

Mimicking Finance

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Introduction

- Agents should not be compensated for behaviors or human capital that can be cheaply replicated.
- Advances in technology and replicable skill acquisition affect equilibrium wages, hiring, and tenure.
- We examine this principle in the \$54 trillion U.S. asset management industry.¹
- Focus: actions and behaviors of asset managers that are predictable from past behavior and observable conditions.
- We train straightforward models to mimic fund-level manager behavior.
- Findings: **71% of portfolio managers' trades can be predicted each quarter**, showing a major technological challenge to the value of asset management labor.

¹Office of Financial Research, Annual Report 2024



Findings

- Using 1990–2023 data, we document strong regularities in asset manager trading predictability.
- **71% of buy/sell/hold decisions predicted each quarter** with streamlined AI models; highly stable and significantly better than a Majority Class baseline ($p < 0.0001$).
- Predictability is large across fund styles, peaking at **75% for Mid-cap Blend funds**.
- **Model vs. Naïve Benchmarks:** Prediction precision is consistently higher with model-based approaches, stable across nearly three decades, resilient to crises, and strongest among large and mid-sized funds.
- **Manager Characteristics:** Longer tenure, multi-fund responsibilities, and broader style coverage increase predictability, while greater ownership stakes and larger teams reduce it.



Findings

- **Fund Characteristics:** Mature funds are more predictable, whereas larger size, high turnover, volatile flows, and competitive pressures reduce predictability; sales restrictions improve it.
- **Security Characteristics:** Stable, mature, and widely monitored firms (e.g., high leverage, free cash flow, payout policies, recent losers) are more predictable, while innovative, volatile, or surprise-driven firms are less predictable.
- **Performance Findings:** High-precision funds underperform, while low-precision, harder-to-predict funds generate superior returns to peers—**79 basis points ($t=3.05$) following formation**—highlighting a fundamental trade-off between transparency/stability and alpha generation.
- **Performance Findings:** Within each manager's portfolio, **those stock positions that are more difficult to predict strongly outperform those that are easier to predict.**
Aggregating across the universe of fund managers each quarter, **stocks whose position changes are least predictable significantly outperform stocks whose position changes are most predictable.**



Data, Variable Construction, and AI-ML Model

Data

- **Fund Holdings:** Core dataset from Morningstar Direct, with fund–security–level shares and market values from SEC filings and prospectuses; sample restricted to actively managed U.S. equity mutual funds (1990–2023), excluding index, sector, balanced, and international funds.
- **Morningstar Characteristics:** Metadata on inception dates, categories, and manager information, with share-level details based on each fund’s oldest share class.
- **CRSP Characteristics:** Monthly data on TNA, returns, expense ratios, turnover, income yield, and other fund attributes, complementing Morningstar’s limited time coverage.
- **Security- and Macro-Level Data:** Security characteristics from the JKP Global Factor Database, and macroeconomic variables from FRED (short-term rates, 10-year Treasury yield, yield curve slope, BAA–Treasury spread, etc.) to capture the investment environment.
- Our sample includes includes 1,706 unique mutual funds, and 5,434,702 fund–security–quarter observations from 1990 to 2023.



Target Variable Construction, Y_t

The prediction task is defined at the fund–security–quarter level. For each fund i and security position at time t , the target variable captures the direction of the subsequent quarter’s share change. Specifically, we compute

$$\Delta sh_{i,t} = \frac{sh_{i,t+1} - sh_{i,t}}{sh_{i,t} + 1}, \quad Y_{i,t} = \begin{cases} -1 & \Delta sh_{i,t} \leq -0.01, \\ 0 & |\Delta sh_{i,t}| < 0.01, \\ +1 & \Delta sh_{i,t} \geq 0.01. \end{cases}$$

Here, -1 denotes trim/sell, 0 denotes no material change, and $+1$ denotes add/buy. A $\pm 1\%$ band around zero counts as “no change.” This is therefore a 3-class classification at the fund–security level.



Feature Variables Construction, $\mathbf{x}_t$

- **Fund-Level Features:** Lagged returns, net cash flows, fund size, and style tilts (value, momentum), based on reported metrics and holdings.
- **Security-Level Features:** Lagged firm characteristics (log market cap, book-to-market, momentum) and exposures to standard risk factors (market, size, value, profitability, investment, reversal).
- **Peer Effects:** Activities within Morningstar style categories (share increases, decreases, no-change), including lags, to capture contemporaneous behavior of similar funds.
- **Macroeconomic Variables:** Lagged term spreads, default spreads, and short-/long-term real and nominal yields to proxy financing and risk conditions.
- **Position-Level Context:** Market value, lagged shares (up to six quarters), weight dynamics, size rank within the fund, and padding indicators for balanced-panel construction.
- All features lagged to ensure observability at prediction time.



Feature Variables Construction, $\mathcal{X}_t$

Variable	Description
Fund-level signals	
<i>Lagged Fund Returns</i>	Prior-quarter and multi-quarter returns of the fund portfolio.
<i>Lagged Fund Flows</i>	Net cash inflow/outflow at the fund level, aggregated to the quarter.
<i>Lagged Fund Characteristics</i>	Size (e.g., AUM), value tilt, and momentum tilt of the fund, constructed from holdings or reported style metrics.
Security-level signals	
<i>Lagged Security Characteristics</i>	Equity size (e.g., log market capitalization), value (e.g., B/M ratio), and momentum (past returns over standard lookbacks).
<i>Risk/Factor Exposures</i>	Predictors from a curated factor list (market, size, value, profitability, investment, short-term reversal), merged at the permno-month level and aligned to quarters.
Peer/Category behavior	
<i>Category Activity Rates</i>	Share-increase, share-decrease, and no-change rates for the fund's Morningstar category (plus their lags), summarizing peer managers' trading behavior within the style bucket.
Macroeconomic backdrop	
<i>Lagged Macroeconomic Factors</i>	Level and slope of the yield curve and credit conditions, including term spreads (e.g., 5y-1y, 10y-3m), default spreads (e.g., BAA-Treasury), and related short/long yields (real and nominal).
Position & within-fund context	
<i>Market Value and Shares</i>	Current market value (mv) and lagged shares (sh) up to six quarters.
<i>Weight Dynamics</i>	Lagged and pass-through values used to compute portfolio weight changes.
<i>Rank Inside Fund (id)</i>	Size rank of the security within the fund each quarter (1 = largest).
<i>Padding Indicator (mask)</i>	Flags placeholder rows created to keep the panel rectangular.

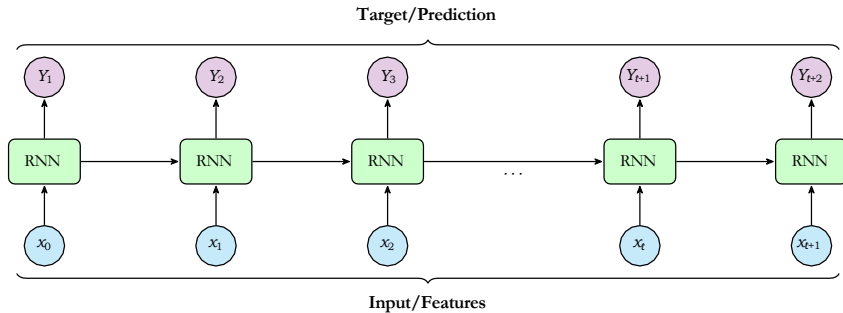


AI-ML Model

- We use LSTM (Long Short-Term Memory), a special kind of RNN (Recurrent Neural Network), capable of learning long-term dependencies, designed to handle sequential data and capture, retain, and reuse key information over long sequences.
- LSTMs overcome vanishing/exploding gradient problems in standard RNNs through a gating mechanism, enabling effective learning of long sequences.
- This approach is well-suited to our setting because fund managers' trading decisions often depend on past choices and long-term strategies.
- The model looks at sequences of past holdings and fund/security characteristics and learns how managers tend to adjust their positions.
- Compared to a simple naive rule (guessing the most common action), the LSTM captures richer, time-dependent patterns.
- We test the model on unseen data, making sure predictions reflect real-world behavior rather than just memorizing history.



RNN Model



LSTM Model

Recurrent Neural Networks (RNNs) struggle with long-term dependencies because of how their hidden state is updated during training and inference.

- Limited Memory Capacity:
 - The hidden state is a compressed representation of the past.
 - As the sequence gets longer, the RNN must squeeze more and more information into the same fixed-size vector.
 - Early information tends to be overwritten by more recent inputs, making long dependencies hard to retain.
- Bias Toward Short-Term Dependencies:
 - Because training emphasizes minimizing immediate prediction error, RNNs naturally focus on shorter, stronger correlations rather than weak long-range ones.
 - In practice, the model often learns local patterns well but fails to capture distant context.

→ LSTM (Long Short-Term Memory) introduce gating mechanisms (input, forget, output gates) to control information flow and mitigate vanishing gradients.



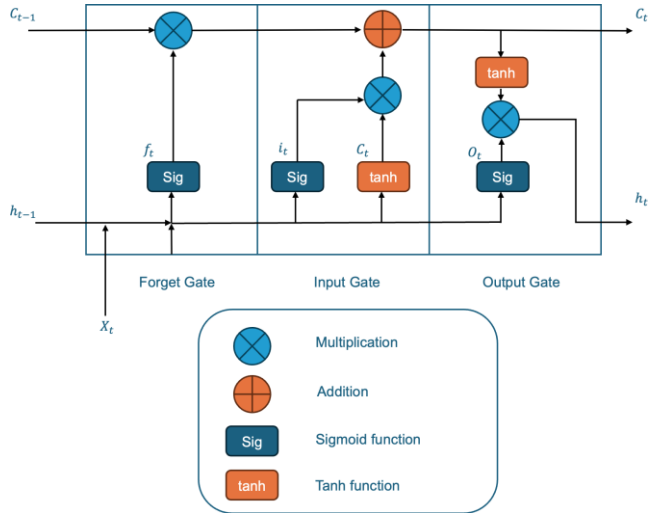
LSTM Model

LSTMs solve the long-term dependency problem by giving the network an explicit memory (Cell State) and by using gates to learn when to remember, when to forget, and when to expose information.

- LSTMs add a dedicated cell state that runs through the sequence with only minor linear interactions.
- LSTMs use three sigmoid-based gates to regulate what gets remembered (Input Gate), forgotten (Forget Gate), or exposed (Output Gate).
- Controlled Memory Update: the model can choose to keep old information for a very long time, solving the long-dependency issue.



LSTM Model



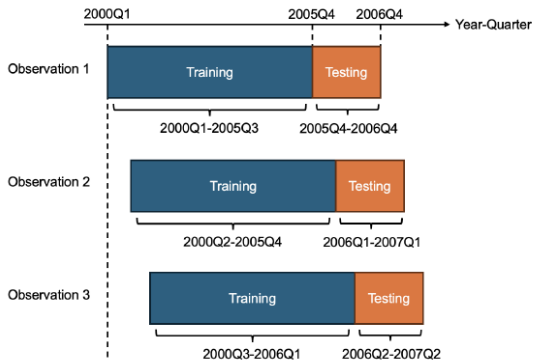
Empirical Design

- **Rolling panel construction:** For each fund, overlapping 28-quarter windows are formed, with the number of securities capped dynamically by the realized cross-sectional size in that window.
- **Observation unit:** All sequences and tensors are constructed at the *fund level*.
- **Sequence generation:** Within each window, fixed-length sequences of 8 quarters are created. Each sample is structured as a 3-D tensor of shape (T, N, F) , where $T = 8$, N is the number of retained securities, and F is the number of features.
- **Train–test split:** Each 28-quarter window is split chronologically: first 20 quarters for training, last 8 for testing. Time ordering is preserved (no random shuffling).



Empirical Design

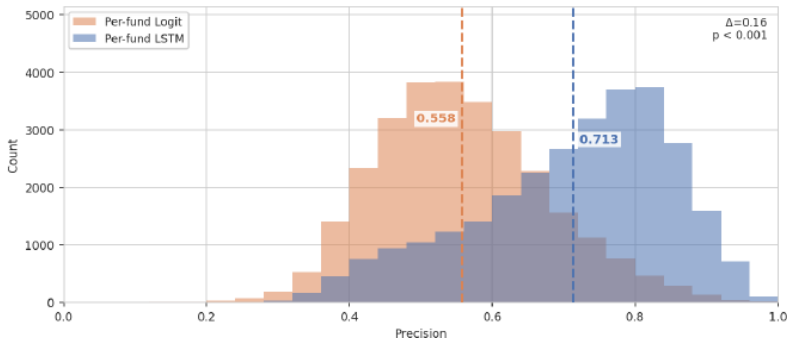
- **Train–test split:** Each 28-quarter window is split chronologically: first 23 quarters for training, last 5 for testing. Time ordering is preserved (no random shuffling).



Main Results

Performance Precision

This figure compares the distribution of model-based Prediction Precision with the Per-fund Logit Prediction Precision. The vertical dashed lines indicate the mean values.



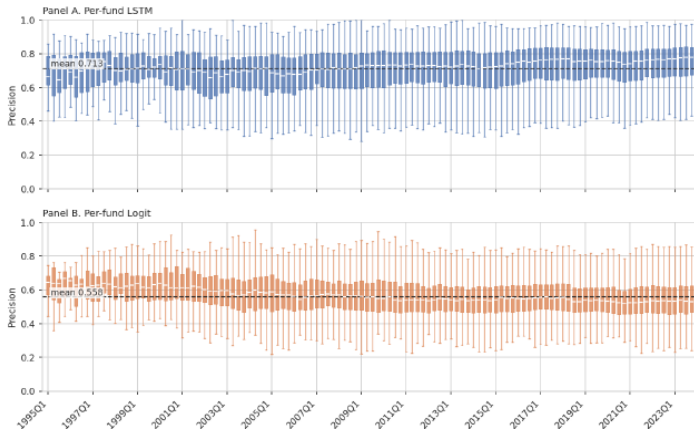
→ The Naive majority-class rule achieves only 55.8% accuracy, while the simple AI model improves average prediction accuracy to 71.3%, a highly significant 28% ($p < .001$) increase.

→ The AI model shifts and tightens the accuracy distribution, showing broad gains in predictability across the manager universe.



Performance Precision Over Time

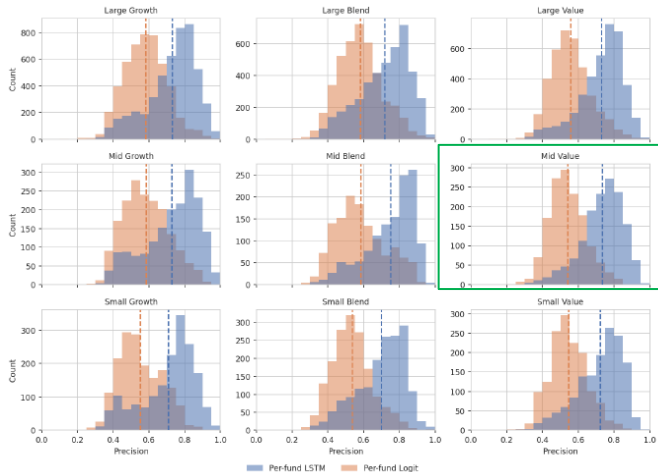
Quarterly distribution of weighted average precision from 1995Q1 to 2023Q1 (Model-based and benchmark Per-fund Logit). Each box plot summarizes the cross-sectional distribution of funds; the dashed horizontal line is the time-series mean.



→ The AI model maintains **stable prediction precision around 71%** with a slight upward trend in recent years — potentially reflecting greater quantitative tools and factor-based investing.



Performance Precision by Morningstar Style Category



→ Prediction precision is consistently higher with the AI model than the naive benchmark across all Morningstar categories, with larger-cap funds showing higher accuracy than small-cap, and the highest precision observed in mid-cap blend funds at 75%.



Dynamics of Prediction Precision at the Fund and Security Level

Manager Characteristics and Prediction Precision

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Manager Ownership	-0.0003*** (10.131)								
Manager Tenure (Max)		0.0007*** (4.253)							
Manager Tenure (Mean)			0.0006*** (9.296)						
Manager # Funds				0.0007*** (3.424)					
Manager # Styles					0.0023*** (4.629)				
Fund Age (years)						0.0021*** (4.234)			
Within Category Competition							-0.0001*** (3.028)		
Within Management Company Competition								-0.0024*** (3.304)	
Number of Managers									-0.0014*** (2.624)
Observations	16,208	53,878	53,878	53,878	53,878	53,878	52,536	40,803	53,878
R-squared	0.723	0.673	0.673	0.673	0.673	0.032	0.671	0.671	0.672
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Fund FE	YES	YES	YES	YES	YES	–	YES	YES	YES

→ **Tenure and Scope Increase Predictability:** Longer managerial tenure, managing more funds, and overseeing multiple styles all make trading behavior more predictable, potentially reflecting standardized processes and stable decision-making patterns.



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Fund FE	YES	YES	YES	YES	YES	–	YES	YES	YES

→ **Fund Age and Predictability:** Older funds display higher prediction precision, consistent with fund-maturity bringing more stable and consistent trading strategies that models can capture more effectively. A 1SD increase in fund age (~6 years), for instance, is associated with 5% more predictable managerial trading behavior, or over 23% of the SD of predictability.

→ **Competition and Team Size:** Greater competition (both within category and within fund families) and larger management teams reduce predictability, as competitive pressures and diverse decision-making could introduce irregularity and complexity into trading behavior.



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Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Fund FE	YES	YES	YES	YES	YES	–	YES	YES	YES

→ **Ownership Reduces Predictability:** Higher managerial ownership lowers prediction precision, consistent with personally invested managers making more idiosyncratic, incentive-driven decisions that reduce regularity in trading behavior. The coefficient implies a 1SD in managerial ownership reduces the ability to predict managerial trading behavior by 3.2% of the mean, or over 16% of the SD of predictability.



Prediction Precision and Security Characteristics

VARIABLES	(1)	(2)	(3)	(4)
		Prediction	Precision	
Portfolio Position	0.0020*** (52.407)			
Market Equity		-0.0000*** (-3.375)		
#Funds Position Held In			-0.0002*** (-4.659)	
Firm Age				0.0000*** (5.114)
Constant	-0.3202*** (-62.793)	-0.2566*** (-52.432)	-0.2563*** (-50.564)	-0.2677*** (-50.839)
Observations	5,958,755	5,316,273	5,958,755	5,327,875
R-squared	0.253	0.252	0.244	0.252
Quarter FE	YES	YES	YES	YES

→ **Smaller portfolio positions**, as well as **older firms**, are more predictable, while larger firms and securities widely held across many funds are less predictable—consistent with stability of mature firms' strategy along with the more predictability in firms playing a more minor role in portfolios.



Prediction Precision and Security Characteristics (Fundamentals)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Prediction Precision										
Total Debt/ME	0.0083*** (4.739)										
Asset Turnover		0.0029** (2.243)									
R&D/Sales			-0.0092*** (2.668)								
Gross Profit/ME				0.0048 (0.110)							
Free Cash Flow/ME					0.0235*** (3.373)						
Book Equity/ME						0.0365*** (16.053)					
Net Equity Payout/ME							0.2564*** (16.216)				
Earnings Surprise								-0.0036*** (11.256)			
Past 1 Month Return									-0.0414*** (5.863)		
Momentum 2-12 Months										-0.0315*** (12.173)	
CAPM Idio. Vol.											0.5843*** (6.829)
Observations	5,323,840	5,320,129	2,995,288	5,318,193	5,234,659	5,209,346	4,983,976	5,119,510	5,286,960	5,213,302	5,248,059
R-squared	0.223	0.223	0.223	0.223	0.223	0.224	0.223	0.224	0.223	0.224	0.224
Quarter-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

→ **Stable, Mature Firms:** Predictability is higher for stable, mature firms with stronger balance sheets and predictable payout policies.

→ **Growth and Shock-Prone Firms:** Predictability appears lower for growth, high R&D, and shock-prone firms, subject to larger earnings surprises. A 1SD lower B/M ratio for instance, is associated with a 2.3% lower ability to predict managerial trading behavior on the firm, or over 11% of the SD of predictability.



Prediction Precision and Security Characteristics (Fundamentals)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
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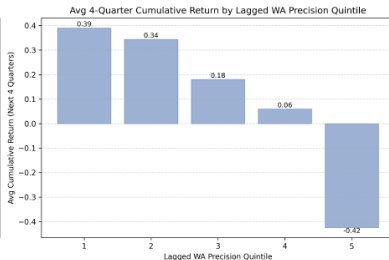
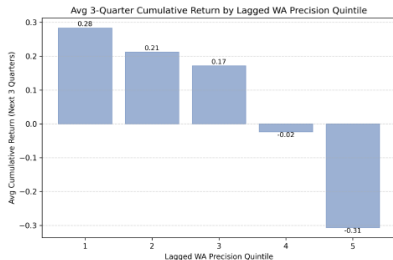
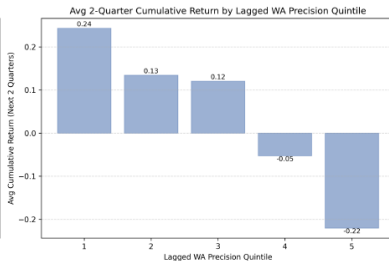
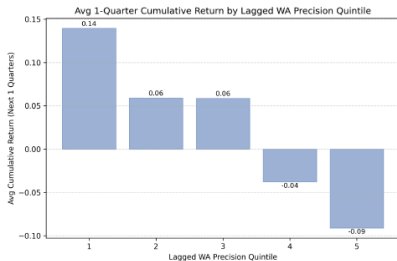
→ Managers' trading behavior is **more predictable in securities with recent losses**, both short- and longer-term, as shown by the significant negative relation between Past 1- and 2-12 Month Returns and predictability.



Implications for Fund Return Predictability

Performance Precision and Future Fund Performance

Funds are sorted into quintiles by lagged weighted-average (WA) precision (Q1 = lowest, Q5 = highest). Panels report average cumulative returns over 1–4 quarters post-formation.



Predictions and Future Fund Performance

Funds sorted into quintiles (Q1–Q5) by predicted precision; future category-adjusted cumulative excess returns ($CRET_{0,1}-CRET_{0,4}$). The column Q5–Q1 reports the spread.

	Q1	Q2	Q3	Q4	Q5	Q1–Q5
CRET[0, 1]	0.133* (1.96)	0.053 (0.73)	0.052 (1.00)	-0.044 (0.74)	-0.097 (1.62)	0.230** (2.13)
CRET[0, 2]	0.231** (2.42)	0.122 (1.19)	0.108 (1.09)	-0.065 (0.69)	-0.233** (2.19)	0.463*** (2.87)
CRET[0, 3]	0.264** (2.29)	0.194 (1.61)	0.153 (1.23)	-0.042 (0.38)	-0.326*** (2.62)	0.590*** (3.34)
CRET[0, 4]	0.365*** (2.86)	0.319** (2.15)	0.156 (1.43)	0.035 (0.26)	-0.449** (2.49)	0.815*** (3.05)

→ Fund managers whose trading is least predictable (Q1) consistently outperform peers, while the most predictable managers (Q5) consistently underperform, with increasingly negative and significant returns.

→ Returns are nearly monotonic across predictability quintiles, with the Q1–Q5 spread widening from 0.23% at one quarter to **0.813% (t=3.05) at four quarters.**



Future Predictability of Fund Performance – Risk Adjusted

Funds sorted into quintiles (Q1–Q5) by predicted precision; future category-adjusted cumulative excess returns ($CRET_{0,4}$). The column Q5–Q1 reports the spread, and risk adjustments by numerous factor models.

	Q1	Q2	Q3	Q4	Q5	Q1–Q5
Excess Return	0.365*** (2.86)	0.319** (2.15)	0.156 (1.43)	0.035 (0.26)	-0.449** (2.49)	0.815*** (3.05)
FF3 Alpha	0.374*** (2.80)	0.285* (1.85)	0.185 (1.62)	0.091 (0.64)	-0.439** (2.33)	0.812*** (2.85)
FF4 Alpha	0.308** (2.24)	0.313* (1.95)	0.281** (2.45)	0.119 (0.80)	-0.475** (2.43)	0.783*** (2.66)
FF5 Alpha	0.370*** (2.58)	0.105 (0.66)	0.249** (2.04)	0.079 (0.51)	-0.409** (2.03)	0.779** (2.53)

→ **The fund-level predictability we document in returns appears unrelated to known risk determinants,** as both the spread and monotonicity of returns across quintile portfolios are not materially impacted by risk-adjustments across numerous factor models.



Performance of Correctly vs. Incorrectly Predicted Portions of Portfolio - Within Manager -

	Incorrect Prediction	Correct Prediction	Difference	Quarters Incorrect > Correct
Excess Return	7.129*** (4.28)	6.125*** (3.77)	1.003*** (5.43)	70.7%*** [82/116]
FF ₃ Alpha	3.897*** (2.95)	2.879** (2.26)	1.018*** (5.83)	74.1%*** [86/116]
FF ₄ Alpha	4.233*** (3.08)	3.283** (2.48)	0.950*** (5.26)	70.7%*** [82/116]
FF ₅ Alpha	2.947** (2.07)	1.923 (1.40)	1.025*** (5.46)	75.0%*** [87/116]

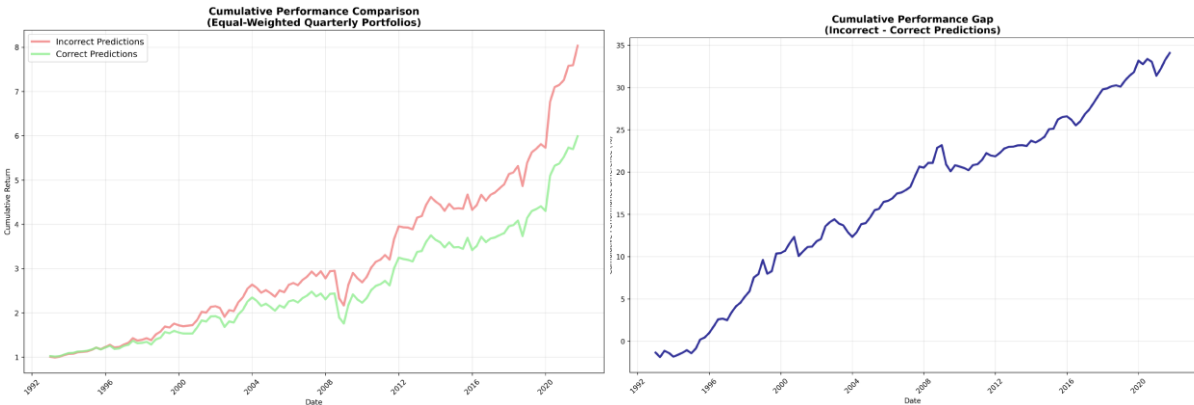
→ The portion of managers' portfolios that are not predictable **consistently and significantly outperform** the portion of the portfolio that is predictable.

→ The magnitude is annualized alpha of over 100 bps per quarter ($t=5.46$).

→ Moreover, the **non-predictable part of their portfolios outperform the predictable portion in 70-75% of future quarters.**



Performance of Correctly vs. Incorrectly Predicted Portions of Portfolio



→ The portion of managers portfolios that are not predictable are consistently outperforming the part of the portfolio that is predictable.

→ The relationship holds roughly stably throughout the sample period.



Least vs. Most Predictable Trades Across all Managers

Table XII. Portfolio Returns of Stocks Sorted on Percent of Correct Prediction

Panel A: Equal-Weighted							Quarters Q1 > Q5
	Q1 (Lowest)	Q2	Q3	Q4	Q5 (Highest)	Q1-Q5	
Excess Return	7.527*** (3.25)	5.768*** (2.65)	4.306** (2.01)	2.990 (1.25)	1.092 (0.40)	6.435*** (6.42)	78.4%*** [91/116]
FF3 Alpha	3.590** (2.01)	1.829 (1.11)	0.393 (0.24)	-1.448 (0.82)	-3.176 (1.48)	6.766*** (7.03)	78.4%*** [91/116]
FF4 Alpha	4.059** (2.19)	2.627 (1.54)	1.446 (0.87)	-0.234 (0.13)	-1.503 (0.69)	5.562*** (6.10)	74.1%*** [86/116]
FF5 Alpha	2.654 (1.37)	0.580 (0.33)	-0.760 (-0.43)	-2.621 (1.38)	-3.815 (1.63)	6.469*** (6.19)	77.6%*** [90/116]

→ Stocks are sorted into quintiles each quarter based upon the percentage of fund managers whose trades can be correctly predicted on the stock, from: least predictable (Q1) to most predictable (Q5) trading behavior of the stock.

→ Returns are monotonically decreasing across predictability quintiles, with the least predictable (Q1) firms outperforming the most predictable (Q5) by **6.469% ($t=6.19$) in Risk-Adjusted Annualized Equal-Weighted Returns** in the following quarter (annualized) over the sample period.



Least vs. Most Predictable Trades Across all Managers

Table XII. Portfolio Returns of Stocks Sorted on Percent of Correct Prediction

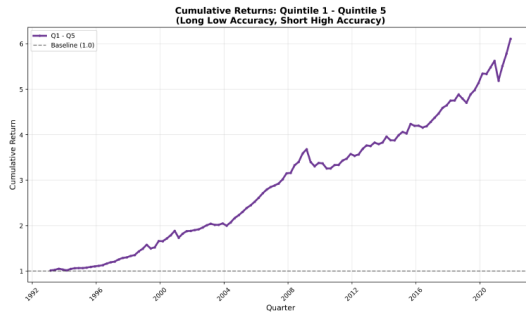
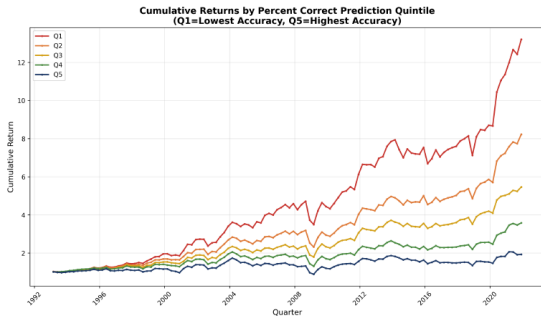
Panel B: Value-Weighted

	Q1 (Lowest)	Q2	Q3	Q4	Q5 (Highest)	Q1-Q5	Quarters Q1 > Q5
Excess Return	10.295*** (5.37)	7.107*** (4.21)	4.847*** (2.90)	3.865** (2.05)	2.472 (1.00)	7.823*** (4.64)	72.4%*** [84/116]
FF3 Alpha	7.258*** (4.50)	3.708*** (2.84)	1.535 (1.17)	0.292 (0.20)	-1.817 (0.95)	9.076*** (6.70)	80.2%*** [93/116]
FF4 Alpha	7.607*** (4.54)	3.837*** (2.82)	1.917 (1.41)	0.894 (0.60)	-0.752 (0.39)	8.359*** (6.01)	79.3%*** [92/116]
FF5 Alpha	5.923*** (3.46)	2.547* (1.82)	0.428 (0.30)	-0.578 (0.37)	-2.665 (1.29)	8.588*** (5.89)	79.3%*** [92/116]

→ This is not driven by small stocks, as it is even larger in VW returns, at **8.588% ($t=5.89$) Annualized Alpha**.



Least vs. Most Predictable Trades Across all Managers



→ Stocks are sorted into quintiles each quarter based upon the percentage of fund managers whose trades can be correctly predicted on the stock, from: least predictable (Q1) to most predictable (Q5) trading behavior of the stock.

→ Returns are monotonic across quintiles, and the (Q1-Q5) spread is stably positive and significant over the sample period.



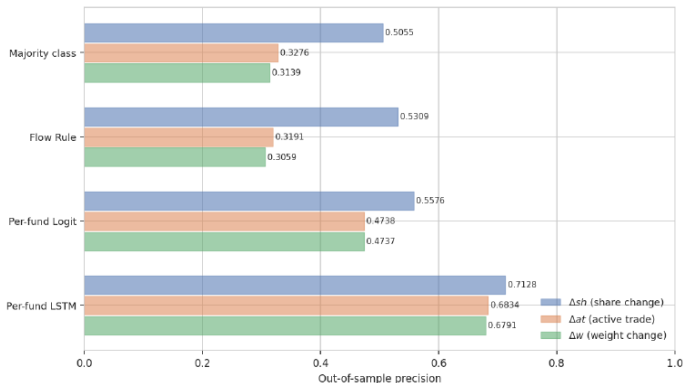
Prediction Precision and Controlling for Measures of Managerial Divergence Activity

VARIABLES	(1)	(2)	(3)	(4)	(5)
			CRET _[0,4]		
Prediction Precision	-0.8554** (2.06)	-1.0074** (2.38)	-1.0261*** (2.70)	-1.1795*** (2.67)	-1.2561*** (2.82)
Active Share		0.0041*** (5.15)	0.0032*** (4.41)	0.0028** (2.51)	0.0016* (1.75)
Tracking Error				-0.0185 (-1.25)	0.0077 (0.32)
R ²					1.3271** (2.14)
RET _[-1,0]			0.1311** (2.09)	0.1070* (1.73)	0.1042* (1.70)
CRET _[-4,0]			0.0628** (2.12)	0.0769** (2.48)	0.0822*** (2.65)
Observations	40585	40585	40585	38648	38104
Avg. R-squared	0.00533	0.00854	0.106	0.127	0.138

→ The predictability of future managerial trading decisions from past behavior that we document is orthogonal to past measures of managerial activeness and divergence activity in predicting returns: using Active Share, Tracking Error, and R² of fund returns from common factors measures, Prediction Precision remains large and significant in predicting future fund returns.



Alternative Definitions of Trading Behavior: Port Weight Chg and Active Trade

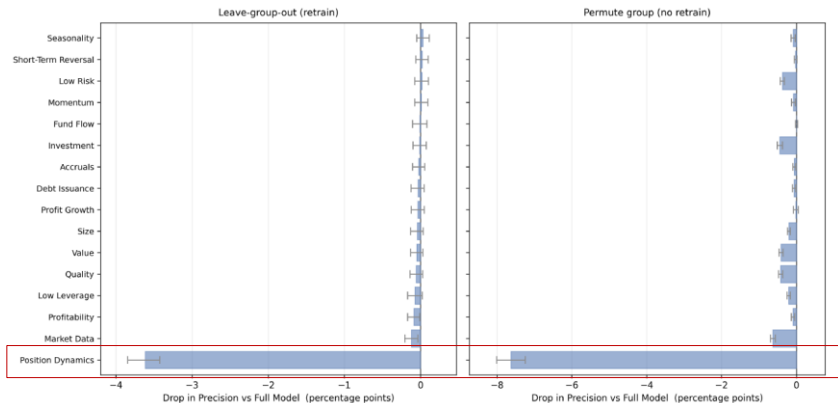


→ We compare and retrain the model to predict instead of trades of buying, selling, or holding shares, changes in portfolio weights, and active trades (changes in weights partialing out the impact of realized returns), and find similar predictability. This holds especially for the LSTM model, along with Per-fund Logit (and less so for Flow-based or Majority Class identifier models with regard to these alternative outcomes and predictability of actions).



Feature-block Ablation

We run feature-block Ablation analyses to explore the importance of each set of features in the predictability of future managerial trading behavior. We run two separate analyses: leaving out the entire block of features, and re-running the model, and permuting all of the values in the given block while keeping all other feature data constant and re-running the model. We then compare the predictability in each to the original model, and below shows the impact on prediction precision.



→ Past managerial trading behavior emerges as having the largest and strongest impact on prediction of future managerial behavior across both methods.



Conclusion

Conclusion

- We are the first paper to explore the fundamental aspects of financial agent behavior that can be learned and repeated given the most recent advances in technology.
- Simple AI model, trained on past trading, fund-, manager-, and firm-level characteristics, predicts **71% of trades (buy/hold/sell)**.
- Predictability is stable across time and manager styles.
- Manager behavior is more predictable and replicable for managers who have a longer history of trading and are in less competitive categories.
- The larger the ownership stake of the manager in the fund, the less predictable their behavior.
- Strong link to performance:
 - **Most predictable managers** → underperform peers.
 - **Least predictable managers** → strong future outperformance.
 - **Performance concentrated in least predictable trades** within each manager's portfolio and across the universe of stocks held.



Conclusion and Moving Ahead

Future research:

- **Strategic response:** Agents may obfuscate or alter behavior to avoid detection/replication.
- **Equilibrium contracts:** Labor and incentive structures must adapt to these tools.
- Extend beyond fund managers to:
 - Other financial agents (e.g., financial analysts, research associates).
 - Firm decision-makers (e.g., CEOs, Risk and Compliance).
 - Consultancy Services



Thank you so much again for your wonderful time and attention!

We really appreciate your comments and suggestions!

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