but similar effect as past performance)*	Morningstar rating and past performance are highly correlated.
Expense Ratio	Gil-Bazo, Ruiz-Verdu (2009)	Fund returns Fund expenses	Negative	Reducing fund costs and fees increases performance.
Size	Chen et al. (2004)	Fund returns AuMs	Negative	Decreasing returns to scale.
Return Gap	Kacperczyk et al. (2008)	Fund returns Portfolio holdings	Positive	Unobserved actions matter for fund performance.

Fund predictors: Activity and distinctiveness

Predictor	Paper	Data Source	Empirical Effect on Future Performance	Rationale
R2 to Factor Models	Amihud, Goyenko (2013)	Fund returns	Negative	Funds with distinctive investment strategies are successful.
Active Share	Cremers, Petajisto (2009)	Fund returns Portfolio holdings	Positive	Funds that strongly deviate from the benchmark outperform.
Industry Concentration	Kacperczyk et al. (2005)	Fund returns Portfolio holdings	Positive	Funds with informational advantages in specific industries outperform.
Risk Shifting	Huang et al. (2011)	Fund returns Portfolio holdings	Negative	Shifting risk is an indication of inferior skill or induced by agency issues,
Risk Factor Exposure	Ammann, Fischer, Weigert (2020)	Fund returns	Negative	Funds unsuccessfully time the market and other risk factors.

Predictors on the fund firm level

Predictor	Paper	Data Source	Empirical Effect on Future Performance	Rationale
Governance	Trahan (2008) Cremers et al. (2009)	Fund returns Governance ratings	Positive	Higher quality of firm governance increases performance.
Personal Investment	Khorana et al. (2007)	Fund returns Ownership data	Positive	Skin in the game leads to superior fund performance.
Fund Firm Size	Gaspar, Massa, Matos (2006) Evans, Prado, Zambrana (2020)	Fund returns Fee and compensation data	Positive / Negative	Larger fund families can transfer performance aross member funds.
Investment Bank Affiliation	Gil-Bazo et al. (2020)	Fund returns Ownership data	Negative	Funds provide funding support to banks' failed products which decreases performance.
City Size of Headquarter	Christoffersen, Sarkissian (2008)	Fund returns City size data	Positive	Higher average skill and productivity in larger cities increases performance.

Fund manager characteristics

Predictor	Paper	Data Source	Empirical Effect on Future Performance	Rationale
Education	Chaudhuri et al. (2020)	Fund returns Manager profiles	Positive	Education increases skill to successfully manage a fund,
Recession Experience	Kempf et al. (2017)	Fund returns Manager profiles	Positive	«Recession experienced» fund managers outperform during volatile periods.
Relevant Work Experience	Cici et al. (2018)	Fund returns Portfolio holdings Manager profiles	Positive	Managers with industry experience outperform in associated stocks.
Connectedness	Cohen et al. (2008) Rossi et al. (2018)	Fund returns Portfolio holdings Manager profiles	Positive	Managers that are well-connected to peers and companies deliver superior performance.
Team Diversity	Evans et al. (2019)	Fund returns Manager profiles	Positive	More diverse fund manager teams outperform homogenous teams.

Fund manager characteristics: But...what about?

Predictor	Paper	Data Source	Empirical Effect on Future Performance and Flows
Gender	Niessen-Ruenzi, Ruenzi (2019)	Fund returns Manager profiles AuMs	No performance differences between female and male managers. Male managers obtain *higher* inflows.
Foreign-Sounding Names	Kumar et al. (2015)	Fund returns Manager profiles AuMs	No performance differences between domestic and foreign managers. Managers with foreign-sounding names receive *lower* inflows.
Appearance	Pareek, Zuckerman (2020)	Fund returns Manager profiles AuMs	Hedge fund managers with photographs that are rated as more trustworthy receive *higher* inflows.
Military Affiliation	Cochardt et al. (2020)	Fund returns Manager profiles AuMs	Fund managers with a well-trusted military background receive *higher* inflows.
Marital Events	Lu et al. (2016)	Fund returns Manager profiles	Hedge fund managers deliver abnormal low performance during periods of marital events (marriages and divorces).
Sport Cars	Brown et al. (2018)	Fund returns Manager profiles	Hedge fund managers who own powerful sport cars take on more investment risk, but deliver inferior performance.

Predictors of fund performance: Caveats

Sample region and period:

- Displayed results are valid for a specific country (usually the USA) and for a specific time period.

Data quality:

- Fund returns and portfolio holdings are usually taken from commercial databases; data extensions are frequently manually added from proprietary sources.

Transaction costs:

- Academic research does not focus on the practical implementation of empirical findings.
- Transaction costs are viewed as "side constraints" or not considered at all.

Academic Bias:

- Academics have to publish in scientific journals to be promoted.
- *Significant* results are much more likely to be published than *null* results.

Practical summary

Factors to consider when investing into an actively-managed fund:

Past Performance and Costs	Activity and Distinctiveness	Fund Firm Level	Manager Characteristics
• High past performance • Moderate size • Low expense ratio	• Deviation from the relevant benchmark • Stable risk exposure	• Transparent governance structure • Managers should be invested in the fund	• Well-educated (CFA, master degree) • Experienced in the respective investment style • Diversified team (if managed by a team)

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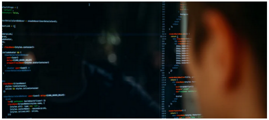
Combining predictor variables

Given the established effect of different characteristics for future fund performance, is there an optimal way to combine the predictors?

Machine learning (ML) approach:

- ML in empirical finance: A collection of high-dimensional models for statistical prediction, where
  (i) the risk of in-sample model overfitting is mitigated, and
  (ii) efficient algorithms search among potential model specifications.
- ML methods allow for the detection of *non-linearities* and *interaction effects* between the different predictors.



Machine learning techniques

1. **Baseline:**
   Simple unconstrained linear regression with all predictor variables.
2. **Penalized linear regression:**
   Punishes the inclusion of new predictor variables and reduces potential overfitting of the model (models: *lasso* and *ridge* regression).
3. **Dimension reduction techniques:**
   Average the impact of all potential predictor variables to an aggregate predictor (*principal component regression* and *partial least squares*).
4. **Penalized generalized linear models:**
   Allow for nonlinearities in the predictor variables.
5. **Boosted regression trees and random forests:**
   Nonparametric models that allow for interactions between the predictor variables.
6. **Neural networks (deep learning):**
   Nonparametric models that use *activation functions* and different *layers* to account for nonlinearities and interactions between predictor variables.

First results: ML in fund selection

Wu et al. (2021): US Hedge funds

- The authors apply different ML techniques based on 21 predictor variables to forecast hedge fund performance.
- The top-decile neural network forecast portfolio outperforms the hedge fund return (HFR) index by a large amount (e.g., by twice of its Sharpe ratio).

DeMiguel et al. (2021): Actively-managed US equity mutual funds

- The authors apply different ML techniques based on 17 predictor variables to forecast mutual fund performance.
- The top-decile boosted regression tree portfolio earns benchmark-adjusted alphas of approximately 4% per annum.

Own research (2021): Actively-managed US equity mutual funds

- A portfolio strategy based on a dimension reduction technique and 8 predictor variables yields a benchmark-adjusted alphas of approximately 5% per annum (without taking account of transaction costs).

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Conclusion

Summary

- Predicting mutual fund performance is a difficult task.

  ⇒ *Arithmetic of active investment*, *efficient market hypothesis*, *disappearing profitability of anomalies*, *return chasing of investors*.

- Nevertheless, academic research finds that some variables are significantly related to future fund performance.

  ⇒ *Fund characteristcs*, *fund firm characteristics*, *fund manager characteristics*.

- Combining different predictor variables with machine learning techniques seems to be a promising approach to improve fund- and manager selection.

Outlook

Can we improve the predictability of fund performance and fund flows using machine learning techniques for Swiss funds?

Combining predictor variables

Active Mutual Funds in Switzerland: New Perspectives on the Measurement and Prediction of Performance and Investor Flows

Jürg Fausch (Lucerne University of Applied Science), Moreno Frigg (Lucerne University of Applied Science) & Florian Weigert (University of Neuchâtel)

Combining academic research with practical relevance:

- Application for a science-based innovation project supported by Innosuisse (Swiss Innovation Agency)
- If you are interested in a collaboration, we are happy to discuss this opportunity with you

Schweizerische Eidgenossenschaft
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Thank you!

Please check out my personal homepage and blog:

https://www.florian-weigert.com/

https://www.florian-weigert.com/the-scientific-investor/


THE SCIENTIFIC INVESTOR

Welcome to the Scientific Investor.

This blog should fill two purposes: It gives access to financial research recently published in the top academic journals and provides an intro to dig deeper into a specific topic (also in the form of a potential Bachelor, Master, and PHD thesis for students).

Moreover, it should inspire practitioners to use these academic insights for the implementation and refinement of investment strategies. It goes without saying that empirical results shown in the papers are based on historical data and there is no guarantee that a proposed strategy will be successful in the future.

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