Real-Time Predictability of Mutual Fund Performance Predictors

Yu Xia

McGill University

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Why mutual fund performance matters?

- Mutual funds are widely used
  - Actively managed funds hold 60% U.S. total net assets in equity
  - ≈ 50% U.S. households own mutual funds

- Hard to gauge their value added to investors

- Question:
  Can investors gain from using predictors to select actively managed mutual funds in real time?
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Can investors gain from using predictors to select actively managed mutual funds in real time?
Main findings

- **Short answer:** Yes!

- Using two adaptive approaches to evaluating predictors in real time
  - Regression-based machine learning: $1.3 \sim 1.7\%$ p.a. real-time alphas
    - Li and Rossi (2020): ML based on stock holdings and stock characteristics.
    - DeMiguel et al. (2021): ML based on fund characteristics and performance.
    - My paper: fund characteristics, performance, and holding-based activeness.
  - Rule-based portfolio sorts: $2.5\%$ p.a. real-time market-adjusted alpha

- Do investors react to predictive information? Yes!
  - Investor flow chases for predictive information
  - Reaction is generally stronger among more growth-oriented funds
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<table>
<thead>
<tr>
<th>Category</th>
<th>Predictor</th>
<th>Study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Characteristics-Based</td>
<td>Expense Ratio (ER)</td>
<td>Elton et al. (1993)</td>
</tr>
<tr>
<td></td>
<td>Fund Flow (Flow)</td>
<td>Zheng (1999)</td>
</tr>
<tr>
<td></td>
<td>Fund Size (Size)</td>
<td>Chen et al. (2004)</td>
</tr>
<tr>
<td>Performance-Based</td>
<td>One-Year Return (Ret1y)</td>
<td>Hendricks et al. (1993)</td>
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<td>Carhart Alpha (Car1y)</td>
<td>Carhart (1997)</td>
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<td></td>
<td>One-Month Return (Ret1m)</td>
<td>Bollen &amp; Busse (2004)</td>
</tr>
<tr>
<td></td>
<td>Return Gap (RG)</td>
<td>Kacperczyk et al. (2006)</td>
</tr>
<tr>
<td>Activeness</td>
<td>Turnover (TR)</td>
<td>Elton et al. (1993)</td>
</tr>
<tr>
<td></td>
<td>Active Share (AS)</td>
<td>Cremers &amp; Petajisto (2009)</td>
</tr>
<tr>
<td></td>
<td>R-Squared ($R^2$)</td>
<td>Amihud &amp; Goyenko (2013)</td>
</tr>
<tr>
<td></td>
<td>Active Weight (AW)</td>
<td>Doshi et al. (2015)</td>
</tr>
<tr>
<td></td>
<td>Fund Duration (Dur)</td>
<td>Cremers &amp; Petajisto (2016)</td>
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</tbody>
</table>
Methodology 1: Machine learning

- Non-ML benchmark: OLS with objective function

\[
\min_{\theta} \mathcal{L}(\theta) = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (r_{i,t+1} - \underbrace{x_{i,t}^{'} \theta}_{\text{Predictors}})^2
\]

- ML: Balance between fit & robustness; allow real-time selection
- Shrinkage/sparsity/both: Ridge, LASSO, elastic net, sparse group LASSO

\[
\min_{\theta} \mathcal{L}(\theta; \cdot) = \mathcal{L}(\theta) + \phi(\theta; \cdot)
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where \( \phi(\theta; \cdot) \) is a penalty term.

- Dimension reduction: PCR, PLS
  - OLS after transforming & reducing predictor space to principal components
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  where \( r_{i,t+1} \) is the net fund return and \( x_{i,t}' \theta \) are the predictors.

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- Fund selection rule
  - Quintile of one predictor (single sort, \( \text{Car}1y, 5 \)), or
  - Quintile of two predictors (dependent double sort, \( R^2, 1 \& \text{Car}1y, 5 \))

- Potential gains:
  - Nonlinearity, interaction, few parametric restrictions
  - (+ pros of other ML such as trees, neural networks)
  - Easy to understand
  - (− cons of other opaque ML)
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Real-time evaluation

- **Expanding window starts with 7 years**

<table>
<thead>
<tr>
<th>Methods</th>
<th>Training</th>
<th>Validation</th>
<th>Real-Time</th>
<th>Tuning Parameter</th>
</tr>
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<tbody>
<tr>
<td>ML</td>
<td>5 (yrs)</td>
<td>1</td>
<td>1</td>
<td>( \phi(\theta; \cdot) ) or # PCs</td>
</tr>
<tr>
<td>Rule-Based</td>
<td>6 ( \uparrow )</td>
<td>0</td>
<td>1</td>
<td>None</td>
</tr>
<tr>
<td></td>
<td>5 ( \uparrow )</td>
<td>1</td>
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<td># Top Rules</td>
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Validation for tuning parameters

- **ML**
  - Training: Estimate parameters
  - Real-time: Pick funds w/ highest predicted net-of-fee return

- **Rule-based**
  - Training: Determine top rules
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- Fund stock holdings from Thomson Reuters to construct predictors
- Mutual fund sample: 1994 - 2016
  - Complete fund characteristics data from 1994 in CRSP
  - Active share and fund duration up to 2015
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## Summary statistics

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Obs.</th>
<th>Mean</th>
<th>SD</th>
<th>AR(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ER (%)</td>
<td>900</td>
<td>1.17</td>
<td>0.36</td>
<td>0.95</td>
</tr>
<tr>
<td>Flow ($M)</td>
<td>900</td>
<td>-1.20</td>
<td>108.04</td>
<td>0.78</td>
</tr>
<tr>
<td>Size ($M)</td>
<td>900</td>
<td>6.12</td>
<td>1.67</td>
<td>0.97</td>
</tr>
<tr>
<td>Ret1y (%)</td>
<td>900</td>
<td>10.81</td>
<td>12.41</td>
<td>0.92</td>
</tr>
<tr>
<td>Car1y (%)</td>
<td>900</td>
<td>-0.05</td>
<td>0.90</td>
<td>0.84</td>
</tr>
<tr>
<td>Ret1m (%)</td>
<td>900</td>
<td>0.87</td>
<td>2.38</td>
<td>0.10</td>
</tr>
<tr>
<td>RG (%)</td>
<td>900</td>
<td>-0.01</td>
<td>1.26</td>
<td>0.13</td>
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<tr>
<td>TR (%)</td>
<td>900</td>
<td>75.74</td>
<td>61.18</td>
<td>0.93</td>
</tr>
<tr>
<td>AS</td>
<td>900</td>
<td>0.81</td>
<td>0.15</td>
<td>0.96</td>
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<tr>
<td>$R^2$</td>
<td>900</td>
<td>0.91</td>
<td>0.07</td>
<td>0.94</td>
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<tr>
<td>AW</td>
<td>900</td>
<td>0.79</td>
<td>0.21</td>
<td>0.93</td>
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<tr>
<td>Dur (yrs)</td>
<td>900</td>
<td>5.64</td>
<td>3.49</td>
<td>0.96</td>
</tr>
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</table>
Main results: Real-time performance

<table>
<thead>
<tr>
<th></th>
<th>Avg. Return</th>
<th>CAPM $\alpha$</th>
<th>FF3 $\alpha$</th>
<th>C4 $\alpha$</th>
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</thead>
<tbody>
<tr>
<td><strong>Panel A: Benchmark</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OLS</td>
<td>0.56</td>
<td>-0.07</td>
<td>-0.14</td>
<td>-0.12</td>
</tr>
<tr>
<td><strong>Panel B: Machine Learning</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ridge</td>
<td>0.58</td>
<td>-0.04</td>
<td>-0.11</td>
<td>-0.11</td>
</tr>
<tr>
<td>LASSO</td>
<td>0.74**</td>
<td>0.14**</td>
<td>0.11**</td>
<td>0.11**</td>
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<tr>
<td>EN</td>
<td>0.74**</td>
<td>0.14**</td>
<td>0.11**</td>
<td>0.11**</td>
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<tr>
<td>PCR</td>
<td>0.61</td>
<td>0.00</td>
<td>-0.08</td>
<td>-0.09</td>
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<tr>
<td>PLS</td>
<td>0.55</td>
<td>-0.07</td>
<td>-0.14</td>
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<tr>
<td>SGL</td>
<td>0.68*</td>
<td>0.07</td>
<td>0.03</td>
<td>0.03</td>
</tr>
<tr>
<td><strong>Validation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>0.79**</td>
<td>0.21*</td>
<td>0.11</td>
<td>0.08</td>
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<tr>
<td>Yes</td>
<td>0.70*</td>
<td>0.11</td>
<td>0.02</td>
<td>-0.01</td>
</tr>
</tbody>
</table>

- Monthly net-of-fee returns in percentage
Does macro information explain performance?

- Empirical specification (Ferson and Schadt, 1996):

\[
R_t - R_{f,t} = \alpha + (\beta + B' z_{t-1}) (R_{M,t} - R_{f,t}) + s R_{SMB,t} + h R_{HML,t} \\
+ m R_{MOM,t} + \epsilon_t,
\]

\(z_{t-1}\): lagged macroeconomic variables.

<table>
<thead>
<tr>
<th></th>
<th>(\alpha)</th>
<th>(\beta)</th>
<th>B (MKT x TB)</th>
<th>B (MKT x DY)</th>
<th>B (MKT x TS)</th>
<th>B (MKT x DS)</th>
<th>s</th>
<th>h</th>
<th>m</th>
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<td></td>
<td></td>
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<tr>
<td>OLS</td>
<td>-0.05</td>
<td>1.01***</td>
<td>0.58**</td>
<td>-0.08</td>
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<td>0.07</td>
<td>0.30***</td>
<td>0.03</td>
<td>-0.02</td>
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<tr>
<td>Ridge</td>
<td>-0.04</td>
<td>0.99***</td>
<td>0.45**</td>
<td>-0.08</td>
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<td>0.02</td>
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<td>0.31***</td>
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<td>1.00***</td>
<td>0.57**</td>
<td>-0.08</td>
<td>0.04**</td>
<td>0.06</td>
<td>0.29***</td>
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<td>0.18***</td>
<td>0.01</td>
<td>0.00</td>
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| **Panel B: Machine Learning** |           |           |              |              |              |              |     |     |     |
| Validation |           |           |              |              |              |              |     |     |     |
| No       | 0.10      | 0.96***   | 0.35         | 0.04         | 0.02         | 0.01          | 0.39*** | 0.05 | **0.11** |
| Yes      | 0.00      | 0.98***   | 0.19         | 0.05         | 0.03         | -0.01         | 0.36*** | 0.03 | **0.10** |
Time variations in performance

Rule-based portfolio (market-adjusted, no validation)

Rule-based portfolio (market-adjusted, validation)

ML (EN) portfolio (market-adjusted)
Investment value

Portfolio
- Market
- ML (EN)
- Rule-Based (w/o Validation)

Dollar Return From $1 Invested

Date

2005  2010  2015
Which predictor matters? - ML

- Key predictor: one-month return (Ret1m)
Which predictor matters? - Rule-based

<table>
<thead>
<tr>
<th>Ranking</th>
<th>2001</th>
<th>2002</th>
<th>...</th>
<th>2011</th>
<th>...</th>
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<th>2016</th>
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<td>Ret1m, 5 &amp;</td>
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<td>...</td>
<td>Car1y, 5 &amp;</td>
<td>...</td>
<td>AW, 2 &amp;</td>
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<td>Ret1y, 5</td>
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<td>Ret1m, 5</td>
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<td>R2, 1</td>
<td>R2, 1</td>
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</table>

- One-year return: 24/48 rules (in total)
- One-month return: 17/48 rules
- $R^2$: 7/48 rules
Which predictor matters? - Rule-based

<table>
<thead>
<tr>
<th>Ranking</th>
<th>2001</th>
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<th>2011</th>
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<th>2015</th>
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<tr>
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<td>...</td>
<td>Ret1m, 5 &amp;</td>
<td>...</td>
<td>Ret1m, 5 &amp;</td>
<td>Ret1m, 5 &amp;</td>
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<td>Ret1m, 5</td>
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<td>Ret1y, 5</td>
<td></td>
<td>Ret1y, 5</td>
<td>Ret1y, 5</td>
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<tr>
<td>2</td>
<td>Car1y, 5 &amp; TR, 5 &amp;</td>
<td>...</td>
<td>AW, 2 &amp;</td>
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<td>Car1y, 5 &amp;</td>
<td>Car1y, 5 &amp;</td>
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<td>Ret1m, 5</td>
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<tr>
<td>3</td>
<td>Ret1m, 5 &amp; Ret1m, 5 &amp;</td>
<td>...</td>
<td>Car1y, 5 &amp;</td>
<td>...</td>
<td>AW, 2 &amp;</td>
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<tr>
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<td>Ret1y, 5</td>
<td>Ret1y, 5</td>
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<td>Ret1m, 5</td>
<td></td>
<td>R2, 1</td>
<td>R2, 1</td>
</tr>
</tbody>
</table>

- **One-year return**: 24/48 rules (in total)
- **One-month return**: 17/48 rules
- **$R^2$**: 7/48 rules
Do investors use predictive information? - Part I

- **Direct** investor reaction measure: Monthly fund flow

\[
F_{i,t+1} = \frac{TN_{A_{i,t+1}}}{TN_{A_{i,t}}} - (1 + R_{i,t+1})
\]

- Key independent variable: Predictor-implied performance (PIP)
  - Capture predictive information embedded in each predictor

**Construction**

- Main specification:

\[
F_{i,t+1} = b_0 + b_\alpha PureAlpha_{i,t} + b_P PIP_{i,t}^P + \sum_j b_j FACTOR_{i,j,t} + \theta' X_{i,t} + \eta_{t+1} + \epsilon_{i,t+1}
\]

  incl. predictor itself

- **PIP_{i,t}^P**: after weighting past 18-month components
Do investors use predictive information? - Part I

- **Direct** investor reaction measure: *Monthly fund flow*

\[
F_{i,t+1} = \frac{TNA_{i,t+1}}{TNA_{i,t}} - (1 + R_{i,t+1})
\]

- Key independent variable: *Predictor-implied performance (PIP)*
  - Capture predictive information embedded in each predictor

**Main specification:**

\[
F_{i,t+1} = b_0 + b_\alpha PureAlpha_{i,t} + b_P PIP_{i,t}^P + \sum_j b_j \text{FACTOR}_{i,j,t} + \theta' X_{i,t} + \eta_{t+1} + \epsilon_{i,t+1}
\]

- \(PIP_{i,t}^P\): after weighting past 18-month components

incl. predictor itself
Do investors use predictive information? - Part I

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  - Capture predictive information embedded in each predictor

**Construction**

- **Main specification:**

\[ F_{i,t+1} = b_0 + b_\alpha PureAlpha_{i,t} + b_P PIP_{i,t}^P + \sum_j b_j FACTOR_{i,j,t} \]

\[ + \theta' X_{i,t} + \eta_{t+1} + \epsilon_{i,t+1} \]

- **$PIP_{i,t}^P$: after weighting past 18-month components**
Do investors use predictive information? - Part I

- **Direct** investor reaction measure: Monthly fund flow

\[ F_{i,t+1} = \frac{TNA_{i,t+1}}{TNA_{i,t}} - (1 + R_{i,t+1}) \]

- Key independent variable: **Predictor-implied performance (PIP)**
  
  - Capture predictive information embedded in each predictor

**Construction**

- **Main specification:**

\[ F_{i,t+1} = b_0 + b_\alpha PureAlpha_{i,t} + b_P PIP_{i,t}^P + \sum_j b_j FACTOR_{i,j,t} \]

\[ + \theta'(X_{i,t}) + \eta_{t+1} + \epsilon_{i,t+1} \]

incl. predictor itself

- \( PIP_{i,t}^P \): after weighting past 18-month components
Do investors use predictive information? - Part II

- Barber et al. (2016): Investors most likely use CAPM

<table>
<thead>
<tr>
<th>Monthly Flow</th>
<th>Predictor P</th>
<th>Size</th>
<th>RG</th>
<th>AS</th>
<th>R²</th>
<th>AW</th>
<th>Dur</th>
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<tbody>
<tr>
<td>Pure Alpha</td>
<td></td>
<td>0.632***</td>
<td>0.625***</td>
<td>0.647***</td>
<td>0.651***</td>
<td>0.625***</td>
<td>0.633***</td>
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<td><strong>PIP</strong></td>
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<td>0.520***</td>
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<td>-0.166***</td>
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<td>R²</td>
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<td></td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Month FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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## Do investors use predictive information? - Part III

<table>
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<tr>
<th>Monthly Flow</th>
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<tbody>
<tr>
<td></td>
<td><strong>Panel A: Aggressive Growth</strong></td>
<td></td>
<td></td>
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<td>Pure Alpha</td>
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<td>0.654***</td>
<td>0.656***</td>
<td>0.662***</td>
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<td>0.655***</td>
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<td><strong>PIP</strong></td>
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<td><strong>Panel B: Growth</strong></td>
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<td>Pure Alpha</td>
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<td><strong>PIP</strong></td>
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<td>0.364</td>
<td>0.422*</td>
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<tr>
<td></td>
<td><strong>Panel C: Growth and Income</strong></td>
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<tr>
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<td>36,859</td>
<td>36,859</td>
<td>36,859</td>
<td>36,859</td>
</tr>
</tbody>
</table>
Conclusions

- Can investors gain from using predictors in real time?
  - Yes! Regression-based ML (only with sparsity) gives $1.3 \sim 1.7\%$ p.a. alphas
  - Short-term one-month return matters the most

- Do investors react to predictive information?
  - Yes! Great variations in using predictive information
  - Investor reaction is stronger for more growth-oriented funds

- Why does real-time predictability exist?
  - Not due to lack of investor attention
  - But compensation for intensive search algorithms to find skilled managers.
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Future work

- Economic gains for long-term investors
- Who incorporate predictive information?
  - Investor heterogeneity: sophisticated v.s. unsophisticated
- When do investors acquire information?
  - Uncertainty may affect investors’ attention or willingness

Thank You!
Future work

- Economic gains for long-term investors
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Thank You!
Why PIP?

- Predictors for **managerial skills** or behavioral biases? Not clear

Solution:

Step 1. Capture skill by similarity in return pattern with a portfolio of funds sorted on predictor (extend Cohen et al., 2005)

Portfolio: Funds with high predictor value — funds with low predictor value

Step 2. Use fitted performance as skill component captured by predictor (PIP)
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1. Estimate performance similarity & risk exposure:

\[ R_{i,\tau} - R_{f,\tau} = \alpha_{i,t} + \gamma^P_{i,t} R^P_{\tau} + \sum_j \beta_{i,j,t} f_{j,\tau} + \epsilon_{i,\tau}, \tau \in \{t - 1, \ldots, t - 60\}. \]

Illustration

2. Decompose returns into three performance components:

\[ R_{i,t} - R_{f,t} = \hat{\alpha}_{i,t} + \hat{\gamma}^P_{i,t} R^P_{t} + \sum_j \hat{\beta}_{i,j,t} f_{j,t}. \]

pure alpha \hspace{1cm} predictor P-implied performance (PIP) \hspace{1cm} risk premia
1. Estimate performance similarity & risk exposure:

\[ R_{i,\tau} - R_{f,\tau} = \alpha_{i,t} + \gamma_{i,t}^P R_{\tau}^P + \sum_j \beta_{i,j,t} f_{j,\tau} + \epsilon_{i,\tau}, \tau \in \{t - 1, \ldots, t - 60\}. \]

Illustration

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- **pure alpha**
- **predictor P-implied performance (PIP)**
- **risk premia**
Portfolio of funds sorted on predictor $P = \text{Size}$

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Value</th>
<th>Group of MFs</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Size}$</td>
<td>Low</td>
<td>MF1</td>
</tr>
<tr>
<td></td>
<td>:</td>
<td>:</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>MF5</td>
</tr>
</tbody>
</table>

\[ R_t^\text{Size} \text{(i.e., } R_t^P) = Ret_t^{MF5} - Ret_t^{MF1} \]