Man vs. Machine: Quantitative and Discretionary Equity Management

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Abstract

I use machine learning to categorize US active equity mutual funds as quantitative (reliant on computer models and fixed-rules) or discretionary (reliant on human judgment). I then formulate hypotheses of how their holdings and performance might differ, based on the conjecture that quantitative funds might have more learning capacity but less flexibility to adapt to changing market conditions than discretionary funds. Consistent with those hypotheses, I find that quantitative funds hold more stocks, specialize in stock picking, and engage in more overcrowded trades. Discretionary funds hold lesser-known stocks, switch between picking and timing and outperform quantitative funds in recessions.

Keywords: Investment Management, Quantitative Mutual Funds, Machine Learning, Rational Inattention.

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INTERNET APPENDIX

A Training Sample

The following section contains details regarding the collection of the pre-classified PIS sample utilized for training the random forest algorithm to recognize quantitative or discretionary strategy descriptions. The sample classifications were collected through IRB # AAAS3044, which contains the full procedure utilized in selecting classifiers, explaining the task at hand and handling the collected data.

A.1 Expert Selection

Students interested in participating in the training sample labeling had to provide answers to the following list of questions:

1. Which degree are you currently enrolled in?
2. How many Finance courses have you taken in your Academic career?
   - List the most relevant courses
3. Have you ever participated in a Research Project in Finance?
   - If yes, what project (if more than one, mention the most relevant)?
4. Have you ever worked in the Finance industry for an investment company or another related job?
   - If yes, what was your role (if more than one, mention the most relevant)?
5. Are you an English language native speaker?
6. If not, please answer the following questions:
   - Have you completed a degree in an English-speaking country?
     - If yes, what type of degree (e.g. High School, Bachelor, Masters, ...)?

  - If not, have you studied for at least 3 years in an English-speaking country? What type of degree were you studying for (e.g. High School, Bachelor, Masters, ...)?

- Have you ever worked in an English-speaking country?
  - If yes, for how long?

B Classification

B.1 Random Forest Algorithm

The random forest is a type of decision tree classifier, specifically it is an ensemble of decision trees, whose final classification is decided by majority voting.

Binary decision tree classifiers consist in breaking down the data into subsets by asking a series of questions inferred from the training sample. More specifically at the root of the tree the algorithm computes the information gain obtained by splitting the data according to each feature in the features matrix. The feature that determines the highest information gain is chosen and the training sample is split into two sub-samples according to the chosen feature. The second iteration includes two nodes, for each of the two nodes the same procedure is repeated and so on iteratively until all samples at each node belong to the same class. In order to avoid over-fitting a limit to the maximum depth of the tree is usually set – this is referred to as pruning. In a binary tree the information gain which is maximized at every split is defined as the difference in impurity between the parent node and the two children nodes:

$$IG(Node_{parent}, f) = I(Node_{parent}) - \frac{N_{left}}{N_p} I(Node_{leftchild}) - \frac{N_{left}}{N_p} I(Node_{rightchild})$$

where $IG(Node_{parent}, f)$ is the information gain at the parent node for feature f and N_p, N_{right} and N_{left} are the number of samples in the parent node, the right and the left children nodes respectively.

The impurity measure $I(node)$ used in this paper is entropy:

$$I(node) = -\sum_{i=1}^{class} p(i|node) log_2 p(i|node)$$

where $p(i|node)$ is the proportion of samples in the node that belong to class i – hence entropy is 0 when all samples in a node belong to the same class and it is maximum when samples are uniformly distributed across classes.

Figure B.1 represents graphically a single decision tree pruned at 3 branches. The representation was created utilizing the pre-classified samples belonging to the training sample.[1]

When utilizing a single decision tree, strong over-fitting issues are generally encountered. A way to minimize these issues is to employ a random forest.

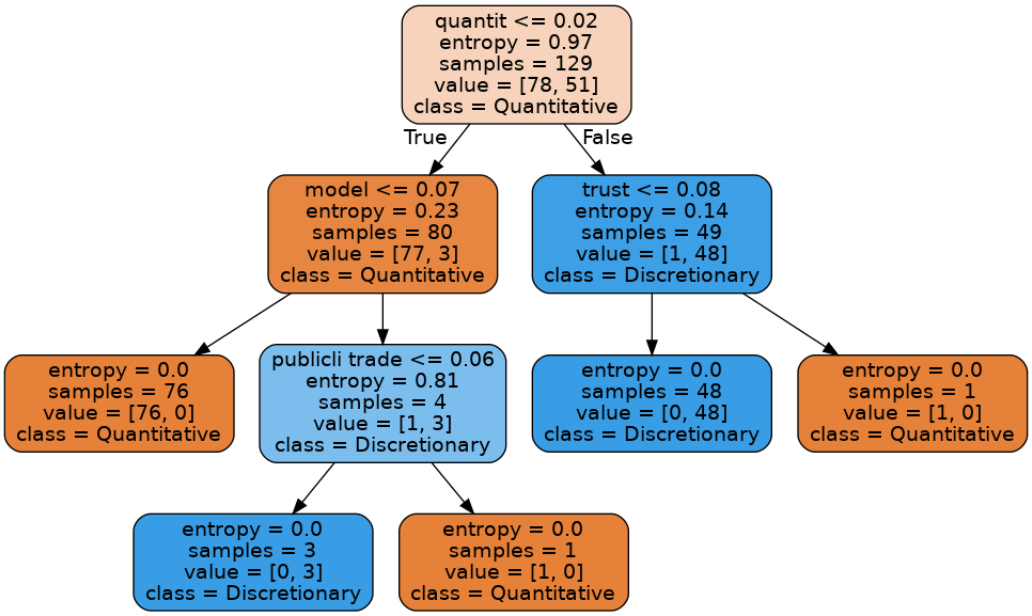
The random forest algorithm can be described in four steps:

1. Randomly choose a sample of size n from the training sample with replacement
2. Grow a decision tree from the selected sample. At each node:
   (a) Randomly select f features from the features matrix without replacement
   (b) Among the selected subset of features (f) choose the one that maximizes the information gain and split the node according to that feature
3. Repeat the above 2 steps k times and record the classification of each item in the training sample by each of the k trees
4. Use majority voting to assign a final classification to each item in the training sample

The key parameter to be chosen is the number of trees in the random forest (k), the larger the number the better the prediction but the higher the computational burden. In this paper $1,000$ trees were used.

[1] This was created for illustration purposes only. This tree was not used in creating the classification.

Figure B.1: **Single decision tree example:** Graphical illustration of the decision making process of a single decision tree. The tree was constructed using the 129 pre-classified sections utilized in training the random forest algorithm (78 pre-classified as *Discretionary* and 51 pre-classified as *Quantitative*)—i.e. it excludes the pre-classified sections belonging to the test sample. Each box displays the stemmed feature (word or bi-gram) with the highest entropy, on the bases of which splitting is decided. Each box additionally displays the computed entropy (to be minimized), the number of total samples, and the number of samples assigned a quantitative or discretionary label. The tree is pruned to have a depth of 3. This tree is just for illustration purposes. This specific tree was not utilized in the creation of the classification utilized in the paper.



B.2 Examples of Classified PIS sections

Excerpt from a PIS section categorized as belonging to a *Quantitative* fund.[2]

> The Fund will be broadly diversified across companies and industries and will invest in companies that the Adviser has identified to have stable businesses with low leverage, low earnings-per-share variability and other measures of risk and high profitability. The Adviser believes that the stocks of these types of companies tend to be lower "beta" stocks and that lower "beta" stocks generally are less volatile than higher "beta" stocks (that is, their value has a lower sensitivity to fluctuations in the securities markets). The Adviser expects low "beta" stocks to produce higher risk-adjusted returns over a full market cycle than high "beta" stocks. The Fund is actively managed and the Adviser will vary the Fund's exposures to issuers and industries based on the Adviser's evaluation of investment opportunities. In constructing the portfolio, the Adviser uses quantitative models, which combine active management to identify quality companies and statistical measures of risk to assure diversification by issuer and industry. (AQR US Defensive Equity Fund. September 2014)

Excerpt from a PIS section categorized as belonging to a *Discretionary* fund.

> Sentinel attempts to identify companies that are expected to grow as a result of the potential long-term return from their investment in research, development, capital spending and market expansion. In addition, Sentinel looks for companies that it perceives to be attractively valued relative to their future growth prospects, as well as to that of the market as a whole. Sentinel utilizes a blended "top-down" and "bottom-up" approach. In top-down analysis, focus is on such macroeconomic factors as inflation, interest and tax rates, currency and political climate. In bottom-up analysis, focus is on company-specific variables, such as competitive industry dynamics, market leadership, proprietary products and services, and management expertise, as well as on financial characteristics, such as returns on sales and equity, debt/equity ratios and earnings and cash flow growth. (Sentinel Capital Growth Fund. March 2008)

[2] The full strategy descriptions were utilized for the categorization. I am reporting excerpts for brevity.

C Switchers

In order to show that classification changes reflect changes in behavior, I focus on switching funds (funds that change *Quant* status in their lifetime). I then check whether the similarity in portfolio allocation between switching funds and the average *Quantitative* fund is greater in months in which they receive a *Quantitative* assignment, through the following regressions:

$$D_{jt} = \alpha + \beta_1 Quant_{jt} + \beta_1 Quant_{jt} \times Recession_t + \gamma X_{jt} + \eta_t + \theta_j + \epsilon_{jt} | Switcher = 1 \quad (1)$$

for $D_{jt} = [Comm^Q_{jt},\ AComm^Q_{jt},\ ln(Disp^Q)_{jt}]$, indicating the portfolio commonality or dispersion of fund j relative to all funds classified as quantitative in month t. *Switcher* is an indicator variable equal to 1 for funds that at any point in time change classification. θ_j indicates fund fixed-effects. All other regression specifications are equivalent to those described for Eq. 1 in the main body of the paper. The outcome of those regressions is displayed in Table C.1, which shows a significant β_1 in all models, providing support to the assumption that changes in language reflect changes in behavior.[3]

Table C.1: **Switchers:** Dependent variables: holdings commonality ($Comm^Q$), active commonality ($AComm^Q$) and dispersion ($ln(Disp^Q)$) of switching funds relative to the average quantitative fund. Independent variables and all regression specifications are the same as described in Table 3, in the paper's body. Control variables are omitted for brevity.

	(1) $Comm^Q$	(2) $AComm^Q$	(3) $ln(Disp^Q)$
Constant	7.408***	-1.060	0.270
	(3.34)	(-0.40)	(0.77)
Quant	0.608***	0.413**	-0.175***
	(3.83)	(2.28)	(-5.05)
Quant × *Recess*	0.198	0.190	-0.057
	(1.04)	(0.97)	(-1.13)
$AdjustedR^2$	0.87	0.78	0.44
Obs	87,529	87,529	87,529
$\bar{y}^D$	15.583	8.654	0.324

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

[3] β_1 is positive (negative) when using commonality (dispersion) as dependent variable–Models 1-2 (3).

D Rater Disagreement

As a further robustness test of rater agreement I re-train the machine learning algorithm by splitting the sample to include 75% and 25% of students (8 and 2 students respectively).

I build a summary classification based on a 50% level of agreement for both samples (i.e., based on the classification of 8 randomly selected students and on that of the remaining 2 students). I chose a 50% level of agreement given the small size of the 2-students sample. I then randomly select 75% of prospectuses to belong to the training set and 25% to the test set. I train the random forest algorithm on the 8-students summary classification, for the prospectuses in the training set. I then test the accuracy of the algorithm in classifying the sections in the test set, based on the summary classification provided by the 2 remaining students. I achieve a test accuracy of 91.07%, which corresponds to a 94% precision and 92% recall for discretionary sections and an 85% precision and 89% recall for quantitative sections. Results are comparable to those obtained in the baseline model, as described in the paper's main Appendix, alleviating concerns of high disagreement among classifiers.

E Accuracy in the Wild

In order to assess the accuracy of the classification in the wild–i.e. among PIS sections that did not belong to the training sample–I asked three students to classify a random selection of 250 PIS sections that had been previously classified (*test sample (wild)*) following the methodology outlined in the paper's main Appendix. The experiment was run similarly to the one utilized to obtain the training sample.[4] Students were provided the same set of instructions as those provided to the original classifiers and were asked to categorize as *Quantitative* or *Discretionary* the PIS sections in the *test sample (wild)*. Importantly, they were not made aware of how the random forest algorithm had previously categorized those same sections. The *test sample (wild)* was chosen randomly among all classified section as follows: first, I excluded the 500 sections that belonged to the training sample; next, I randomly selected one PIS section per fund; finally, among the remaining sections, I randomly selected 125 that the random forest had classified as *Quantitative* and 125 that it had classified as *Discretionary*.

[4] Students were all Master Students at Columbia University, coming from a variety of programs and were fluent in the English language.

All students agreed on a *Discretionary* assignment for 128 sections, 115 of which had been classified as *Discretionary* by the random forest algorithm. At least two of the three students then agree on a *Quantitative* assignment for the majority of the remaining sections. To assess the goodness of the random forest in the *test sample (wild)* I built two summary classifications from the answers of the three students to utilize as ground truth: method (1) I consider as *Quantitative* those sections that at least one student classified as such; method (2) I consider as *Quantitative* those sections that at least two students classified as such. I then compute the overall accuracy, recall, precision, Fleiss Kappa and Gwet's gamma of the random forest classification relative to these summary classifications.

Utilizing method (1) the random forest classification displays a 90.8% level of observed agreement (Accuracy), an 81.6% Fleiss Kappa, and an 81.6% Gwet's gamma with respect to the summary classification.[5] That corresponds to a 92% precision and a 90% recall (90% precision and a 92% recall) for the *Discretionary* (*Quantitative*) assignments (confusion matrix in Panel 1 of Table E.1). Utilizing Method (2) the random forest classification displays an 84% level of observed agreement (Accuracy), a 67.65% Fleiss Kappa, and a 67.99% Gwet's gamma with respect to the summary classification. That corresponds to a 94% precision and a 78% recall (74% precision and a 93% recall) for the *Discretionary* (*Quantitative*) assignments (confusion matrix in Panel 2 of Table E.1).

Given the small scale of this experiment and the fact that the outcome is still quite close to that obtained in the training sample; I assume the accuracy of the classification in the full sample to be comparable to that obtained in the training sample.

Table E.1: **Confusion Matrices:** Confusion matrices in assessing the quality of the random forest classification in the wild, utilizing method (1) to construct a summary classification (Panel 2) and utilizing method (2) (Panel 3). Rows indicate Random Forest assignments, columns indicate human assignments; 0 indicates *Discretionary* assignments, 1 *Quantitative*.

		Method (1)				*Method* (2)	
		Human				*Human*	
		0	1			0	1
Random Forest	0	115	10	*Random Forest*	0	118	7
Random Forest	1	13	112	*Random Forest*	1	33	92

[5]Here Fleiss Kappa and Gwet's gamma have the same score as there is no skewness in the classification distribution by construction (I selected 125 sections classified as quantitative and 125 as discretionary).

F Training Sample Alternative Threshold

I replicate the paper's key results by utilizing a 50% agreement threshold for training sample construction. In baseline results I construct a summary classification utilizing a 75% agreement threshold—i.e., I consider as quantitative those sections for which at least 8 out of the 10 reliable classifiers agree on a quantitative assignment. Here I lower that threshold to 50%—i.e. I construct a summary classification by considering as quantitative those sections for which at least 6 out of the 10 reliable classifiers agree on a quantitative assignment.

Table F.1: **Age, Size and Style:** Dependent variables: funds' age ($ln(Age)$), size ($ln(TNA)$), turnover ratio ($Turnover$), amount of cash held in percentage of TNA ($Cash$), style ($Market$, $Size$, $Value$, Mom, $Invest.$ and $Profit.$). Independent variables: a dummy identifying quantitative funds ($Quant$); the interaction between $Quant$ and a dummy identifying NBER recessions ($Quant \times Recess$); expense ratio ($Expenses$); turnover ratio ($Turnover$); growth in net fund flows ($FlowsGrowth$); volatility in net fund flows growth ($FlowsVol$); fund loads ($Loads$); fund style, size and age as listed above. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's main body. Controls have been omitted for brevity. Each regression excludes the control variable corresponding to the dependent variable. All regressions include month fixed–effects (FE); standard errors are clustered at the month and fund level (Cl).

	(1) ln(Age)	(2) ln(TNA)	(3) Turnover	(4) Cash	(5) Market	(6) Size	(7) Value	(8) Mom	(9) Investment	(10) Profitability
Constant	3.99***	3.93***	58.18***	3.70***	0.73***	-0.15***	0.02	0.11***	0.21***	0.10***
	(54.28)	(17.56)	(7.44)	(9.50)	(98.29)	(-3.66)	(0.65)	(5.14)	(4.91)	(3.91)
Quant	-0.09***	-0.32***	26.08***	-0.49***	0.01**	-0.02*	0.01**	0.01***	0.01***	0.03***
	(-3.47)	(-5.40)	(10.58)	(-5.22)	(2.45)	(-1.74)	(2.18)	(4.39)	(2.60)	(6.20)
Quant X Recess	-0.03	0.07	-4.12	-0.33**	0.01	-0.01	0.01	0.01	0.00	-0.01
	(-1.17)	(1.11)	(-1.42)	(-2.29)	(1.51)	(-0.57)	(0.70)	(1.33)	(0.35)	(-0.62)
Adjusted R2	0.28	0.31	0.14	0.08	0.94	0.15	0.36	0.18	0.16	0.30
Obs	331,660	331,660	331,660	314,850	331,660	331,660	331,660	331,660	331,660	331,660

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table F.2: **Flows and Fees:** Dependent variables: growth in net fund flows ($FlowGrowth$), volatility of net fund flows growth ($FlowVol$), funds' expense ratio ($Expenses$), management fees ($Mgmt$), Actual 12b1 fees ($12b1$) and fund loads ($Loads$). Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's main body. Independent variables and all regression specifications are the same as described in Table F.1. Control variables are omitted for brevity.

	(1) FlowsGrowth	(2) FlowsVol	(3) Expenses	(4) Mgmt	(5) Actual 12b1	(6) Loads
Constant	2.672***	0.129***	1.642***	0.652***	0.471***	-0.024***
	(13.38)	(28.01)	(41.65)	(17.58)	(12.91)	(-16.38)
Quant	-0.069	0.001	-0.060***	-0.016	0.005	-0.000
	(-1.22)	(0.68)	(-4.98)	(-1.48)	(0.43)	(-1.03)
Quant X Recess	-0.341***	0.003	-0.008	-0.024*	0.003	-0.001
	(-2.95)	(0.88)	(-0.59)	(-1.83)	(0.27)	(-1.59)
Adjusted R2	0.06	0.08	0.35	0.07	0.31	0.19
Obs	331,660	331,660	331,660	331,320	227,653	331,660

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table F.3: **Investment Style:** Dependent variables: funds' gross of fees excess return ($ExcessRet$), for quants (Model (1)) or discretionaries (Model (2)); Fama-French 6–factor idiosyncratic volatility ($IVol - ff6$). Models (1)-(2) include factor returns as per Fama-French 6 factor model (MKT, HML, SMB, UMD, RMW, CMA) and no other control variables or fixed-effects. Models (3)-(4) include the same independent variables as described in Table F.1 (control variables are omitted for brevity), and month fixed-effects. Standard errors are clustered at the fund and month level in all regressions. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's main body.

	R		$ln(IVol - ff6)$	
	Quant	*Discretionary*	24m	36m
	(1)	(2)	(3)	(4)
Constant	-0.044	0.014	-0.398***	-0.318***
	(-1.20)	(0.38)	(-6.64)	(-4.66)
Quant			-0.094***	-0.090***
			(-6.09)	(-5.66)
Quant X Recess			0.037**	0.030*
			(1.99)	(1.74)
MKT	1.018***	1.013***		
	(68.68)	(65.90)		
HML	0.015	0.009		
	(0.54)	(0.36)		
SMB	0.212***	0.211***		
	(9.47)	(10.60)		
UMD	0.039***	0.010		
	(3.09)	(0.75)		
RMW	0.051**	0.019		
	(2.31)	(1.01)		
CMA	-0.040	-0.025		
	(-1.28)	(-0.87)		
Adjusted R2	0.83	0.78	0.47	0.49
Obs	56,807	298,464	304,136	279,137

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table F.4: **Prediction 1: High Ability Funds:** Graphical representation of regression coefficients. Panel 1 Dependent variables: macro-timing in recessions with respect to innovations in industrial production ($IndPro$ (R)) or non-farm payrolls ($NFPay$ (R)); and characteristic-timing in recessions ($DGTW$ (R)). Panel 2 Dependent variables: stock picking in recessions ($Picking$ (R)); characteristic-timing in expansions ($DGTW$ (E)); and macro-timing in expansions with respect to innovations in industrial production ($IndPro$ (E)) or non-farm payrolls ($NFPay$ (E)) respectively. Independent variables: a dummy identifying quantitative funds ($Quant$), dummy variables identifying the top $q\%$ of funds with the highest timing ability in recessions ($TopT\_R$) or picking ability in expansions ($TopP\_E$); and the interaction between the $Quant$ dummy (in interactions abbreviated with: Q) and the high-ability dummies ($TopP\_ExQ$, $TopT\_RxQ$). Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's main body. Coefficients are estimated using high-ability cut-offs of $q = 10\%$ to $q = 25\%$. Bars indicate 90% confidence intervals. Control variables and all regression specifications are the same as described in Table F.1. Control variables are omitted for brevity.

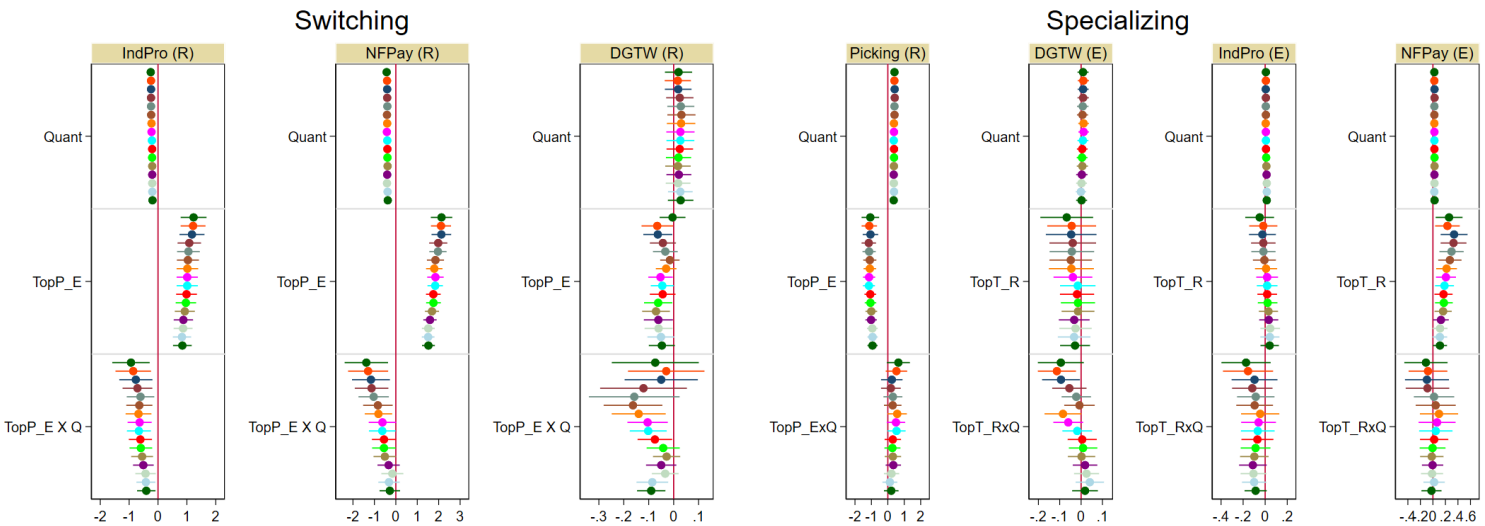


Table F.5: **Prediction 1: Average Picking and Timing Abilities:** Dependent variables: stock picking (SP_SUE), macro-timing (MT_IndPro, MT_NFPay) and characteristics-timing (CT_DGTW) abilities. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's main body. Independent variables and all regression specifications are the same as described in Table F.1. Control variables are omitted for brevity.

	SP_SUE (1)	MT_IndPro (2)	MT_NFPay (3)	CT_DGTW (4)
Constant	0.0383	0.2874***	-0.0891	-0.0964
	(0.23)	(3.25)	(-0.71)	(-0.76)
Quant	-0.0552**	0.0119	0.0297	0.0170
	(-2.08)	(0.66)	(1.27)	(0.97)
Quant X Recess	0.5590***	-0.3885***	-0.6182***	-0.0644
	(5.94)	(-4.00)	(-6.54)	(-1.59)
R2	0.18	0.37	0.38	0.57
Obs	331,269	290,626	290,626	331,660
Controls	Yes	Yes	Yes	Yes
FE: Month	Yes	Yes	Yes	Yes
Cl: Month+Fund	Yes	Yes	Yes	Yes

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table F.6: **Prediction 2: Portfolio Diversification:** Dependent variables: the natural log of the number of stocks held ($ln(NStocks)$), and of the volatility of fund returns ($ln(RetVol)$). Independent variables and all regression specifications are the same as described in Table F.1; control variables are omitted for brevity. Model (6) also controls for the percentage of cash held ($Cash$). Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's body.

	$ln(NStocks)$		$ln(RetVol)$	
			$24m$	$36m$
	(1)	(2)	(3)	(4)
Constant	4.490***	4.605***	1.240***	1.298***
	(42.20)	(41.84)	(49.11)	(46.36)
Quant	0.211***	0.193***	-0.022***	-0.022***
	(7.11)	(6.49)	(-3.91)	(-3.78)
Quant X Recess	0.023	0.015	0.018**	0.021***
	(0.76)	(0.47)	(2.39)	(2.86)
Cash		-0.017***		
		(-7.75)		
Adjusted R2	0.19	0.20	0.77	0.77
Obs	331,660	314,850	304,136	279,137
Controls	Yes	Yes	Yes	Yes
FE: Month	Yes	Yes	Yes	Yes
Cl: Month+Fund	Yes	Yes	Yes	Yes

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table F.7: **Prediction 3: Information Gap:** Dependent variables: TNA-weighted average of the natural log of market capitalization ($ln(MktCap)$), of age in months (Age), of the natural log of monthly media mentions ($ln(News)$), and of the number of analysts following the stocks held ($Analysts$). Independent variables are the same as described in Table F.1, plus the illiquidity of stocks held—measured using Amihud ratio—($Illiquidity$). Control variables omitted for brevity. Models (4), (6), and (8) additionally control for $ln(MktCap)$. Model (1) excludes from the control variables set the size style ($Size$). All regression specifications are the same as described in Table F.1. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's body.

	Stock Characteristics							
	$ln(MktCap)$		Age		$ln(News)$		$Analysts$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	10.228***	9.565***	345.222***	-120.310***	3.872***	-1.886***	5.909***	-7.336***
	(38.60)	(67.87)	(27.32)	(-7.94)	(36.23)	(-16.61)	(20.19)	(-10.09)
Quant	0.098	0.027	11.392***	10.077***	0.037	0.020	-0.032	-0.069*
	(1.34)	(0.77)	(4.03)	(4.59)	(1.53)	(1.53)	(-0.51)	(-1.84)
Quant X Recess	-0.016	-0.039	-0.205	1.675	-0.034	-0.010	-0.078	-0.025
	(-0.24)	(-1.03)	(-0.05)	(0.56)	(-1.24)	(-0.57)	(-1.14)	(-0.45)
Illiquidity	-0.941***	-0.318***	7.187**	22.662***	-0.050***	0.142***	-0.428***	0.012
	(-3.06)	(-4.38)	(2.41)	(5.35)	(-2.72)	(3.47)	(-4.45)	(0.17)
Size		-3.988***	-200.835***	-6.760	-2.301***	0.101**	-6.361***	-0.839**
		(-126.07)	(-52.17)	(-1.32)	(-67.06)	(2.13)	(-26.12)	(-2.38)
n(MktCap)				48.670***		0.602***		1.385***
				(42.52)		(61.15)		(18.91)
Adjusted R2	0.11	0.60	0.50	0.69	0.52	0.85	0.63	0.76
Obs	331,656	331,656	331,656	331,656	331,510	331,510	331,656	331,656
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cl: Month+Fund	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table F.8: **Prediction 4: Commonality:** Dependent variables: holdings commonality ($Comm$), active commonality ($AComm$), and the natural log of dispersion ($Log(Disp)$). Independent variables and all regression specifications are the same as described in Table F.1. Control variables are omitted for brevity. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's body.

	$Comm$	$AComm$	$ln(Disp)$
	(1)	(2)	(3)
Constant	8.381***	2.588***	0.181
	(12.98)	(4.11)	(1.38)
Quant	2.538***	1.313***	-0.091***
	(16.47)	(11.73)	(-2.92)
Quant X Recess	0.541**	0.438**	-0.138***
	(2.42)	(2.34)	(-3.36)
Adjusted R2	0.58	0.54	0.16
Obs	331,660	331,660	331,656
Controls	Yes	Yes	Yes
FE: Month	Yes	Yes	Yes
Cl: Month+Fund	Yes	Yes	Yes

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table F.9: **Prediction 5: Performance:** Dependent variables: 24–months (Models (1, 2) and 36–months (Models (3, 4)) rolling Fama-French 6 *Alpha* (Panel 1) and Value Added (VA, Panel 2); constructed monthly and averaged within a quarter. Independent variables are the same as described in Table F.1, but they are lagged. Controls are omitted for brevity. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's main body. Models (1, 3) utilize OLS regressions. Models (2, 4) median quantile regressions (50th quantile). All regressions are run at the quarterly frequency and include quarter fixed–effects (FE); standard errors are clustered (Cl) at the quarter and fund level. For median regressions that is achieved through bootstrapping with 100 repetitions.

	$24m\ OLS$ (1)	$24m\ q50$ (2)	$36m\ OLS$ (3)	$36m\ q50$ (4)
		$Alpha - ff6$		
Constant	0.171**	0.503***	0.155**	0.783***
	(2.33)	(6.32)	(2.11)	(9.78)
Quant	-0.030**	-0.011**	-0.033**	-0.020***
	(-2.23)	(-2.00)	(-2.58)	(-3.17)
QuantXRecession	-0.087*	-0.071***	-0.089**	-0.067**
	(-1.97)	(-2.85)	(-2.21)	(-2.55)
		$VA - ff6$		
Constant	1.440	0.835***	2.236	2.168***
	(0.44)	(6.49)	(0.58)	(6.89)
Quant	-0.417**	-0.012*	-0.388*	-0.009
	(-2.25)	(-1.78)	(-1.95)	(-1.10)
QuantXRecession	1.126	-0.090***	0.945	-0.113***
	(1.04)	(-2.62)	(0.69)	(-3.54)
Obs	100,499	100,499	92,487	92,487

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table F.10: **Prediction 5: Performance and Information Gap:** Dependent variables: 24–months (Models (1)-(3)), and 36–months (Models (4)-(6)) rolling Fama-French 6 Value Added (VA); constructed monthly and averaged within a quarter. Independent variables are the same as described in Table F.1, plus: information gap proxies, measured as: the age of stocks held (Age), the natural logarithm of the number of times stocks held are mentioned monthly in Dow Jones news ($ln(News)$), the natural logarithm of the market capitalization of stocks held ($ln(MktCap)$). Are also included interactions between information gap proxies and the $Quant$ dummy. Independent variables are lagged. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's main body. Estimates are obtained for the median fund through quantile regressions ($q = 50$). Control variables are omitted for brevity. All regressions are run at the quarterly frequency and include quarter fixed–effects (FE); standard errors are clustered (Cl) at the quarter (Qt) and fund (F) level, achieved through bootstrapping with 100 repetitions.

	VA_24m			VA_36m		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.8964***	0.9366***	1.1092***	2.2128***	2.2528***	2.4250***
	(6.32)	(6.86)	(7.93)	(5.86)	(5.67)	(6.99)
Quant	-0.0884***	-0.0457*	-0.1064***	-0.0965***	-0.0376	-0.1009*
	(-3.95)	(-1.88)	(-3.05)	(-3.87)	(-1.29)	(-1.84)
Quant X Recess	-0.0955***	-0.1036***	-0.0910***	-0.1110***	-0.1124***	-0.1106***
	(-2.86)	(-3.68)	(-3.20)	(-3.74)	(-3.92)	(-3.18)
Age	-0.0004***			-0.0003***		
	(-10.27)			(-8.84)		
Age X Quant	0.0002***			0.0003***		
	(3.86)			(4.10)		
ln(News)		-0.0317***			-0.0253***	
		(-7.98)			(-5.06)	
ln(News) X Quant		0.0088			0.0073	
		(1.51)			(1.09)	
ln(MktCap)			-0.0287***			-0.0262***
			(-8.81)			(-7.01)
ln(MktCap) X Quant			0.0096***			0.0095*
			(2.78)			(1.79)
Obs	99,765	99,726	99,764	91,814	91,783	91,813
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: Qt	Yes	Yes	Yes	Yes	Yes	Yes
Cl: Qt+Fund	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table F.11: **Prediction 5: Performance and Commonality or Overcrowding:** Dependent variables: 24–months and 36–months rolling Fama-French 6 Value Added (VA); constructed monthly and averaged within a quarter. Independent variables are the same as described in Table F.1 (where *Quant* is abbreviated as Q, and *Recession* as R), plus: commonality, active commonality, overcrowding and active overcrowding (C, AC, OC, AOC, respectively), and their interaction with Q. Independent variables are lagged. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's main body. Estimates are obtained for the median fund through quantile regressions ($q = 50$). Control variables are omitted for brevity. All regressions are run at the quarterly frequency and include quarter fixed–effects (FE); standard errors are clustered (Cl) at the quarter (Qt) and fund (F) level, achieved through bootstrapping with 100 repetitions.

	$VA - ff6$							
	24m	36m	24m	36m	24m	36m	24m	36m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
intercept	0.894***	2.234***	0.863***	2.197***	0.880***	2.229***	0.863***	2.203***
	(5.69)	(6.39)	(7.49)	(6.55)	(6.68)	(7.19)	(5.94)	(6.39)
Q	-0.028*	-0.040**	-0.013	-0.016	-0.060***	-0.058***	-0.027**	-0.026*
	(-1.90)	(-1.98)	(-1.10)	(-1.29)	(-3.89)	(-3.35)	(-2.16)	(-1.75)
Q X R	-0.095***	-0.119***	-0.093***	-0.115***	-0.086**	-0.101***	-0.086***	-0.114***
	(-2.75)	(-3.41)	(-3.08)	(-3.81)	(-2.42)	(-3.29)	(-2.73)	(-3.17)
C	-0.007***	-0.007***						
	(-8.87)	(-8.52)						
C X Q	0.003**	0.003**						
	(2.42)	(2.51)						
AC			-0.010***	-0.011***				
			(-9.94)	(-8.70)				
AC X Q			0.002	0.003*				
			(1.17)	(1.71)				
OC					-0.004***	-0.003***		
					(-9.02)	(-6.73)		
OC X Q					-0.010*	-0.009		
					(-1.83)	(-1.48)		
AOC							-0.005***	-0.006***
							(-11.43)	(-11.37)
AOC X Q							-0.033***	-0.035***
							(-3.44)	(-3.10)
Obs	99,766	91,815	99,766	91,815	99,766	91,815	99,766	91,815
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Qt	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cl: Qt+F	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

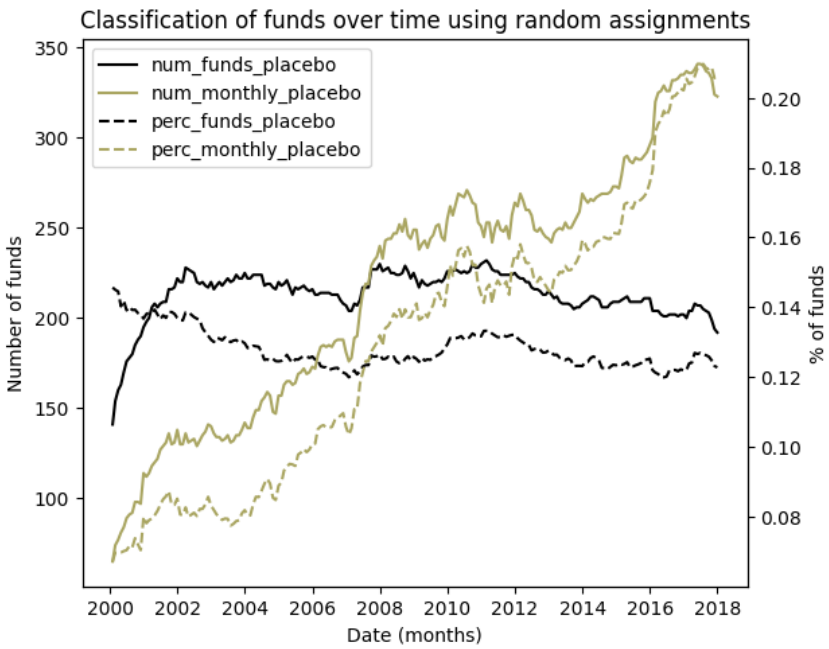
t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

G Placebo Classifications

G.1 Construction

The first placebo (*funds_placebo*) takes as input the overall percentage of observations classified as being quantitative (13.05%), then randomly selects 13.05% of funds from the overall sample (415 funds) and it permanently assigns a value of 1 to those funds (0 otherwise). The second (*months_placebo*) is constructed by randomly assigning a value of 1 every month to as many observations as those classified to belong to quantitative funds in that month (0 otherwise). Figure G.1 shows both the number of funds and the percentage of funds assigned to the two placebo classifications over time.

Figure G.1: **Placebo classifications:** Number of funds (left index) and percentage of funds (right index) belonging to the two placebo classifications over time.



G.2 Regressions

I replicate all regressions in the paper using the two placebo classifications instead of the quantitative classification constructed using the random forest algorithm. All results are included next.

Table G.1: **Age, size and style:** Dependent variables: funds' age ($ln(Age)$), size ($ln(TNA)$), turnover ratio ($Turnover$), the amount of cash held in percentage of TNA ($Cash$), and style ($Market$, $Size$, $Value$, Mom, $Invest.$ and $Profit.$). Independent variables: funds_placebo (F – Panel 1) and months_placebo (M – Panel 2) dummies and their interaction with a dummy identifying NBER recessions periods ($Recess$); expense ratio ($Expenses$); turnover ratio ($Turnover$); growth in net fund flows ($FlowsGrowth$); the volatility in net fund flows growth ($FlowsVol$); total fund loads ($Loads$); fund style, size and age as listed above. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's body. All explanatory variables are de-meaned such that the $Constant$ can be interpreted as the unconditional mean of the dependent variable for Discretionary funds. Control variables have been omitted for brevity. Each regression excludes the control variable corresponding to the dependent variable. All regressions include month fixed–effects (FE); standard errors are clustered at the month and fund level (Cl).

	ln(Age) (1)	ln(TNA) (2)	Turnover (3)	Cash (4)	Market (5)	Size (6)	Value (7)	Mom (8)	Invest. (9)	Profit. (10)
Constant	3.96***	3.85***	69.22***	3.47***	0.74***	-0.16***	0.02	0.12***	0.21***	0.11***
	(54.21)	(17.20)	(8.64)	(8.97)	(97.69)	(-3.91)	(0.86)	(5.42)	(5.03)	(4.23)
F	0.03	-0.14	0.11	0.09	-0.00	0.01	-0.01	0.00	-0.01	0.00
	(0.80)	(-1.58)	(0.04)	(0.72)	(-1.42)	(0.74)	(-0.86)	(0.36)	(-0.85)	(0.96)
F X Recess	-0.00	-0.02	0.14	0.26	0.00	0.01	-0.01**	-0.00	-0.02*	0.01
	(-0.11)	(-0.41)	(0.07)	(1.32)	(0.51)	(0.92)	(-2.05)	(-0.60)	(-1.85)	(1.04)
R2	0.28	0.31	0.12	0.08	0.94	0.15	0.35	0.18	0.16	0.30
Obs	331,660	331,660	331,660	314,850	331,660	331,660	331,660	331,660	331,660	331,660
Constant	3.97***	3.83***	69.26***	3.48***	0.74***	-0.16***	0.02	0.12***	0.21***	0.11***
	(54.27)	(17.15)	(8.63)	(9.02)	(98.46)	(-3.88)	(0.81)	(5.42)	(5.00)	(4.28)
M	0.00	-0.01	-0.09	0.04**	-0.00	0.00	0.00*	0.00***	0.00	-0.00**
	(0.36)	(-0.86)	(-0.25)	(2.08)	(-1.14)	(0.96)	(1.71)	(3.17)	(0.34)	(-2.47)
M X Recess	0.02*	-0.03	-0.88	0.04	0.00	-0.00	-0.00	-0.01***	0.00	-0.00
	(1.80)	(-1.13)	(-0.72)	(0.53)	(1.60)	(-0.42)	(-1.25)	(-2.98)	(0.15)	(-0.44)
R2	0.28	0.31	0.12	0.08	0.94	0.15	0.35	0.18	0.16	0.30
Obs	331,660	331,660	331,660	314,850	331,660	331,660	331,660	331,660	331,660	331,660

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table G.2: **Flows and Fees:** Dependent variables: growth in net fund flows ($FlowGrowth$), the volatility of net fund flows growth ($FlowVol$), funds' expense ratio ($Expenses$), management fees ($Mgmt$), Actual 12b1 fees ($12b1$) and fund loads ($Loads$). Variables construction is detailed in Table 1; summary statistics are reported in Table 2. Independent variables and all regression specifications are the same as described in Table G.1. Control variables are omitted for brevity.

	Flow		*Fees*			
	Growth (1)	*Vol* (2)	*Expenses* (3)	*Mgmt* (4)	12*b*1 (5)	*Loads* (6)
Constant	2.642***	0.130***	1.628***	0.645***	0.472***	-0.025***
	(13.22)	(28.11)	(41.42)	(17.44)	(12.96)	(-16.65)
F	-0.060	-0.002	-0.009	0.016	0.000	0.001
	(-1.03)	(-1.65)	(-0.49)	(1.07)	(0.01)	(1.19)
F X Recess	-0.005	0.003	-0.007	-0.005	-0.003	0.000
	(-0.05)	(1.08)	(-0.79)	(-0.49)	(-0.70)	(0.38)
R2	0.06	0.08	0.35	0.07	0.31	0.19
Obs	331,660	331,660	331,660	331,320	227,653	331,660
Constant	2.629***	0.129***	1.627***	0.647***	0.473***	-0.025***
	(13.18)	(27.99)	(41.38)	(17.54)	(13.00)	(-16.63)
M	0.023	0.000	-0.003	0.000	-0.003**	0.000
	(1.07)	(0.23)	(-1.54)	(0.01)	(-2.57)	(0.48)
M X Recess	0.002	0.000	-0.002	-0.002	-0.001	0.000
	(0.03)	(0.42)	(-0.30)	(-0.57)	(-0.20)	(0.73)
R2	0.06	0.08	0.35	0.07	0.31	0.19
Obs	331,660	331,660	331,660	331,320	227,653	331,660

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table G.3: **Prediction 1: High Ability Funds—funds placebo:** Graphical representation of regression coefficients. Panel 1 Dependent variables: macro-timing in recessions with respect to innovations in industrial production ($IndPro$ (R)) or non-farm payrolls ($NFPay$ (R)); and characteristic-timing in recessions ($DGTW$ (R)). Panel 2 Dependent variables: stock picking in recessions ($Picking$ (R)); characteristic-timing in expansions ($DGTW$ (E)); and macro-timing in expansions with respect to innovations in industrial production ($IndPro$ (E)) or non-farm payrolls ($NFPay$ (E)) respectively. Independent variables: a dummy identifying the funds_placebo classification ($F\_placebo$), dummy variables identifying the top $q\%$ of funds with the highest timing ability in recessions ($TopT\_R$) or picking ability in expansions ($TopP\_E$); and the interaction between the $F\_placebo$ dummy (in interactions abbreviated with: F) and the high-ability dummies ($TopP\_ExQ$, $TopT\_RxQ$). Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's body. Coefficients are estimated using high-ability cut-offs of $q = 10\%$ to $q = 25\%$. Bars indicate 90% confidence intervals. Control variables and all regression specifications are the same as described in Table G.1. Control variables are omitted for brevity.

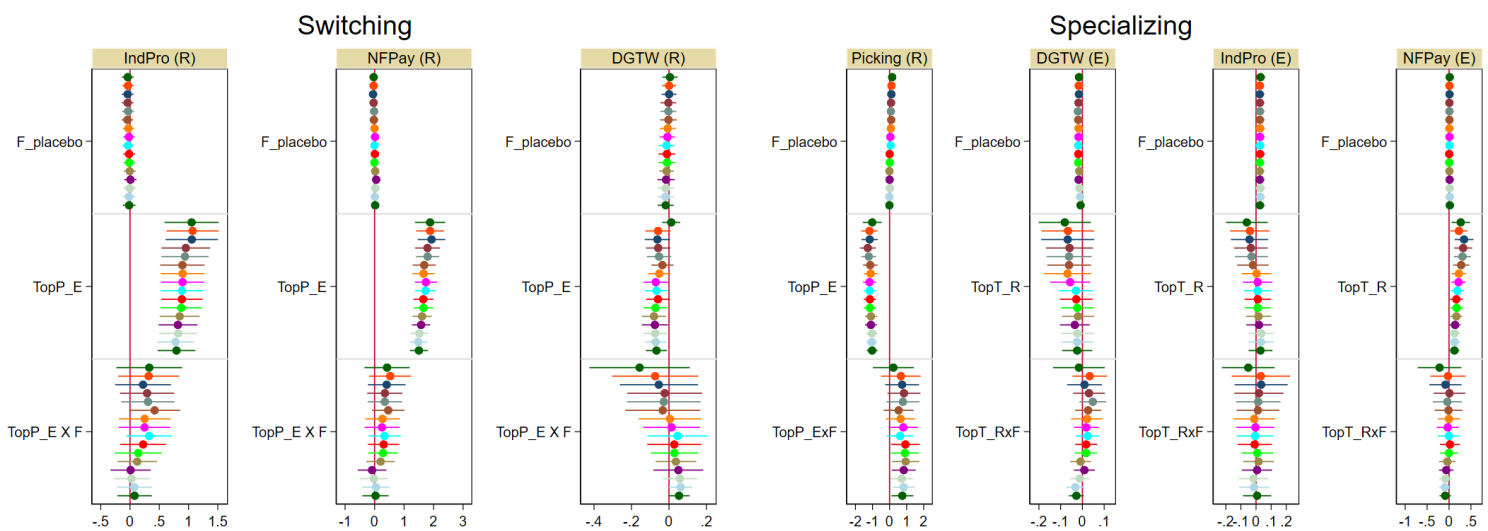


Table G.4: **Prediction 1: High Ability Funds—months placebo:** Graphical representation of regression coefficients. Panel 1 Dependent variables: macro-timing in recessions with respect to innovations in industrial production ($IndPro$ (R)) or non-farm payrolls ($NFPay$ (R)); and characteristic-timing in recessions ($DGTW$ (R)). Panel 2 Dependent variables: stock picking in recessions ($Picking$ (R)); characteristic-timing in expansions ($DGTW$ (E)); and macro-timing in expansions with respect to innovations in industrial production ($IndPro$ (E)) or non-farm payrolls ($NFPay$ (E)) respectively. Independent variables: a dummy identifying the months_placebo classification ($M\_placebo$), dummy variables identifying the top $q\%$ of funds with the highest timing ability in recessions ($TopT\_R$) or picking ability in expansions ($TopP\_E$); and the interaction between the $M\_placebo$ dummy (in interactions abbreviated with: M) and the high-ability dummies ($TopP\_ExQ$, $TopT\_RxQ$). Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's body. Coefficients are estimated using high-ability cut-offs of $q = 10\%$ to $q = 25\%$. Bars indicate 90% confidence intervals. Control variables and all regression specifications are the same as described in Table G.1. Control variables are omitted for brevity.

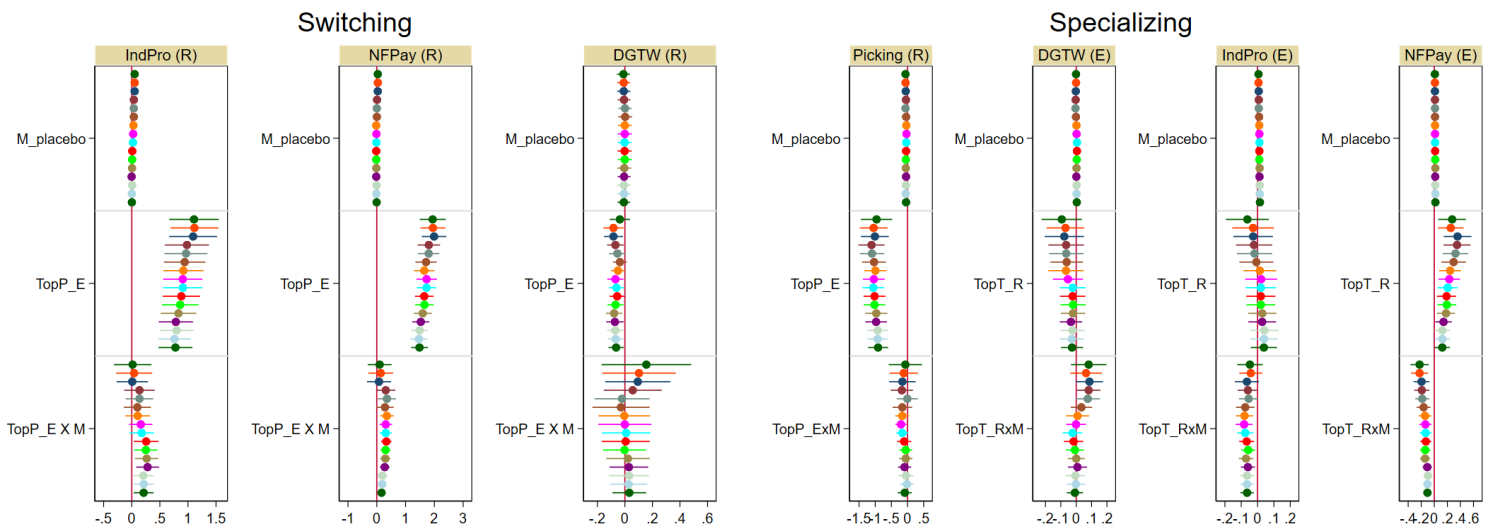


Table G.5: **Prediction 1: Average Picking and Timing Abilities:** Dependent variables: stock picking (SP_SUE), macro-timing (MT_IndPro, MT_NFPay) and characteristics-timing (CT_DGTW) abilities. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's body. Independent variables and all regression specifications are the same as described in Table G.1. Control variables are omitted for brevity.

	SP_SUE (1)	MT_IndPro (2)	MT_NFPay (3)	CT_DGTW (4)
Constant	0.0428	0.2711***	-0.1067	-0.0908
	(0.25)	(3.07)	(-0.83)	(-0.72)
F	-0.0284	0.0262	0.0086	-0.0148*
	(-1.17)	(1.44)	(0.38)	(-1.66)
F X Recess	0.2104*	-0.0092	0.0372	0.0140
	(1.72)	(-0.14)	(0.36)	(0.58)
Adjusted R2	0.18	0.37	0.38	0.57
Obs	331,269	290,626	290,626	331,660
Constant	0.0451	0.2740***	-0.1058	-0.0931
	(0.27)	(3.10)	(-0.82)	(-0.74)
M	-0.0138	0.0037	0.0034	0.0016
	(-1.18)	(0.65)	(0.52)	(0.19)
M X Recess	-0.0777	0.0532**	0.0626*	0.0013
	(-1.08)	(2.00)	(1.71)	(0.05)
Adjusted R2	0.18	0.37	0.38	0.57
Obs	331,269	290,626	290,626	331,660

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.0

Table G.6: **Prediction 2: Portfolio Diversification:** Dependent variables: the natural log of the number of stocks held ($ln(NStocks)$), and of the volatility of fund returns ($ln(RetVol)$). Independent variables and all regression specifications are the same as described in Table G.1; control variables are omitted for brevity. Model (6) also controls for the percentage of cash held ($Cash$). Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's body.

	$ln(NStocks)$		$ln(RetVol)$	
			$24m$	$36m$
	(1)	(2)	(3)	(4)
Constant	4.564***	4.676***	1.232***	1.290***
	(43.17)	(42.78)	(49.17)	(46.51)
F	0.040	0.044	0.003	0.004
	(1.10)	(1.22)	(0.50)	(0.53)
F X Recess	-0.014	-0.003	-0.008	-0.008
	(-0.70)	(-0.12)	(-0.92)	(-1.20)
Cash %		-0.018***		
		(-8.11)		
R2	0.18	0.19	0.77	0.77
Obs	331,660	314,850	304,136	279,137
Constant	4.571***	4.684***	1.232***	1.290***
	(43.16)	(42.79)	(49.29)	(46.62)
M	-0.002	0.000	0.001	0.001
	(-0.45)	(0.06)	(1.15)	(1.27)
M X Recess	-0.008	-0.011	-0.001	-0.003
	(-0.62)	(-0.89)	(-0.15)	(-1.02)
Cash %		-0.018***		
		(-8.09)		
R2	0.18	0.19	0.77	0.77
Obs	331,660	314,850	304,136	279,137

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table G.7: **Prediction 3: Information Gap—funds placebo:** Dependent variables: TNA-weighted average of the natural logarithm of market capitalization ($ln(MktCap)$), of age in months (Age), of the natural logarithm of monthly media mentions ($ln(News)$), and of the number of analysts following the stocks held ($Analysts$). Independent variables are the same as described in Table G.1, plus the illiquidity of stocks held—measured using Amihud ratio—($Illiquidity$). The key variable of interest is the funds_placebo (F). Control variables are omitted for brevity. Models (4), (6), and (8) additionally control for $ln(MktCap)$. Model (1) excludes from the control variables set the size style ($Size$). All regression specifications are the same as described in Table G.1. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 of the paper's main body.

	Stock Characteristics							
	$ln(MktCap)$		Age		$ln(News)$		$Analysts$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	10.271***	9.571***	349.045***	-116.963***	3.883***	-1.879***	5.885***	-7.367***
	(39.10)	(68.09)	(27.66)	(-7.72)	(36.43)	(-16.57)	(20.15)	(-10.14)
F	-0.035	0.011	2.477	1.926	0.002	-0.005	0.042	0.027
	(-0.33)	(0.23)	(0.62)	(0.64)	(0.06)	(-0.34)	(0.54)	(0.58)
F X Recess	0.004	0.025	2.403	1.196	0.014	-0.002	0.086	0.052
	(0.11)	(1.07)	(0.92)	(0.52)	(0.60)	(-0.10)	(1.54)	(1.05)
Illiquidity	-0.942***	-0.318***	7.053**	22.545***	-0.050***	0.142***	-0.427***	0.013
	(-3.07)	(-4.38)	(2.40)	(5.31)	(-2.75)	(3.45)	(-4.43)	(0.19)
Size		-3.988***	-201.130***	-6.947	-2.301***	0.101**	-6.360***	-0.839**
		(-126.22)	(-52.20)	(-1.35)	(-67.10)	(2.13)	(-26.13)	(-2.38)
ln(MktCap)				48.689***		0.602***		1.385***
				(42.48)		(61.15)		(18.90)
R2	0.11	0.60	0.50	0.69	0.52	0.85	0.63	0.76
Obs	331,656	331,656	331,656	331,656	331,510	331,510	331,656	331,656

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.0

Table G.8: **Prediction 3: Information Gap—months placebo:** Dependent variables: TNA-weighted average of the natural logarithm of market capitalization ($ln(MktCap)$), of age in months (Age), of the natural logarithm of monthly media mentions ($ln(News)$), and of the number of analysts following the stocks held ($Analysts$). Independent variables are the same as described in Table G.1, plus the illiquidity of stocks held—measured using Amihud ratio—($Illiquidity$). The key variable of interest is the months_placebo (M). Control variables are omitted for brevity. Models (4), (6), and (8) additionally control for $ln(MktCap)$. Model (1) excludes from the control variables set the size style ($Size$). All regression specifications are the same as described in Table G.1. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 of the paper's main body.

	Stock Characteristics							
	$ln(MktCap)$		Age		$ln(News)$		$Analysts$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	10.266***	9.574***	349.549***	-116.622***	3.884***	-1.880***	5.898***	-7.357***
	(39.18)	(68.31)	(27.71)	(-7.70)	(36.50)	(-16.58)	(20.23)	(-10.12)
M	-0.010	-0.003	-0.464	-0.298	-0.003	-0.001	-0.038***	-0.033***
	(-1.03)	(-0.56)	(-1.00)	(-0.77)	(-0.66)	(-0.30)	(-2.72)	(-2.75)
M X Recess	0.007	-0.002	0.988	1.068	0.014	0.015*	0.014	0.016
	(0.22)	(-0.08)	(0.67)	(1.09)	(0.90)	(1.86)	(0.39)	(0.49)
Illiquidity	-0.942***	-0.318***	7.042**	22.537***	-0.050***	0.142***	-0.427***	0.013
	(-3.06)	(-4.38)	(2.39)	(5.30)	(-2.75)	(3.46)	(-4.44)	(0.19)
Size		-3.988***	-201.091***	-6.908	-2.301***	0.101**	-6.360***	-0.838**
		(-126.15)	(-52.19)	(-1.35)	(-67.07)	(2.13)	(-26.13)	(-2.38)
ln(MktCap)				48.692***		0.602***		1.385***
				(42.49)		(61.15)		(18.91)
R2	0.11	0.60	0.50	0.69	0.52	0.85	0.63	0.76
Obs	331,656	331,656	331,656	331,656	331,510	331,510	331,656	331,656

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.0

Table G.9: **Prediction 4: Commonality:** Dependent variables: holdings commonality ($Comm$), active commonality ($AComm$), and the natural log of dispersion ($Log(Disp)$). Independent variables and all regression specifications are the same as described in Table G.1. Control variables are omitted for brevity. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's body.

	$Comm$ (1)	$AComm$ (2)	$ln(Disp)$ (3)
Constant	9.940***	3.457***	0.114
	(14.78)	(5.45)	(0.88)
F	0.140	0.029	-0.024
	(0.67)	(0.19)	(-0.55)
F X Recess	0.143	0.051	-0.020
	(1.02)	(0.43)	(-0.54)
R2	0.55	0.53	0.16
Obs	331,660	331,660	331,656
Constant	9.969***	3.466***	0.109
	(14.81)	(5.46)	(0.84)
M	-0.028	-0.026	0.004
	(-1.09)	(-1.30)	(0.74)
M X Recess	0.019	0.037	-0.001
	(0.23)	(0.55)	(-0.09)
R2	0.55	0.53	0.16
Obs	331,660	331,660	331,656

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table G.10: **Prediction 5: Performance:—funds placebo:** Dependent variables: 24–months (Models (1) and (3)) and 36–months (Models (2) and (4)) rolling Fama-French 6 *Alpha* (Panel 1) and Value Added (VA, Panel 2; constructed monthly and averaged within a quarter. Independent variables are the same as in Table G.1, but they are lagged. Control variables are omitted for brevity. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's body. Models (1) and (3) utilize OLS regressions. Models (2) and (4) utilize quantile regressions for the 50th quantile. All regressions are run at the quarterly frequency and include quarter fixed–effects (FE); standard errors are clustered at the quarter and fund level (Cl). For quantile regressions that is achieved through bootstrapping with 100 repetitions.

	$24m\ OLS$ (1)	$24m\ q50$ (2)	$36m\ OLS$ (3)	$36m\ q50$ (4)
		$Alpha - ff6$		
Constant	0.154**	0.501***	0.137*	0.783***
	(2.08)	(6.67)	(1.85)	(9.89)
F	0.009	0.008	0.006	0.004
	(0.99)	(1.14)	(0.67)	(0.49)
F X Recess	-0.024	-0.014	-0.008	0.001
	(-0.91)	(-0.61)	(-0.69)	(0.05)
Obs	100,499	100,499	92,487	92,487
		$VA - ff6$		
Constant	1.270	0.826***	2.065	2.165***
	(0.38)	(5.74)	(0.52)	(5.93)
F	0.270	0.002	0.318	-0.001
	(0.40)	(0.27)	(0.41)	(-0.08)
F X Recess	0.330	-0.013	0.072	-0.015
	(0.35)	(-0.35)	(0.07)	(-0.52)
Obs	100,499	100,499	92,487	92,487

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table G.11: **Prediction 5: Performance:—months placebo:** Dependent variables: 24–months (Models (1) and (3)) and 36–months (Models (2) and (4)) rolling Fama-French 6 *Alpha* (Panel 1) and Value Added (VA, Panel 2; constructed monthly and averaged within a quarter. Independent variables are the same as in Table G.1, but they are lagged. Control variables are omitted for brevity. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's body. Models (1) and (3) utilize OLS regressions. Models (2) and (4) utilize quantile regressions for the 50th quantile. All regressions are run at the quarterly frequency and include quarter fixed–effects (FE); standard errors are clustered at the quarter and fund level (Cl). For quantile regressions that is achieved through bootstrapping with 100 repetitions.

	$24m\ OLS$ (1)	$24m\ q50$ (2)	$36m\ OLS$ (3)	$36m\ q50$ (4)
		$Alpha - ff6$		
Constant	0.155**	0.503***	0.138*	0.782***
	(2.09)	(7.84)	(1.86)	(9.77)
M	0.003	0.001	0.004	0.004
	(0.49)	(0.11)	(0.52)	(0.66)
M X Recess	-0.034	-0.005	-0.030	0.009
	(-1.29)	(-0.22)	(-1.27)	(0.30)
Obs	100,499	100,499	92,487	92,487
		$VA - ff6$		
Constant	1.289	0.828***	2.089	2.166***
	(0.39)	(5.58)	(0.53)	(5.59)
M	0.243	-0.000	0.233	0.001
	(0.89)	(-0.04)	(0.70)	(0.06)
M X Recess	0.044	0.025	0.336	0.006
	(0.08)	(0.72)	(0.47)	(0.19)
Obs	100,499	100,499	92,487	92,487

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table G.12: **Prediction 5: Performance and Information Gap—funds placebo:** Dependent variables: 24–months (Models (1)-(3)), and 36–months (Models (4)-(6)) rolling Fama-French 6 Value Added (VA); constructed monthly and averaged within a quarter. Independent variables are the same as described in Table G.1, plus: information gap proxies, measured as: the age of stocks held (Age), the natural logarithm of the number of times stocks held are mentioned monthly in Dow Jones news ($ln(News)$), the natural logarithm of the market capitalization of stocks held ($ln(MktCap)$). Are also included interactions between information gap proxies and the funds_placebo (F)y. Independent variables are lagged. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's main body. Estimates are obtained for the median fund through quantile regressions ($q = 50$). Control variables are omitted for brevity. All regressions are run at the quarterly frequency and include quarter fixed–effects (FE); standard errors are clustered (Cl) at the quarter (Qt) and fund (F) level, achieved through bootstrapping with 100 repetitions.

	VA_24m			VA_36m		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.9058***	0.9258***	1.1070***	2.2222***	2.2485***	2.4102***
	(6.07)	(6.95)	(8.23)	(7.01)	(5.69)	(5.95)
F	-0.0358	-0.0034	-0.0656	-0.0272	0.0293	-0.0180
	(-1.60)	(-0.10)	(-1.37)	(-1.08)	(0.81)	(-0.33)
F X Recess	-0.0104	-0.0115	-0.0160	-0.0051	-0.0083	-0.0081
	(-0.30)	(-0.40)	(-0.50)	(-0.15)	(-0.29)	(-0.25)
Age	-0.0004***			-0.0003***		
	(-10.19)			(-6.49)		
Age X F	0.0001**			0.0001		
	(1.97)			(1.18)		
ln(News)		-0.0305***			-0.0238***	
		(-6.13)			(-4.95)	
ln(News) X F		0.0009			-0.0076	
		(0.12)			(-0.98)	
ln(MktCap)			-0.0283***			-0.0247***
			(-9.79)			(-7.47)
ln(MktCap) X F			0.0067			0.0016
			(1.37)			(0.31)
Obs	99,765	99,726	99,764	91,814	91,783	91,813

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table G.13: **Prediction 5: Performance and Information Gap—months placebo:** Dependent variables: 24–months (Models (1)-(3)), and 36–months (Models (4)-(6)) rolling Fama-French 6 Value Added (VA); constructed monthly and averaged within a quarter. Independent variables are the same as described in Table G.1, plus: information gap proxies, measured as: the age of stocks held (Age), the natural logarithm of the number of times stocks held are mentioned monthly in Dow Jones news ($ln(News)$), the natural logarithm of the market capitalization of stocks held ($ln(MktCap)$). Are also included interactions between information gap proxies and the months_placebo (M)y. Independent variables are lagged. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's main body. Estimates are obtained for the median fund through quantile regressions ($q = 50$). Control variables are omitted for brevity. All regressions are run at the quarterly frequency and include quarter fixed–effects (FE); standard errors are clustered (Cl) at the quarter (Qt) and fund (F) level, achieved through bootstrapping with 100 repetitions.

	VA_24m			VA_36m		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.8966***	0.9306***	1.1065***	2.2261***	2.2490***	2.4077***
	(5.78)	(7.27)	(7.15)	(5.87)	(7.47)	(6.35)
M	-0.0481*	-0.0233	-0.0902*	-0.0358	-0.0198	-0.0346
	(-1.76)	(-0.65)	(-1.85)	(-1.12)	(-0.54)	(-0.53)
M X Recess	0.0207	0.0189	0.0176	0.0082	0.0063	0.0124
	(0.67)	(0.56)	(0.55)	(0.23)	(0.20)	(0.37)
Age	-0.0004***			-0.0003***		
	(-11.07)			(-7.53)		
Age X M	0.0001**			0.0001		
	(2.06)			(1.27)		
ln(News)		-0.0307***			-0.0253***	
		(-7.03)			(-5.16)	
ln(News) X M		0.0057			0.0049	
		(0.71)			(0.59)	
ln(MktCap)			-0.0285***			-0.0250***
			(-9.69)			(-6.93)
ln(MktCap) X M			0.0092*			0.0034
			(1.89)			(0.51)
Obs	99,765	99,726	99,764	91,814	91,783	91,813

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table G.14: **Prediction 5: Performance and Commonality or Overcrowding—funds placebo:** Dependent variables: 24–months and 36–months rolling Fama-French 6 Value Added (VA); constructed monthly and averaged within a quarter. Independent variables are the same as described in Table G.1 (where $funds\_placebo$ is abbreviated as F, and *Recession* as R), plus: commonality, active commonality, overcrowding and active overcrowding (C, AC, OC, AOC, respectively), and their interaction with F. Independent variables are lagged. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's main body. Estimates are obtained for the median fund through quantile regressions ($q = 50$). Control variables are omitted for brevity. All regressions are run at the quarterly frequency and include quarter fixed–effects (FE); standard errors are clustered (Cl) at the quarter (Qt) and fund (F) level, achieved through bootstrapping with 100 repetitions.

	$VA - ff6$							
	24m	36m	24m	36m	24m	36m	24m	36m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
intercept	0.89***	2.24***	0.85***	2.20***	0.84***	2.19***	0.86***	2.20***
	(7.16)	(6.21)	(7.36)	(6.95)	(6.08)	(5.92)	(6.01)	(6.12)
F	-0.02	-0.01	-0.01	0.01	-0.01	0.00	-0.00	0.01
	(-1.30)	(-0.32)	(-0.87)	(0.58)	(-0.39)	(0.13)	(-0.05)	(0.36)
F X Recess	-0.02	-0.01	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01
	(-0.47)	(-0.35)	(-0.46)	(-0.48)	(-0.33)	(-0.45)	(-0.31)	(-0.39)
C	-0.01***	-0.01***						
	(-9.88)	(-6.84)						
C X F	0.00*	0.00						
	(1.70)	(0.28)						
AC			-0.01***	-0.01***				
			(-10.52)	(-9.47)				
AC X F			0.00	-0.00				
			(1.38)	(-0.90)				
OC					-0.00***	-0.00***		
					(-6.90)	(-6.65)		
OC X F					0.00	-0.00		
					(0.62)	(-0.38)		
AOC							-0.00***	-0.00***
							(-9.86)	(-8.00)
AOC X F							-0.00	-0.00
							(-0.01)	(-0.91)
Obs	99,766	91,815	99,766	91,815	99,766	91,815	99,766	91,815

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table G.15: **Prediction 5: Performance and Commonality or Overcrowding—months placebo:** Dependent variables: 24–months and 36–months rolling Fama-French 6 Value Added (VA); constructed monthly and averaged within a quarter. Independent variables are the same as described in Table G.1 (where *months_placebo* is abbreviated as M, and *Recession* as R), plus: commonality, active commonality, overcrowding and active overcrowding (C, AC, OC, AOC, respectively), and their interaction with M. Independent variables are lagged. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's main body. Estimates are obtained for the median fund through quantile regressions ($q = 50$). Control variables are omitted for brevity. All regressions are run at the quarterly frequency and include quarter fixed–effects (FE); standard errors are clustered (Cl) at the quarter (Qt) and fund (F) level, achieved through bootstrapping with 100 repetitions.

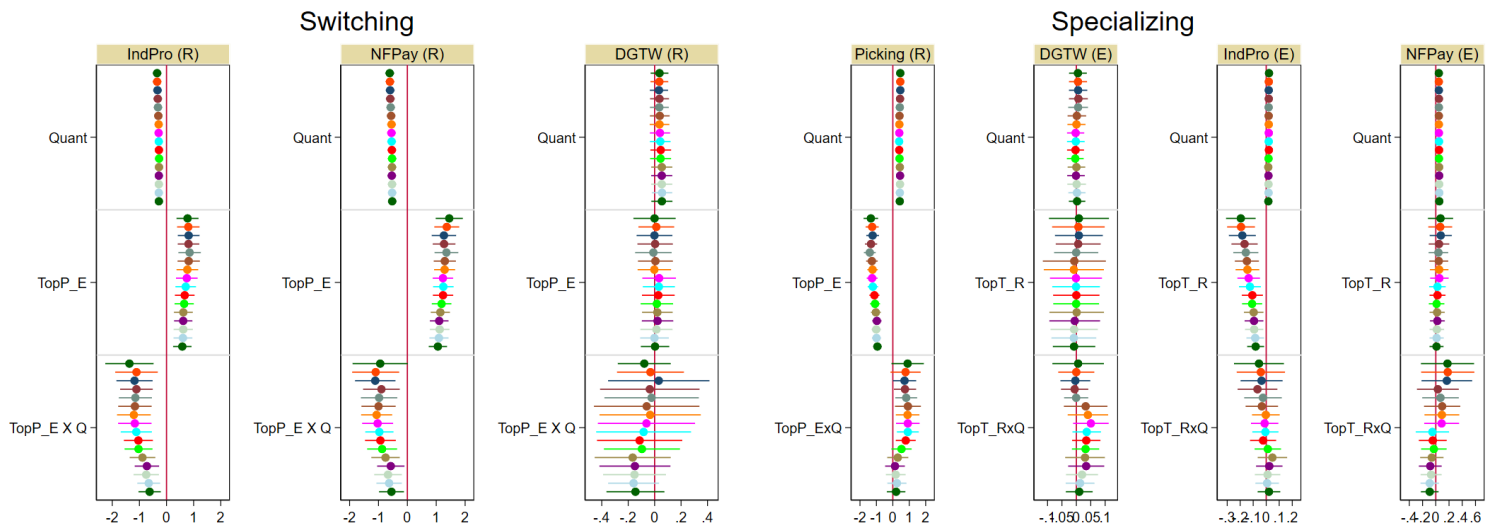
	$VA - ff6$							
	24m	36m	24m	36m	24m	36m	24m	36m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
intercept	0.89***	2.24***	0.86***	2.20***	0.85***	2.20***	0.85***	2.20***
	(7.48)	(5.47)	(8.12)	(6.91)	(5.86)	(7.30)	(6.92)	(6.13)
M	-0.02	-0.01	-0.01	0.00	-0.04**	-0.02	-0.02*	-0.01
	(-1.16)	(-0.32)	(-0.57)	(0.02)	(-2.20)	(-1.06)	(-1.71)	(-0.51)
M X Recess	0.02	0.01	0.02	0.01	0.02	0.01	0.02	0.01
	(0.52)	(0.21)	(0.53)	(0.24)	(0.69)	(0.34)	(0.49)	(0.20)
C	-0.01***	-0.01***						
	(-10.35)	(-6.43)						
C X M	0.00	0.00						
	(1.40)	(0.41)						
AC			-0.01***	-0.01***				
			(-11.45)	(-9.21)				
AC X M			0.00	0.00				
			(0.82)	(0.01)				
OC					-0.00***	-0.00***		
					(-7.44)	(-5.63)		
OC X M					0.00***	0.00		
					(3.01)	(1.41)		
AOC							-0.00***	-0.00***
							(-10.50)	(-8.55)
AOC X M							0.00**	0.00
							(2.28)	(0.92)
Obs	99,766	91,815	99,766	91,815	99,766	91,815	99,766	91,815

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

H Dynamic high-ability measures

I replicate Table 6 of the paper's main body utilizing a dynamic version of the high-ability measures described in Section 4.1. More specifically, for each recession (expansion) I identify the high-ability sample as those funds that most frequently belong to the top of the picking (timing) distribution in the *previous* expansion (recession).

Table H.1: **Prediction 1: High Ability Funds:** Graphical representation of regression coefficients. Panel 1 Dependent variables: macro-timing in recessions with respect to innovations in industrial production ($IndPro$ (R)) or non-farm payrolls ($NFPay$ (R)); and characteristic-timing in recessions ($DGTW$ (R)). Panel 2 Dependent variables: stock picking in recessions ($Picking$ (R)); characteristic-timing in expansions ($DGTW$ (E)); and macro-timing in expansions with respect to innovations in industrial production ($IndPro$ (E)) or non-farm payrolls ($NFPay$ (E)) respectively. Independent variables: a dummy identifying quantitative funds ($Quant$), dummy variables identifying the top $q\%$ of funds with the highest timing ability in recessions ($TopT\_R$) or picking ability in expansions ($TopP\_E$), constructed dynamically; and the interaction between the $Quant$ dummy and the high-ability dummies ($TopP\_ExQ$, $TopT\_RxQ$). Coefficients are estimated using high-ability cut-offs of $q = 10\%$ to $q = 25\%$. Bars indicate 90% confidence intervals. Control variables and all regression specifications are the same described in Table F.1. Control variables are omitted for brevity.



I Technological Changes

I.1 Analysis

I replicate the results that illustrate differences in characteristics and holdings of quantitative and discretionary funds for two sub-periods: 2000-2014 and 2015-2017. That is because the later part of the sample is characterized by sizable technological advancements, particularly in the usage of AI for investment management. In the main body of the paper I hypothesized that quantitative mutual funds should not be at the forefront of technological development. Hence, I do not expect to observe sizable differences in results before and after 2015.

I.2 Results

As can be seen Table I.1 the age, size and factor exposure differences between quantitative and discretionary funds are broadly consistent across the two sub-periods. A few notable exceptions are: (1) the difference in size is less pronounced in the second sub-period, as would be expected given the passing of time alone; (2) the turnover ratio of discretionary funds decreases in the second sub-period, hence the difference in turnover between quantitative and discretionary funds marginally increases; (3) There doesn't seem to be a difference in exposure to the Investment factor in the second sub-period.

From Table I.2 we see that differences in flows and fees are also consistent. In the second sub-period, though, quantitative funds experience a marginally lower decrease in fund-flows than discretionary funds. There also appears to be a decrease in fees for both groups, quantitative funds still charging lower fees than discretionary ones.

Table I.3 shows that differences in the number of stocks held and in return volatility between quantitative and discretionary funds are also consistent across the two sub-periods.

Tables I.4 and I.5 show differences in information availability of stocks held between quantitative and discretionary funds. Results are consistent between the two sub-periods. The only notable difference being that all funds increase the size of stocks held in the second sub-period, quantitative funds increasing it by a larger amount.

Finally Table I.6 shows that the commonality (dispersion) in holdings remains higher (lower) for quantitative funds. Consistently with Figure 9, in the paper's main body, we observe an overall decrease in commonality in the second sub-period.

Table I.1: **Age, size and style:** Dependent variables: funds' age ($ln(Age)$), size ($ln(TNA)$), turnover ratio ($Turnover$), the amount of cash held in percentage of TNA ($Cash$), and style ($Market$, $Size$, $Value$, Mom, $Invest.$ and $Profit.$). Independent variables: $Quant$ dummy and its interaction with a dummy identifying NBER recessions periods ($Recess$); expense ratio ($Expenses$); turnover ratio ($Turnover$); growth in net fund flows ($FlowsGrowth$); the volatility in net fund flows growth ($FlowsVol$); total fund loads ($Loads$); fund style, size and age as listed above. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's body. Control variables have been omitted for brevity. Each regression excludes the control variable corresponding to the dependent variable. All regressions include month fixed–effects (FE); standard errors are clustered at the month and fund level (Cl).

	ln(Age) (1)	ln(TNA) (2)	Turnover (3)	Cash (4)	Market (5)	Size (6)	Value (7)	Mom (8)	Invest. (9)	Profit. (10)
					Sub-period 2000 to 2014					
Constant	4.03***	3.70***	59.89***	4.12***	0.74***	-0.15***	0.02	0.10***	0.17***	0.09***
	(54.58)	(15.85)	(7.16)	(9.82)	(91.03)	(-3.36)	(0.73)	(4.35)	(3.89)	(3.11)
Quant	-0.11***	-0.31***	26.10***	-0.79***	0.00	-0.02*	0.02***	0.02***	0.02***	0.03***
	(-3.65)	(-4.56)	(8.93)	(-7.80)	(1.62)	(-1.96)	(3.63)	(4.60)	(3.31)	(5.74)
Quant X Recess	-0.02	-0.01	-4.12	-0.36**	0.00	0.00	0.00	0.01	0.02	-0.01
	(-0.84)	(-0.10)	(-1.37)	(-2.50)	(0.44)	(0.36)	(0.42)	(0.93)	(1.44)	(-0.83)
R2	0.27	0.30	0.13	0.08	0.94	0.15	0.37	0.17	0.16	0.30
Obs	275,003	275,003	275,003	258,193	275,003	275,003	275,003	275,003	275,003	275,003
					Sub-period 2015 to 2017					
Constant	3.60***	4.87***	53.32***	2.32***	0.69***	-0.16**	-0.03	0.17***	0.40***	0.18***
	(24.25)	(14.01)	(4.24)	(3.41)	(71.99)	(-2.35)	(-0.77)	(4.41)	(5.17)	(5.35)
Quant	-0.11**	-0.14*	31.68***	-0.76***	-0.00	-0.05***	0.02**	0.01**	0.00	0.03***
	(-2.50)	(-1.75)	(9.78)	(-4.79)	(-0.30)	(-3.13)	(2.48)	(2.07)	(0.42)	(4.71)
R2	0.25	0.39	0.15	0.07	0.97	0.22	0.36	0.31	0.16	0.33
Obs	56,657	56,657	56,657	56,657	56,657	56,657	56,657	56,657	56,657	56,657

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table I.2: **Flows and Fees:** Dependent variables: growth in net fund flows ($FlowGrowth$), the volatility of net fund flows growth ($FlowVol$), funds' expense ratio ($Expenses$), management fees ($Mgmt$), Actual 12b1 fees ($12b1$) and fund loads ($Loads$). Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's body. Independent variables and all regression specifications are the same as described in Table I.1. Control variables are omitted for brevity.

	Flow		*Fees*			
	Growth (1)	*Vol* (2)	*Expenses* (3)	*Mgmt* (4)	12*b*1 (5)	*Loads* (6)
			Sub-period 2000 to 2014			
Constant	2.653***	0.127***	1.699***	0.695***	0.467***	-0.025***
	(12.14)	(27.11)	(41.27)	(18.52)	(12.71)	(-16.52)
Quant	-0.110	0.002	-0.091***	-0.043***	0.018	-0.000
	(-1.45)	(1.34)	(-6.24)	(-3.32)	(1.22)	(-0.16)
Quant X Recess	-0.507***	0.004	-0.000	-0.007	-0.002	-0.000
	(-3.77)	(1.22)	(-0.01)	(-0.48)	(-0.19)	(-0.15)
R2	0.06	0.08	0.34	0.07	0.32	0.19
Obs	275,003	275,003	275,003	274,663	196,124	331,660
			Sub-period 2015 to 2017			
Constant	2.698***	0.126***	1.373***	0.466***	0.466***	-0.025***
	(6.16)	(11.29)	(19.64)	(5.67)	(8.31)	(-16.52)
Quant	0.190*	0.002	-0.043**	-0.031*	0.013	-0.000
	(1.73)	(0.81)	(-2.69)	(-1.83)	(0.71)	(-0.16)
R2	0.05	0.09	0.35	0.08	0.26	0.19
Obs	56,657	56,657	56,657	56,657	31,529	331,660

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table I.3: **Prediction 2: Portfolio Diversification:** Dependent variables: the natural log of the number of stocks held ($ln(NStocks)$), and of the volatility of fund returns ($ln(RetVol)$). Independent variables and all regression specifications are the same as described in Table I.1; control variables are omitted for brevity. Model (6) also controls for the percentage of cash held ($Cash$). Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's body.

	$ln(NStocks)$		$ln(RetVol)$	
			$24m$	$36m$
	(1)	(2)	(3)	(4)
Sub-period 2000 to 2014				
Constant	4.409***	4.532***	1.292***	1.356***
	(41.83)	(41.45)	(47.57)	(45.74)
Quant	0.312***	0.283***	-0.028***	-0.031***
	(9.39)	(8.63)	(-3.95)	(-4.42)
Quant X Recess	0.067**	0.061*	0.017**	0.026***
	(2.18)	(1.88)	(1.98)	(3.10)
Cash		-0.016***		
		(-7.52)		
R2	0.20	0.20	0.77	0.75
Obs	275,003	258,193	251,690	231,192
Sub-period 2015 to 2017				
Constant	4.928***	4.964***	0.980***	1.003***
	(24.92)	(25.02)	(21.72)	(22.38)
Quant	0.313***	0.301***	-0.032***	-0.027***
	(6.83)	(6.57)	(-3.77)	(-3.17)
Cash		-0.016***		
		(-3.35)		
R2	0.23	0.23	0.50	0.51
Obs	56,657	56,657	52,446	47,945

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table I.4: **Prediction 3: Information Gap—before:** Dependent variables: TNA-weighted average of the natural logarithm of market capitalization ($ln(MktCap)$), of age in months (Age), of the natural logarithm of monthly media mentions ($ln(News)$), and of the number of analysts following the stocks held ($Analysts$). Independent variables are the same as described in Table I.1, plus the illiquidity of stocks held—measured using Amihud ratio—($Illiquidity$). Control variables are omitted for brevity. Models (4), (6), and (8) additionally control for $ln(MktCap)$. Model (1) excludes from the control variables set the size style ($Size$). All regression specifications are the same as described in Table I.1. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's main body. This table reports only results for the sub-period 2000-2015.

	Stock Characteristics							
	$ln(MktCap)$		Age		$ln(News)$		$Analysts$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sub-period 2000 to 2014							
Constant	10.104***	9.467***	335.984***	-127.943***	3.882***	-1.928***	5.987***	-6.227***
	(36.32)	(63.49)	(25.79)	(-7.99)	(34.38)	(-16.50)	(20.04)	(-9.15)
Quant	0.147*	0.051	13.930***	11.441***	0.059**	0.026*	-0.072	-0.138***
	(1.70)	(1.21)	(4.36)	(4.73)	(1.98)	(1.70)	(-1.04)	(-3.09)
Quant X Recess	-0.077	-0.061	0.854	3.821	-0.040	-0.002	-0.073	0.005
	(-1.18)	(-1.54)	(0.19)	(1.10)	(-1.39)	(-0.10)	(-0.93)	(0.07)
Illiquidity	-1.125***	-0.362***	6.947**	24.691***	-0.081***	0.142***	-0.586***	-0.119
	(-2.82)	(-5.18)	(2.02)	(5.75)	(-2.94)	(5.17)	(-4.99)	(-1.16)
Size		-3.937***	-197.803***	-4.846	-2.338***	0.079*	-6.234***	-1.154***
		(-120.70)	(-46.78)	(-0.84)	(-63.60)	(1.65)	(-25.07)	(-3.42)
ln(MktCap)				49.005***		0.614***		1.290***
				(38.49)		(59.53)		(18.60)
R2	0.11	0.60	0.50	0.69	0.53	0.86	0.64	0.76
Obs	275,003	275,003	275,003	275,003	274,925	274,925	275,003	275,003

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table I.5: **Prediction 3: Information Gap—after:** Dependent variables: TNA-weighted average of the natural logarithm of market capitalization ($ln(MktCap)$), of age in months (Age), of the natural logarithm of monthly media mentions ($ln(News)$), and of the number of analysts following the stocks held ($Analysts$). Independent variables are the same as described in Table I.1, plus the illiquidity of stocks held—measured using Amihud ratio—($Illiquidity$). Control variables are omitted for brevity. Models (4), (6), and (8) additionally control for $ln(MktCap)$. Model (1) excludes from the control variables set the size style ($Size$). All regression specifications are the same as described in Table I.1. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's main body. This table reports only results for the sub-period 2015-2017.

	Stock Characteristics							
	$ln(MktCap)$		Age		$ln(News)$		$Analysts$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sub-period 2015 to 2017							
Constant	10.874***	10.038***	374.311***	-114.675***	3.955***	-1.407***	5.260***	-13.951***
	(26.01)	(46.65)	(13.33)	(-3.72)	(23.46)	(-6.63)	(8.90)	(-5.76)
Quant	0.338***	0.138**	22.251***	15.510***	0.085**	0.010	0.142	-0.123**
	(3.37)	(2.72)	(4.68)	(4.43)	(2.65)	(0.64)	(1.28)	(-2.07)
Illiquidity	-0.607**	-0.215**	7.951**	18.408**	0.000	0.115**	-0.008	0.403**
	(-2.72)	(-2.06)	(2.10)	(2.66)	(0.02)	(2.16)	(-0.07)	(2.69)
Size		-4.232***	-221.979***	-15.833**	-2.022***	0.242**	-7.169***	0.930
		(-73.09)	(-41.64)	(-2.67)	(-31.09)	(2.55)	(-9.25)	(0.74)
ln(MktCap)				48.716***		0.535***		1.914***
				(34.90)		(30.16)		(7.94)
R2	0.13	0.62	0.50	0.68	0.50	0.83	0.62	0.79
Obs	56,653	56,653	56,653	56,653	56,585	56,585	56,653	56,653

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table I.6: **Prediction 4: Commonality:** Dependent variables: holdings commonality ($Comm$), active commonality ($AComm$), and the natural log of dispersion ($Log(Disp)$). Independent variables and all regression specifications are the same as described in Table I.1. Control variables are omitted for brevity. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 in the paper's body.

	$Comm$ (1)	$AComm$ (2)	$ln(Disp)$ (3)
	Sub-period 2000 to 2014		
Constant	8.456***	2.692***	0.160
	(12.04)	(3.89)	(1.16)
Quant	4.236***	2.499***	-0.076**
	(20.19)	(14.05)	(-2.12)
Quant X Recess	0.604***	0.342	-0.113***
	(2.68)	(1.58)	(-2.73)
R2	0.59	0.54	0.14
Obs	275,003	275,003	275,003
	Sub-period 2015 to 2017		
Constant	8.032***	3.606***	0.142
	(10.31)	(10.08)	(0.69)
Quant	5.272***	1.992***	-0.250***
	(20.85)	(16.72)	(-5.52)
R2	0.63	0.58	0.14
Obs	56,657	56,657	56,653

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

J Alternative performance measurement

J.1 Performance regressions run at the monthly frequency – Eq. 17

Table J.1: **Prediction 5: Performance:** Dependent variables: 24–months (Models $(1,2)$), and 36–months (Models $(3,4)$) Fama-French 6 monthly *Alpha* (Panel 1) and Value Added (VA, Panel 2). Independent variables are the same as described in Table 3, but they are lagged. Controls are omitted for brevity. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 of the paper's body. Models $(1,3)$ utilize OLS regressions. Models $(2,4)$ utilize median quantile regressions ($q50$). All regressions are run at the monthly frequency and include month fixed–effects (FE); standard errors are clustered at the month and fund level (Cl). For quantile regressions that is achieved through bootstrapping with 100 repetitions.

	$24m\ OLS$ (1)	$24m\ q50$ (2)	$36m\ OLS$ (3)	$36m\ q50$ (4)
		$Alpha - ff6$		
Constant	0.190***	0.039	0.136*	-0.156**
	(2.81)	(0.72)	(1.88)	(-2.35)
Quant	-0.026*	-0.015***	-0.026*	-0.008
	(-1.73)	(-3.08)	(-1.71)	(-1.38)
Quant X Recess	-0.116**	-0.098***	-0.094*	-0.066**
	(-2.07)	(-4.35)	(-1.72)	(-2.52)
Obs	302,667	302,667	277,915	277,915
		$VA - ff6$		
Constant	1.387	0.099	1.680	-0.397*
	(0.46)	(1.18)	(0.45)	(-1.73)
Quant	-0.365	-0.020***	-0.268	-0.013
	(-1.65)	(-2.70)	(-1.10)	(-1.46)
Quant X Recess	1.498	-0.095***	1.370	-0.104***
	(1.53)	(-3.58)	(1.16)	(-3.15)
Obs	302,667	302,667	277,915	277,915

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table J.2: **Prediction 5: Performance and Information Gap:** Dependent variable: 24–months (Models (1)-(3)), and 36–months (Models (4)-(6)) rolling Fama-French 6 monthly Value Added (VA). Independent variables are the same as described in Table 3, plus: information gap proxies, measured as: the age of stocks held (Age), the natural logarithm of the number of times stocks held are mentioned monthly in Dow Jones news ($ln(News)$), the natural logarithm of the market capitalization of stocks held ($ln(MktCap)$). Are also included interactions between information gap proxies and the $Quant$ dummy. Independent variables are lagged. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 of the paper's body. Estimates are obtained for the median fund through quantile regressions ($q = 50$). Control variables are omitted for brevity. All regressions are run at the monthly frequency and include month fixed–effects (FE); standard errors are clustered at the month (M) and fund (F) level (Cl), achieved through bootstrapping with 100 repetitions.

	VA_24m			VA_36m		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.1251	0.1664**	0.2886***	-0.3612	-0.3523	-0.2187
	(1.23)	(2.04)	(3.03)	(-1.54)	(-1.43)	(-0.83)
Quant	-0.1350***	-0.0811***	-0.1468***	-0.1261***	-0.0598*	-0.1049**
	(-6.94)	(-3.15)	(-3.60)	(-4.70)	(-1.72)	(-2.24)
Quant X Recess	-0.1192***	-0.1240***	-0.1134***	-0.1203***	-0.1206***	-0.1160***
	(-4.73)	(-4.61)	(-3.55)	(-3.68)	(-3.95)	(-3.94)
Age	-0.0003***			-0.0003***		
	(-9.25)			(-7.23)		
Age X Quant	0.0003***			0.0003***		
	(6.66)			(4.98)		
ln(News)		-0.0269***			-0.0200***	
		(-7.53)			(-4.31)	
ln(News) X Quant		0.0146**			0.0115	
		(2.57)			(1.51)	
ln(MktCap)			-0.0224***			-0.0221***
			(-8.85)			(-6.70)
ln(MktCap) X Quant			0.0129***			0.0097**
			(3.20)			(2.07)
Obs	301,462	301,338	301,460	276,815	276,721	276,813
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: Month	Yes	Yes	Yes	Yes	Yes	Yes
Cl: Month+Fund	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table J.3: **Prediction 5: Performance and Commonality or Overcrowding:** Dependent variable: 24–months, and 36–months rolling Fama-French 6 monthly Value Added (VA). Independent variables are the same as described in Table 3 (where *Quant* is abbreviated as Q, and *Recession* as R), plus: commonality, active commonality, overcrowding and active overcrowding (C, AC, OC, AOC, respectively), and their interaction with Q. Independent variables are lagged. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 of the paper's body. Estimates are obtained for the median fund through quantile regressions ($q = 50$). Control variables are omitted for brevity. All regressions are run at the monthly frequency and include month fixed–effects (FE); standard errors are clustered at the month (M) and fund (F) level (Cl), achieved through bootstrapping with 100 repetitions.

	$VA - ff6$							
	24m	36m	24m	36m	24m	36m	24m	36m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.136	-0.379	0.109	-0.388*	0.106	-0.382*	0.100	-0.410
	(1.43)	(-1.59)	(1.21)	(-1.69)	(1.08)	(-1.65)	(1.17)	(-1.61)
Q	-0.059***	-0.038*	-0.032***	-0.012	-0.087***	-0.082***	-0.052***	-0.041**
	(-3.97)	(-1.83)	(-3.02)	(-0.89)	(-6.86)	(-4.39)	(-3.85)	(-2.31)
Q X R	-0.102***	-0.103***	-0.102***	-0.100***	-0.095***	-0.092***	-0.105***	-0.102***
	(-3.89)	(-3.19)	(-4.18)	(-2.86)	(-3.70)	(-3.05)	(-3.57)	(-3.16)
C	-0.007***	-0.007***						
	(-9.86)	(-7.98)						
C X Q	0.004***	0.004***						
	(5.17)	(3.00)						
AC			-0.011***	-0.011***				
			(-13.75)	(-9.86)				
AC X Q			0.005***	0.003**				
			(4.61)	(2.14)				
OC					-0.003***	-0.003***		
					(-11.55)	(-7.99)		
OC X Q					-0.002	-0.002		
					(-0.58)	(-0.30)		
AOC							-0.006***	-0.006***
							(-12.69)	(-11.32)
AOC X Q							-0.024**	-0.029**
							(-2.53)	(-2.22)
Obs	301,466	276,819	301,466	276,819	301,466	276,819	301,466	276,819
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: M	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cl: M+F	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

J.2 Alpha constructed from after fee returns – Eq. 14

Table J.4: **Prediction 5: Performance:** Dependent variables: 24–months (Models $(1,2)$), and 36–months (Models $(3,4)$) Fama-French 6 *Alpha* (Panel 1) and Value Added (VA, Panel 2), based on net-of-fees excess returns; constructed monthly and averaged within quarters. Independent variables are the same as described in Table 3, but they are lagged. Controls are omitted for brevity. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 of the paper's body. Models $(1,3)$ utilize OLS regressions. Models $(2,4)$ utilize median quantile regressions ($q50$). All regressions are run at the quarterly frequency and include quarter fixed–effects; standard errors are clustered at the quarter and fund level, for quantile regressions that is achieved through bootstrapping with 100 repetitions.

	$24m\ OLS$ (1)	$24m\ q50$ (2)	$36m\ OLS$ (3)	$36m\ q50$ (4)
		$Alpha - ff6$		
Constant	0.178**	0.520***	0.135*	0.771***
	(2.56)	(7.40)	(1.94)	(10.84)
Quant	-0.029*	-0.011*	-0.027	-0.011*
	(-1.79)	(-1.82)	(-1.63)	(-1.72)
Quant X Recess	-0.111*	-0.106***	-0.089*	-0.091***
	(-1.92)	(-4.72)	(-1.91)	(-3.38)
Obs	102,721	102,721	94,502	94,502
		$VA - ff6$		
Constant	7.844***	1.658***	9.761***	3.021***
	(2.74)	(9.81)	(2.83)	(10.72)
Quant	-0.390*	0.006	-0.230	0.026**
	(-1.81)	(0.76)	(-1.10)	(2.28)
Quant X Recess	1.372	-0.123***	1.103	-0.157***
	(1.21)	(-3.65)	(0.74)	(-4.30)
Obs	102,721	102,721	94,502	94,502

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table J.5: **Prediction 5: Performance and Information Gap:** Dependent variable: 24–months (Models (1)-(3)), and 36–months (Models (4)-(6)) rolling FF6 Value Added (VA), based on net-of-fees excess returns; computed monthly and averaged withing a quarter. Independent variables are the same as described in Table 3, plus: information gap proxies, measured as: the age of stocks held (Age), the natural logarithm of the number of times stocks held are mentioned monthly in Dow Jones news ($ln(News)$), the natural logarithm of the market capitalization of stocks held ($ln(MktCap)$). Are also included interactions between information gap proxies and the $Quant$ dummy. Independent variables are lagged. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 of the paper's body. Estimates are obtained for the median fund through quantile regressions ($q = 50$). Control variables are omitted for brevity. All regressions are run at the quarterly frequency and include quarter fixed–effects (FE); standard errors are clustered at the quarter (Qt) and fund (F) level (Cl), achieved through bootstrapping with 100 repetitions.

	VA_24m			VA_36m		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	1.7418***	1.7598***	1.9154***	3.0875***	3.1015***	3.3002***
	(11.41)	(12.57)	(13.96)	(9.51)	(10.02)	(11.05)
Quant	-0.0855***	-0.0523**	-0.1531***	-0.0789***	-0.0332	-0.1494**
	(-3.27)	(-2.02)	(-3.46)	(-2.77)	(-0.83)	(-2.57)
Quant X Recess	-0.1202***	-0.1305***	-0.1302***	-0.1491***	-0.1617***	-0.1486***
	(-3.90)	(-3.72)	(-3.83)	(-3.86)	(-4.04)	(-4.17)
Age	-0.0004***			-0.0004***		
	(-11.43)			(-7.59)		
Age X Quant	0.0003***			0.0003***		
	(4.20)			(4.03)		
ln(News)		-0.0305***			-0.0235***	
		(-7.72)			(-4.17)	
ln(News) X Quant		0.0150***			0.0143	
		(2.59)			(1.57)	
ln(MktCap)			-0.0305***			-0.0288***
			(-9.28)			(-7.40)
ln(MktCap) X Quant			0.0165***			0.0176***
			(3.69)			(2.91)
Obs	101,971	101,931	101,970	93,815	93,782	93,814
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: Qt	Yes	Yes	Yes	Yes	Yes	Yes
Cl: Qt+Fund	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table J.6: **Prediction 5: Performance and Commonality or Overcrowding:** Dependent variable: 24–months, and 36–months rolling FF6 Value Added (VA), based on net-of-fees excess returns; computed monthly and averaged withing a quarter. Independent variables are the same as described in Table 3 (where *Quant* is abbreviated as Q, and *Recession* as R), plus: commonality, active commonality, overcrowding and active overcrowding (C, AC, OC, AOC, respectively), and their interaction with Q. Independent variables are lagged. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 of the paper's body. Estimates are obtained for the median fund through quantile regressions ($q = 50$). Control variables are omitted for brevity. All regressions are run at the quarterly frequency and include quarter fixed–effects (FE); standard errors are clustered at the quarter (Qt) and fund (F) level (Cl), achieved through bootstrapping with 100 repetitions.

	$VA - ff6$							
	24m	36m	24m	36m	24m	36m	24m	36m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	1.692***	3.059***	1.703***	3.063***	1.686***	3.054***	1.689***	3.043***
	(12.10)	(8.12)	(12.54)	(8.95)	(10.82)	(9.77)	(13.06)	(10.42)
Q	-0.023	-0.020	0.004	0.010	-0.055***	-0.063***	-0.017	-0.013
	(-1.35)	(-0.94)	(0.27)	(0.66)	(-3.24)	(-3.01)	(-1.13)	(-0.64)
Q X R	-0.131***	-0.152***	-0.131***	-0.145***	-0.126***	-0.131***	-0.137***	-0.145***
	(-4.10)	(-3.63)	(-4.27)	(-3.74)	(-3.54)	(-3.19)	(-3.44)	(-4.04)
C	-0.007***	-0.006***						
	(-8.56)	(-4.98)						
C X Q	0.004***	0.004***						
	(3.50)	(3.00)						
AC			-0.009***	-0.009***				
			(-10.31)	(-7.72)				
AC X Q			0.003**	0.004**				
			(2.13)	(2.56)				
OC					-0.003***	-0.003***		
					(-8.40)	(-6.08)		
OC X Q					-0.002	0.009		
					(-0.38)	(1.43)		
AOC							-0.005***	-0.005***
							(-10.15)	(-8.54)
AOC X Q							-0.023*	-0.011
							(-1.94)	(-0.83)
Obs	101,972	93,816	101,972	93,816	101,972	93,816	101,972	93,816
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Qt	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cl: Qt+F	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

J.3 Benchmark exposures constructed using information up to $(\tau - 1)$ – Eq. 15

Table J.7: **Prediction 5: Performance:** Dependent variables: 24–months (Models $(1, 2)$), and 36–months (Models $(3, 4)$) Fama-French 6 *Alpha* (Panel 1) and Value Added (VA, Panel 2). *Alpha* are obtained as the intercept of monthly rolling regressions, and then averaged within a quarter. Independent variables are the same as described in Table 3, but they are lagged. Controls are omitted for brevity. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 of the paper's body. Models $(1, 3)$ utilize OLS regressions. Models $(2, 4)$ utilize median quantile regressions ($q50$). All regressions are run at the quarterly frequency and include quarter fixed–effects; standard errors are clustered at the quarter and fund level, for quantile regressions that is achieved through bootstrapping with 100 repetitions.

	$24m\ OLS$ (1)	$24m\ q50$ (2)	$36m\ OLS$ (3)	$36m\ q50$ (4)
		$Alpha - ff6$		
Constant	0.167*	0.163*	0.119	0.849***
	(1.67)	(1.67)	(1.31)	(8.02)
Quant	-0.031	-0.007	-0.034*	-0.007
	(-1.47)	(-0.89)	(-1.71)	(-0.99)
Quant X Recess	-0.109*	-0.161***	-0.075	-0.106***
	(-1.69)	(-3.34)	(-1.43)	(-2.65)
Obs	99,153	99,153	91,284	91,284
		$VA - ff6$		
Constant	5.157	0.543***	4.676	2.336***
	(1.15)	(4.83)	(0.96)	(5.22)
Quant	-0.548*	-0.006	-0.410	0.010
	(-1.80)	(-0.50)	(-1.46)	(0.93)
Quant X Recess	2.441	-0.172***	1.902	-0.191***
	(1.19)	(-3.50)	(0.85)	(-3.90)
Obs	99,153	99,153	91,284	91,284

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table J.8: **Prediction 5: Performance and Information Gap:** Dependent variable: 24–months (Models (1)-(3)), and 36–months (Models (4)-(6)) rolling FF6 Value Added (VA). *Alpha* (used in VA construction) are obtained as the intercept of monthly rolling regressions, and then averaged within a quarter. Independent variables are the same as described in Table 3, plus: information gap proxies, measured as: the age of stocks held (Age), the natural logarithm of the number of times stocks held are mentioned monthly in Dow Jones news ($ln(News)$), the natural logarithm of the market capitalization of stocks held ($ln(MktCap)$). Are also included interactions between information gap proxies and the *Quant* dummy. Independent variables are lagged. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 of the paper's body.Estimates are obtained for the median fund through quantile regressions ($q = 50$). Control variables are omitted for brevity. All regressions are run at the quarterly frequency and include quarter fixed–effects (FE); standard errors are clustered at the quarter (Qt) and fund (F) level (Cl), achieved through bootstrapping with 100 repetitions.

	VA_24m			VA_36m		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.6219***	0.6581***	0.8664***	2.3630***	2.4048***	2.6168***
	(5.49)	(6.93)	(7.48)	(5.88)	(5.72)	(6.08)
Quant	-0.1343***	-0.1029***	-0.2119***	-0.0871***	-0.0409	-0.1115**
	(-4.48)	(-2.99)	(-3.67)	(-2.70)	(-1.00)	(-2.02)
Quant X Recess	-0.1696***	-0.1747***	-0.1713***	-0.1953***	-0.1925***	-0.1865***
	(-3.55)	(-3.12)	(-3.56)	(-3.60)	(-3.72)	(-3.93)
Age	-0.0004***			-0.0004***		
	(-6.81)			(-7.26)		
Age X Quant	0.0004***			0.0003***		
	(4.61)			(3.37)		
ln(News)		-0.0328***			-0.0248***	
		(-6.18)			(-4.23)	
ln(News) X Quant		0.0242***			0.0133	
		(3.25)			(1.36)	
ln(MktCap)			-0.0327***			-0.0298***
			(-7.50)			(-6.59)
ln(MktCap) X Quant			0.0211***			0.0124**
			(3.67)			(2.27)
Obs	98,425	98,387	98,424	90,623	90,595	90,622
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: Qt	Yes	Yes	Yes	Yes	Yes	Yes
Cl: Qt+Fund	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Table J.9: **Prediction 5: Performance and Commonality or Overcrowding:** Dependent variable: 24–months, and 36–months rolling FF6 Value Added (VA). *Alpha* (used in VA construction) are obtained as the intercept of monthly rolling regressions, and then averaged within a quarter. Independent variables are the same as described in Table 3 (where *Quant* is abbreviated as Q, and *Recession* as R), plus: commonality, active commonality, overcrowding and active overcrowding (C, AC, OC, AOC, respectively), and their interaction with Q. Independent variables are lagged. Variables construction is detailed in Table 1; summary statistics are reported in Table 2 of the paper's body. Estimates are obtained for the median fund through quantile regressions ($q = 50$). Control variables are omitted for brevity. All regressions are run at the quarterly frequency and include quarter fixed–effects (FE); standard errors are clustered at the quarter (Qt) and fund (F) level (Cl), achieved through bootstrapping with 100 repetitions.

	$VA - ff6$							
	24m	36m	24m	36m	24m	36m	24m	36m
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.605***	2.371***	0.589***	2.371***	0.598***	2.373***	0.593***	2.375***
	(5.48)	(5.10)	(5.30)	(5.77)	(5.88)	(5.77)	(4.75)	(5.52)
Q	-0.064***	-0.036	-0.033**	-0.015	-0.085***	-0.040*	-0.067***	-0.020
	(-3.15)	(-1.60)	(-2.05)	(-0.88)	(-3.73)	(-1.90)	(-3.56)	(-0.94)
Q X R	-0.180***	-0.192***	-0.182***	-0.188***	-0.158***	-0.181***	-0.173***	-0.186***
	(-3.55)	(-3.51)	(-3.43)	(-3.51)	(-2.66)	(-3.61)	(-3.13)	(-3.29)
C	-0.007***	-0.007***						
	(-6.13)	(-6.37)						
C X Q	0.006***	0.005***						
	(4.46)	(3.55)						
AC			-0.010***	-0.011***				
			(-8.03)	(-8.19)				
AC X Q			0.007***	0.007***				
			(3.98)	(3.23)				
OC					-0.003***	-0.003***		
					(-6.02)	(-5.19)		
OC X Q					0.005	-0.007		
					(0.62)	(-1.04)		
AOC							-0.006***	-0.006***
							(-8.57)	(-7.99)
AOC X Q							0.005	-0.026
							(0.39)	(-1.63)
Obs	98,426	90,624	98,426	90,624	98,426	90,624	98,426	90,624
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Qt	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cl: Qt+F	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01