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 quants (reliant on computer models and fixed-rules) or discretionaries (reliant on human judgment). I then formulate hypotheses of how their skills, holdings and returns might differ, based on the conjecture that quants might have more learning capacity but less flexibility to adapt to changing market conditions than discretionaries. Consistent with those hypotheses, I find that quants hold more stocks, specialize in stock picking, and engage in more overcrowded trades. Discretionaries hold lesser-known stocks, switch between picking and timing and display higher active returns than quants in recessions.

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

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1 Introduction

> This is only a foretaste of what is to come, and only the shadow of what is going to be. We have to have some experience with the machine before we really know its capabilities. It may take years before we settle down to the new possibilities, but I do not see why it should not enter any one of the fields normally covered by the human intellect, and eventually compete on equal terms.
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> Alan Turing (The Times, June 11, 1949: "The Mechanical Brain")

Since the first appearance of computers, there has been a debate about whether the use of algorithms and computing power for decision making would ever be able to compete with human judgment in equal terms. That debate is nowadays more relevant than ever, as advances in artificial intelligence (AI) together with the wider availability of big data and computing power, promise to enhance computer capabilities (Haenlein and Kaplan (2019)).

This paper studies how differences in the decision making process of discretionaries (funds reliant on human judgment) and quants (funds reliant on computer programs and fixed-rules) impact their skills, holdings, and returns. I focus on active equity mutual funds in the US and analyze the implications of two commonly understood differences between humans and computers: "capacity" and "flexibility". On the one hand, computing power can ensure a greater capacity for processing information than human cognition, leading to a higher precision of private signals. On the other hand, humans are more flexible in adapting to changing market conditions, as the traditional fixed-rules approach to computer programming limits its adaptability. Finally, information accessible to humans might not be machine-processable and vice-versa. While computers' superior information processing capacity and humans' superior flexibility are not surprising, exploring the nature of these advantages and how they play out in an equilibrium asset market teaches us about what market conditions are most favorable to each.

It is important to study the learning trade-offs between investments based primarily on human judgment and those based on a fixed-rules approach to computer programming for two reasons. First, it informs on the difference between two investment styles that likely still represent a sizable

portion of the market.[1] Second, it provides a framework to think about how greater data availability and more sophisticated AI algorithms might revolutionize those traditional trade-offs.

The active equity mutual funds industry represents a good laboratory to study those traditional trade-offs as mutual funds are not considered to be the most sophisticated of institutional investors, hence are less likely to be at the forefront of AI innovation. Nonetheless, studies of the differences in strategy and returns between quant and discretionary mutual funds are scarce and often based on small samples, as quants are not easily identifiable. That is despite industry evidence (e.g. Becker and Reinganum (2018)) that quant equity management emerged in the 1980s and grew steadily afterwards, due to improvements in computing power, information technologies and finance theories. As commonly understood, the approach of quant mutual funds is based on the development and back-testing of fixed-rules, grounded on the academic research on factor investing and anomalies, utilized to over-/under-weight securities relative to a benchmark, with the objective of outperforming it. The use of computing power to back-test fixed-rules is in stark contrast with an investment approach centered around human judgment.

To enable this analysis, I start by developing a novel classification that identifies quant mutual funds, and use it to provide a number of new facts about their prevalence and characteristic. Next, I consider the findings of Kacperczyk et al. (2016), who model the behavior of investors who are constrained in their information processing capacity but flexible to adapt their strategies. I formulate various hypotheses for why their predictions might differ for quants, based on the conjecture that the trade-off between information processing capacity and flexibility should differ for those investors. Finally, I use the developed classification to test my hypotheses empirically.

To construct the classification, I collect $35,661$ prospectuses for $3,176$ mutual funds from 2000 to 2017. I isolate the "Principal Investment Strategy" (PIS) section, in which funds are required to disclose the key methods utilized in selecting securities. I then ask experts to categorize a randomly selected sample of 500 of these sections as belonging to quant or discretionary funds. This serves as a training sample for a machine learning algorithm, the random forest. The random forest

[1] The fixed-rules approach to quant investment has been prevalent in the last decades. Abis and Veldkamp (2021) show that the skills required from investment analysts in the US up to 2015 were almost exclusively based on traditional statistical analysis. The hiring of investment analysts with AI-related skills only started around 2015 and in 2018 still represented a small fraction of all analysis jobs.

endogenously develops a rule to categorize funds as quant or discretionary by analyzing differences in the text of their pre-classified strategy descriptions. In out-of sample testing, I obtain 97.67% accuracy using this decision rule. I then use it to classify all funds as quant or discretionary.[2]

I merge this novel classification with the CRSP mutual fund and stock databases, Thompson Financial Spectrum holdings, Compustat earnings, IBES forecasts, Ravenpack news, and macro variables from the Federal Reserve Bank of St. Louis. This allows reporting various stylized facts about quants. Unsurprisingly, I find that their presence has been steadily growing between 2000 and 2017: they quintupled in number and experienced a more than 7-fold increase in Total Net Assets (TNA). They grew at a faster rate than discretionaries, going from 2.29% to 7.08% of the market's TNA and from 6.10% to 18.61% of the total number of funds. On average, quants are 9.52% younger and 28.11% smaller; they charge 6.39% lower expense ratios and 4.58% lower management fees, exhibit 38.22% higher holdings turnover, hold 23.24% less cash, experience larger outflows during recessions and hold stocks that are more exposed to the book-to-market, momentum investment and profitability factors and less exposed to the size factor than discretionaries.

I then formulate hypotheses about how the skills, holdings and returns of quants and discretionaries might differ. I start from the model by Kacperczyk et al. (2016) (KVV). Theirs is a static general equilibrium model with multiple assets subject to a common aggregate shock and individual idiosyncratic shocks. Assets are traded by skilled and unskilled Bayesian investors who both learn from prices. Skilled investors also optimally allocate a limited capacity to learning from private signals. KVV show that skilled but capacity constrained investors optimally shift from learning about idiosyncratic shocks in expansions to learning about the aggregate shock in recessions. I consider their skilled investors to be discretionary. I then conjecture that quants should be *relatively* less constrained in their information processing capacity (i.e., they might not need to choose which assets to focus on but should be able to construct factors/fixed-rules based on the universe of securities); but should be less flexible, due to their reliance on fixed-rules and pre-specified models. Based on those conjectures, I formulate the following hypotheses, which I test empirically using the previously described classification.

[2] A more detailed description of the algorithm can be found in Section 2.2 and in the Internet Appendix. Sections 2.2 and 4.6 also provide additional statistics and robustness tests to validate and interpret this method.

First, I focus on differences in skill. I hypothesize that quants, given their reliance on fixed-rules, might not be able to flexibly shift strategies across the business cycle. I measure stock-picking ability and the ability to time macroeconomic shocks (i.e., macro-timing ability) as the covariance of funds' holdings with future earning surprises and with future surprises in industrial production (or non-farm payrolls) respectively. I find that in recessions discretionaries display higher macro-timing ability and lower stock-picking ability than quants. Moreover, discretionaries with the highest stock-picking ability in expansions also display the highest macro-timing ability in recessions. For quants that is not the case, indicating that they are indeed less flexible in switching strategies.

Next, I focus on differences in the following features of holdings: diversification, characteristics of stocks held, and similarity. Regarding diversification, I hypothesize that quants should hold a larger number of securities than discretionaries. Being less constrained in the amount of information they can process, they should be able to analyze a larger number of securities. That should lead to them holding more stocks. The greater portfolio diversification should determine a lower volatility of returns. I find support for this hypothesis in the data. Indeed, quants hold on average 36.89% more stocks than discretionaries. This translates into a 3.15% lower return volatility.

Regarding stocks held, I hypothesize that quants should invest in stocks for which more information is available. KVV show that discretionaries focus on learning about stocks that relatively fewer other investors learn about. In the presence of quants then, they should invest in stocks for which less machine-processable information is available and potentially more soft information can be obtained. Empirically, I proxy for the information availability of stocks held with their average size, age and media mentions. The idea being that, more information should be available about larger, older firms, with more media mentions, making them more easily processable with quant methods. I find that quants hold stocks that are on average 9.64% larger, 5.65% older and have 7.57% more monthly media mentions.

Regarding similarity, I hypothesize that there should be a greater dispersion in portfolio holdings among discretionaries than among quants. KVV show that dispersion increases with the precision of private signals and with the distance between an investor's private signals and those of the average investor. For quants, relative to discretionaries: greater capacity for information processing might

lead to higher dispersion, while more homogeneous information consumption and the usage of likely similar models might lead to lower dispersion. I hypothesize that the second effect should prevail, since quant mutual funds are not considered to be particularly sophisticated. I find empirical support for that hypothesis: the holdings of quants display an 11.57% lower dispersion, and a 39.66% higher commonality. I then measure overcrowding by multiplying commonality by the total TNA of funds of the same type. I find that the overcrowding of discretionary strategies has been stable over time, while that of quant ones has been increasing.

Finally, I focus on differences in returns. I hypothesize that the active returns (returns in excess of a benchmark) of quants relative to those of discretionaries should be less dispersed, given their greater diversification; and lower in recessions, given their lower flexibility. I find that quants display a less dispersed distribution of active returns, and earn on average 17.8 *bps* less active return per recession month (2.14% less in annualized terms).

Related Literature This paper contribute to the growing literature on the differences in decision making between "humans" and "machines" (e.g., D'Acunto et al. (2019), Birru et al. (2019), Loos et al. (2020), Coleman et al. (2021) Erel et al. (2021), Fuster et al. (2022), Aubry et al. (2022), Cao et al. (2022)). I provide a learning-based explanation for the differences in skills, holdings and returns of quant and discretionary equity mutual funds by hypothesizing that quants are less flexible, but have a larger capacity for information processing. That provides a framework to think about how a greater availability of machine-processable information and more flexible AI-based algorithms might impact the traditional relative advantages of humans and machines. In that sense, this work also relates to recent studies that analyze the impact of data abundance and improved technologies on financial decision making (e.g., Dugast and Foucault (2018), Goldstein and Yang (2019), Farboodi and Veldkamp (2020), Abis and Veldkamp (2021)).

Additionally, this paper is the first to analyze how the skills and returns of quant and discretionary equity mutual funds differ across the business cycle. Empirically, differences in the active returns of quant and discretionary fund have been studied by Harvey et al. (2017) in the hedge funds context; by Ahmed and Nanda (2005) and Casey et al. (2005), using a small sample

of quant mutual funds (22 and 32, respectively); and more recently by Dyer et al. (2021) around changes in accounting standards. None of these papers analyze skill and return differences across the business cycle. Various studies have shown that mutual funds' active returns vary over the business cycle (Glode (2011); Kosowski (2011); Kacperczyk et al. (2014)). From a theoretical perspective, this has been explained with rational inattention–i.e., investors with limited information processing capacity rationally choose what information to focus on, depending on market conditions (Sims (2003); Sims (2006); Maćkowiak and Wiederholt (2015); Kacperczyk et al. (2016)). I further characterize those findings by distinguishing between the behavior of quants and discretionaries that face different learning capacities and flexibilities.

Finally, I contribute to the emerging literature using machine learning to better understand mutual fund abilities (e.g.; Li and Rossi (2020), DeMiguel et al. (2021), Kaniel et al. (2022)). Other studies utilize data about returns, holdings, and characteristics to identify outperforming funds. Here I take a different approach. I utilize machine learning to identify funds with different strategies from textual disclosures, I then study their differences in abilities. A key innovation of my approach is the use of the random forest, as opposed to a more traditional keywords-based approach (e.g., Harvey et al. (2017), Dyer et al. (2021), Beggs et al. (2022)). In a classification problem, the main advantage of using machine learning is that it allows to endogenously identify a comprehensive list of terms that are informative in splitting the sample, while simultaneously accounting for the relationships among those terms in the text. This helps avoiding false positives, as for instance the presence of a single phrase (e.g., quantitative analysis) would not be sufficient in determining a quant assignment. Conversely, considering patterns in language across documents, allows providing a quant classification even when the most common terms (e.g., quantitative) are missing.[3]

More generally, I contribute to the literature utilizing natural language processing in financial research (see Loughran and McDonald (2016) for a literature survey). A few recent papers also study mutual fund prospectuses (e.g., Hwang and Kim (2017); Kostovetsky and Warner (2020), Krakow and Schäfer (2020), Akey et al. (2021), Sheng et al. (2021), Beggs et al. (2022), Abis and Lines (2021), Abis et al. (2021); Bonelli et al. (2021), Dyer et al. (2021)). Many other studies utilize

[3]Section C of the Appendix provides examples showcasing those scenarios.

PIS excerpts from Morningstar, or summary prospectuses available since 2011. I isolate the full strategy section for all US active equity mutual funds since 2000, directly from the SEC-EDGAR platform. The longer sample allows studying the implications of business cycle fluctuations; whereas focusing on a single section limits misinterpretations as, for instance, mentions of quant methods in the risk or performance sections might be unrelated to a fund's strategy.

The paper proceeds as follows. Section 2 describes the classification and new facts about quants. Section 3 proposes a theoretical framework. Section 4 develops and tests predictions. Section 5 concludes. The Appendix provides details about the classification and robustness.

2 Quantitative versus Discretionary Funds

In this section I describe the data and methodology used to classify funds as quantitative or discretionary; I then report a series of new facts based on this classification.

2.1 Data

I focus on US active equity mutual funds from January 2000 to December 2017. I obtain the sample of interest starting from funds featured in the CRSP Survivorship-Bias-Free Mutual Fund Dataset; I then restrict the sample to equity funds and further exclude international funds, sector funds, index funds, and underlying variable annuities[4]. To remove incubation bias, I keep only observations dated after the fund's first offer date. I also exclude small funds, i.e. with less than $5 million TNA. Data is available at the share class level, i.e. sub-funds with the same portfolio but marketed to different audiences. So, I aggregate all share classes of the same fund at every point in time into one observation. I do so by: keeping the first offer date of the oldest fund, summing the TNA of all share classes, and weighting all other variables (e.g. fees, returns) by lagged TNA. I identify share classes of the same fund by constructing a comprehensive identifier using the CRSP_CL_GRP and WFICN identifiers, and fund names. This improves matching quality between returns/characteristics and

[4] I do so by utilizing primarily the CRSP objective code, when missing, I also check the Lipper, Strategic Insight and Wiesenberger codes and the funds' investment policy. I also use the ETF and variable annuity fund flags and I remove funds which contain any of the following stings in their name: "Index", "Ind", "Idx", "Indx", "iShares", "SPDR", "HOLDRs", "ETF", "Exchange-Traded Fund", "PowerShares" "StreetTRACKS".

holdings. I finally exclude funds with less that 12 months of observations.

Holdings are obtained by merging the Thomson CDA/Spectrum Mutual Fund Holdings dataset from January 2000 to August 2008 and the CRSP Mutual Fund Holdings dataset from September 2008 to December 2017. Thomson Holdings are merged using the WFICN identifier, while CRSP holdings are merged using CRSP's mapping between funds (FUNDNO) and portfolios (PORTNO), adjusted using fund names. I merge the two datasets, rather than using Thomson Holdings for the entire period, as Thomson's coverage deteriorates in 2008 leading to the exclusion of many funds of interest, especially younger ones (Zhu (2020)). The date of switch is chosen to maximize coverage for the funds of interest. This is particularly relevant as quantitative funds are more prevalent in recent years. Using holdings data, I finally remove small funds (i.e. holding fewer than 10 stocks) and balanced funds (i.e. investing on average less than 80% of their assets, excluding cash, in common stocks). I then forward fill holdings to the monthly frequency.[5]

The start date (January 2000) is dictated by the availability of fund prospectuses. I remove all fund-month observations that cannot be matched to a prospectus (see Section 2.2 for details). The final sample consists of $3,176$ funds and $360,642$ fund-month observations. To construct other variables, I also use the CRSP stock-level database, macroeconomic indicators from the Federal Reserve Bank of St. Louis, Compustat earnings, IBES forecasts, Fama–French factors, and Ravenpack News. Table 1 provides a description of the construction of all fund-level variables utilized in subsequent tables; Table 2 provides summary statistics for those same variables.

2.2 Classification

I classify funds using information contained in the "Principal Investment Strategies" (PIS) section of mutual fund prospectuses. This corresponds to item 9 of the N-1A mandatory disclosure in which funds must "*Explain in general terms how the Fund's adviser decides which securities to buy and sell.*" This requirement was added after the 1998 amendment of mandatory disclosures; all funds were required to comply beginning in December 1999, hence I start my analysis in January 2000. Focusing on mandatory disclosures allows for more reliable information than analyzing other

[5] For 42% of the final sample monthly holdings were already available. 90% of the dataset is forward filled for at most 1 quarter and 99% for at most 2 quarters. Maximum forward filling is restricted to 1 year.

self-reported material. In fact, funds are liable to be sued by the SEC for misrepresenting their investment method.[6] Additionally, isolating the strategy description and excluding other sections of the prospectus (e.g. risk or performance) allows for a more precise classification. Indeed, mentions of quantitative methods in other sections might be unrelated to a fund's strategy. The procedure utilized to classify all funds is summarized below, Appendix A contains additional details.

Data Collection First, I collect prospectuses for the $3,176$ funds of interest from January 2000 to December 2017 from the SEC online database – EDGAR; from which I am able to isolate $35,661$ PIS sections. Prospectuses may be published in any day of the year and are often published less than once per quarter. Since any material change to the management of the fund must be reported to the SEC, for any month in which a prospectus is not available I fill that information using the latest available prospectus. All observations in the final dataset are matched to a strategy description. When no material changes take place, funds often re-submit an identical description. Among the matched sections, I identify $24,732$ unique ones.

Training Sample Classification Next, I obtain a pre-classified training sample. To do so, I begin by randomly selecting one PIS section per fund of interest and among those I randomly select 500 sections. The random selection roughly mimics the distribution of fund-month observations in the full dataset, with more observations in later years. I then ask 12 experts—*classifiers*—to classify the random sample as quant or discretionary. Classifiers are chosen among Columbia University students with Finance expertise. Students interested in participating were asked a series of questions to verify their level of understanding of the English language and their prior experience in Finance. All selected students were either native English speakers or had prior experience studying or working in an English speaking country. They all had prior work experience in the finance industry in varied roles and were enrolled in a variety of Master programs.[7]

Figure 1 provides the pairwise level of inter-rater agreement among the 12 classifiers measured as:

[6] An exemplary case is that of the quant mutual fund AXA Rosenberg. The SEC heavily fined it for not promptly disclosing an error in their quant model which was argued misrepresented its capabilities and risk-taking behavior (https://www.sec.gov/news/press/2011/2011-189.htm). Anecdotally, other quant managers mention this case as impacting their accuracy in describing their strategy in prospectuses.

[7] Section A of the Internet Appendix contains more details about classifiers selection.

observed agreement (Panel 1), Gwet's gamma (Panel 2), and Fleiss's Kappa (Panel 3).[8] We observe a high level of agreement among 10 of the 12 classifiers. The remaining 2 (C11 and C12) present negative chance-adjusted agreement with all other classifiers and a low positive agreement with each other. This indicates that they provided systematically opposite answers from the remaining classifiers. Additionally, when including C11 and C12 there are 282 prospectuses for which only 1 or 2 classifiers provided a quant assignment, there are only 56 when excluding them. Hence, for 226 prospectuses C11 and C12 are the only ones to assign a quant classification. That would be expected when a classifier, unaware that one category (discretionary) is more prevalent than the other (quant), provides a random classification.[9] For those reasons, C11 and C12 are excluded; all analysis that follows utilizes the categorization provided by the remaining 10 reliable classifiers.

Among the 10 reliable classifiers, we observe the following overall inter-rater agreement: 86.94% observed agreement, 80.36% Gwet's gamma, and 62.60% Fleiss's Kappa. There is no ultimate consensus on the appropriate level of chance-adjusted agreement, but agreement between 61% and 80% is generally considered good, while agreement above 80% is considered very good (Altman (1990)). Measuring agreement in the context of this exercise is non-trivial. In fact, the unbalancedness of the sample (discretionary being more prevalent) translates into a skewed distribution of answers (i.e., a greater proportion of prospectuses receives a discretionary assignment). This leads to the well documented *prevalence bias* in agreement measurement (Di Eugenio and Glass (2004), Quarfoot and Levine (2016)). In this setting, most chance-adjusted metrics underestimate the true level of agreement. Quarfoot and Levine (2016) show that bias is more pronounced for agreement measurements that rely on the marginal distribution of the two classes, such as Fleiss's Kappa. Measurements that impose restrictions on the usage of the marginal distributions, such as Gwet's gamma, are less biased under these conditions. Hence, the obtained level of agreement should be considered good to very good.

I then construct a summary classification based on the 10 reliable classifiers: I consider as quant

[8] Pairwise observed agreement measures the percentage of observations that any two classifiers assign to the same category. Fleiss's Kappa and Gwet's gamma, additionally, correct for chance agreement—i.e. the level of agreement that would be expected if two classifiers had randomly assigned all samples.

[9] Classifiers were also asked to provide a brief explanation for their choices. While all other classifiers provided differentiated explanations for each answer, C11 and C12 provided a standardized explanation for all quant or discretionary assignments. That suggests an increased likelihood of a random assignment.

the 69 descriptions for which more than 75% of classifiers (at least 8) agree on a quant assignment. There are 386 sections for which at least 8 classifiers agree on a discretionary assignment. To reduce unbalancedness, I randomly select 104 of them ($69 * 1.5$) to belong to the pre-classified sample.

Random Forest Next, I train a machine learning algorithm, the random forest, to classify all strategy descriptions as quant or discretionary. The random forest is a decision–tree based algorithm which uses bootstrapping and majority voting to assign a classification to each item of a pre-classified training sample on the bases of the classifications obtained with multiple decision trees.[10] This procedure allows to increase generalizability and reduce overfitting. The random forest is a relatively transparent algorithm in that it allows one to visualize the list of features (words and two-word combinations) being utilized, along with their relative informativeness – measured as the reduction in entropy obtained with each specific feature. Thanks to the conditional nature of the algorithm, the list of relevant features is determined endogenously by considering the joint presence of features in the text. This also allows avoiding false positives as, for instance, containing the word *quantitative* (e.g. "quantitative easing") wouldn't be sufficient to determine a quant assignment.

Following the procedure detailed in Appendix A, I obtain a final decision rule which uses 853 features, the first 15 of which account for 30.26% of informativeness (Panel 1, Figure 2). The most discriminating features are "quantit" and "model", other highly interpretable features are "use quantit", "rank", "quantit model", "proprietari", "momentum" and "process". "Momentum" is in line with survey evidence that active equity quant mutual funds use trend-based measures to incorporate aggregate dynamics into their models (Fabozzi et al. (2007)). Most other relevant features are interpretable when bearing in mind the algorithm's conditional nature.[11] When applied to a sample of pre-classified sections that were not used in training the algorithm, I obtain 97.67% accuracy. That decision rule is then used to categorize all strategy descriptions.

Validation For a pure out of sample validation, I ask 3 students (different from the original ones) to classify a randomly selected sample of 250 PIS sections, not part of the training sample. I

[10] Section B of the Internet Appendix contains a detailed description of the Random Forest algorithm.
[11] More details on interpretation are provided in Section 2.2.

then compare the accuracy of the random forest algorithm for those sections relative to summary classifications constructed from the assignments of the 3 students. Section B of the Appendix reports all details of that experiment. I obtain similar results as those obtained for the training sample, strengthening the confidence in the overall classification.

We might still worry that the growth in the share of quants might be driven by discretionaries introducing typical quantitative words in their prospectuses, as it becomes more in fashion over time. To mitigate that concern, Panel 1 of Figure 5 displays for every month the number of quants split between funds classified as quant or discretionary at inception. Most of the growth in quants comes from funds categorized as such at inception ($\approx 80\%$ by 2017).[12] Moreover, to ascertain that a switch in classification reflects changes in behavior, Section 4.6 shows that the holdings of switching funds have a greater commonality with the holdings of quants when they are classified as such.

To validate the supervised learning approach, Figure 6 display the distribution in cosine similarity among different PIS sections of the same fund. Panel 1 displays the distribution in similarity at different prior lags across all funds in the sample. We observe a high similarity (close to 100%) between any two consecutive PIS sections (lag -1). Similarity decreases monotonically when comparing PIS sections further apart in time (lags -2 to -25), suggesting that funds tend to make incremental updates to strategy descriptions.[13] Similarity remains high even at the longest lags, with an average cosine similarity at lag -25 of 61.77%. Panel 2 focuses on consecutive prospectuses (lag -1) and splits the distribution in cosine similarity between switching and non-switching months. Switching months are defined as months in which the random forest classifications switches from quant to discretionary or vice versa. The distribution of similarity for non-switching months is more skewed to the right than the unconditional distribution (as shown in lag -1 of Panel 1), with most pairs of non-switching prospectuses having a cosine similarity closer to 1 and a long left tail. The same distribution for switching months is less skewed and has a higher variance. These differences point to the importance of adopting a supervised classification methodology. In fact, the long left tail of the distribution for non-switching months indicates that

[12] Note that both quants and discretionaries might change type throughout the sample period.

[13] The number of available pairs also decreases monotonically with the number of prior lags being considered. The median number of prospectuses available per funds is 8.

there might be cases in which a large change in strategy description does *not* reflect changes in quant or discretionary behavior. Similarly, the variance in the distribution for switching months indicates that a small change in strategy description might be enough to change the classification of a fund along the quant or discretionary dimension, if that change touches upon the distinguishing features of the two categories. That is because PIS sections are multi-dimensional: there funds not only describe the key methodology utilized in selecting securities but also the benchmark they follow, whether they have a growth/value tilt, etc. Changes in any of those other dimensions would determine a potentially large change in the text but would *not* be indicative of changes to the dimension of interest. Hence, textual similarity changes are not sufficient to identify the desired outcome; a supervised approach—such as the random forest—is required.

Interpretation I utilize the ExplanableAI method SHAP (SHapley Additive exPlanations), applied to all unique PIS sections, to better understand the random forest's decision rule. SHAP is a model-free method which applies the game-theory concept of shapley values (Shapley (1997)) to assess the importance of features in determining the outcome of any machine learning model (Lundberg and Lee (2017), Lundberg et al. (2018), Lundberg et al. (2020)). The benefit of assessing features importance using SHAP is that it allows to analyze how features contribute to the classification of each PIS section. Overall feature importances by class can then be retrieved by averaging across their SHAP values in all sections. SHAP values are additive and expressed in the same units as the model's outcome. In a random forest classification, SHAP value by feature-class correspond to how much a feature contributes to the probability of belonging to a given class. In this context, as in any binary classification, features contribute equally to each class: a probability increase of belonging to the quant class corresponds to an equal probability decrease of belonging to the discretionary one. Panel 2 of Figure 2 displays the mean SHAP value for the 15 most informative features across all PIS sections. Reassuringly, the list of most relevant features is similar when measured using SHAP values (Panel 2) or entropy reduction (Panel 1).[14]

Figure 3 displays the per-feature distribution of SHAP values for the quant class.[15] For each

[14] As expected, the absolute relevance of each feature is the same for the two classes.
[15] For the discretionary class we obtain an equivalent representation of opposite sign.

feature, dots represent sections, two of their characteristics are relevant: SHAP values, illustrated on the x-axis; and color, interpreted through the right bar. SHAP values of 0 indicate no importance of the feature in determining the sections' classification, while greater absolute SHAP values (positive or negative) indicate a greater importance. A lighter color indicates a higher frequency of the feature in the section relative to its frequency in the whole corpus (tf-idf). We observe that a higher frequency of all features contributes to a higher quant probability. The top two features are "quantit" and "model". Their absence decreases the quant probability of up to 6% and 3% respectively; their inclusion increases the quant probability of up to 12% and 8% respectively. When they appear jointly, "quantit model", the quant probability is further increased (of up to 6%). The same is true for the bi-gram "use quantit" (up to a 10% increase). Given the additive nature of SHAP values, the inclusion of the phrase "use quantit model" contributes to the quant probability of at most 36% (12+8+6+10).[16] For a quant assignment a minimum quant probability of 50% is required. Hence, even though the inclusion of *use quantit model* has the largest importance, it cannot determine a quant assignment independently. The full structure of the text and the contribution of other features need to be considered. Looking at the importance of other features, we note that their absence has a very small impact on the classification (negative SHAP values close to zero), whereas their inclusion positively contributes to a quant assignment (positive SHAP values of up to 9%).

Figure 4 explores the relationship between "quantit" and other features. In each Panel, dots displays sections, the x-axis the feature's relative frequency (tf-idf), the y-axis its SHAP value; color indicates frequency of the term "quantit", as read off Panel 1. One-term features, aside for "quantit", display an increasing relationship between SHAP values and frequency. For those features, SHAP values are usually higher when "quantit" is *not* present (darkest dots on top), indicating that is when they have the greatest impact on the classification. For "quantit" (and features including it), frequency and SHAP values are not related, inclusion/exclusion has the greatest impact.

Of course, these representations only provides a partial view, a longer list of features beyond the top 15 (e.g., "disciplin", "factor", "weight", "screen") and co-occurrences (e.g., "rank stock", "quantit invest", "price momentum") also matter. Yet, this depiction already showcases the iterative nature

[16] Likely less as features assume a greater relevance when others are missing (see discussion of Figure 4).

of the random forest: when "quantit" is present, it increases the likelihood of a quant classification; when it appears together with other terms commonly used by quants (e.g., "use", "model"), that likelihood is increased; when it is *not* present, the frequent appearance of terms that commonly appear with it (e.g., "rank", "proprietary") increases the likelihood of a quant classification.[17]

2.3 Basic Facts about Quantitative and Discretionary Funds

I merge my classification with the CRSP Mutual Fund dataset, thus I am able to quantify the prevalence of quants. Over 2000–2017, quants quintupled in number (from 59 to 291) and experienced a more than 7-fold increase in TNA (from 31 bn to 241 bn). During this period, quants grew at a faster rate than discretionaries, going from 2.29% to 7.08% of the market's TNA and from 6.10% to 18.61% of the total number of funds (Figure 7). I then check for differences in the characteristics of quants or discretionaries as follows:

$$Char_{j,t} = \alpha + \beta_1 Quant_{j,t} + \beta_2 Quant_{j,t} \times Recession_t + \gamma X_{j,t} + \eta_t + \epsilon_{j,t} \tag{1}$$

where $Char$ is the fund characteristic of interest; $Quant_{j,t}$ and $Recession_t$ are dummy variables indicating respectively whether fund j is categorized as quant in month t by the random forest algorithm, and whether month t is categorized as a recession by the NBER. $X_{j,t}$ is a vector of control variables; namely: the natural logarithm of fund age ($ln(Age)$); the natural logarithm of fund size ($ln(TNA)$); expense ratio ($Expenses$); turnover ratio ($Turnover$); monthly growth rate in net fund flows ($FlowGrowth$); 12-months rolling volatility in the growth in net fund flows ($FlowVol$), total loads ($Loads$); and style controls obtained as the average exposure of stocks held to the Fama and French (2015) factors plus momentum ($Market$, $Size$, $Value$, Mom, $Profit.$ and $Invest.$). I include month fixed-effects (η_t), exclude the dependent variable from the vector of controls, and cluster standard errors at the fund and month level.

A significant β_1 quantifies the difference in the mean of the dependent variable for quants, relative to discretionaries. A significant β_2 represents an incremental difference in recessions.

[17] Section C of the Appendix provides various examples that further highlight these concepts.

Given the inclusion of time fixed-effects and fund-level controls, the intercept does not have a direct interpretation. Hence, in my discussion of economic magnitudes in the text, I express β_1 in percentage of the mean of the dependent variable for discretionaries ($\overline{Char^D}$) as follows: $sign(\beta_1)\left|\frac{\beta_1}{\overline{Char^D}}\right| * 100$.[18] That measure should be interpreted as the percentage-difference of the dependent variable for quants relative to discretionaries.

Table 3 shows differences in fund characteristics. Quants are on average 9.52% ($\left(e^{-0.1}-1\right)*100$) younger and 28.11% ($\left(e^{-0.33}-1\right)*100$) smaller than discretionaries–β_1 significant at 1% level, Models (1) and (2). They have an average turnover ratio of 29.53 percentage points higher than that of discretionaries—β_1 significant at 1% level, Model (3). The average discretionary has a turnover ratio of 77.26%; that of quants is 38.22% higher ($29.53/77.26 * 100$). They hold 0.73 percentage points less cash than discretionaries–β_1 significant at 1% level, Model (4). The average discretionary holds 3.14% of TNA in cash; quants hold 23.24% less ($-0.73/3.141 * 100$). Quants also hold less cash in recessions: $\beta_2 = -0.52$, significant at 1% level. Models (5)-(10) show differences in style: dependent variables are the average exposures of stocks held to factors. There isn't a significant difference in the sensitivity of stocks held by quants or discretionaries to the market factor. The stocks held by quants, though, have a 24.84% lower size exposure ($-0.04/0.161$)–i.e. they tend to be larger; a 58.82% higher value exposure ($0.02/0.034$); a 105.26% higher momentum exposure ($0.02/0.019$); a 30.77% higher investment exposure ($0.02/0.065$); and a 76.92% higher profitability exposure ($0.04/0.052$). All β_1 coefficients are significant at 1% level. These are average effects, Figure 8 also shows a sizable variation in exposures distribution. For instance, splitting quants and discretionaries into deciles based on the exposures of the stocks they hold to the *Momentum* factor (Row 2, Panel 1), we see a similar percentage of discretionaries assigned to each decile, while there are 5% more quants assigned to the top momentum decile than to the bottom one.

Table 4 shows differences in flows and fees. The growth in net fund flows is not significantly different across the two fund types in good times, but quants experience more outflows in recessions: $\beta_2 = -0.573$, significant at 1% level, Model (1). Quants also face higher volatility in the growth of

[18] I report the mean of the dependent variable for discretionaries at the bottom of each table, computed using the same set of observations as those included in each regression. When the dependent variable is log-transformed, an approximation with an equivalent interpretation is given by: $\left(e^{\beta_1}-1\right)*100$.

net fund flows in recessions–$\beta_2 = 0.007$ significant at 5% level, Model (2). The annual expense ratio charged by quants is 7.8 basis point (*bps*) lower than that charged by discretionaries–β_1 significant at 1% level, Model (3). The average discretionary charges 1.221%, quants charge 6.39% (-0.078/1.221) less. Breaking down the expense ratio into its components, we see that this difference is coming from management fees (Model (4)) and not from 12b1 fees, which include marketing expenses (Model (5)). The management fee of quants is 3.3 *bps* lower than that of discretionaries–β_1 significant at 5% level. The average discretionary charges 0.721% management fees, quants charge 4.58% less (-0.033/0.721). There are no differences in total loads, Model (6).

3 Theoretical Framework

Aside for the outlined differences, quants and discretionaries might also differ in their skills, strategy and returns. To gain insights on those potential differences I adopt the framework of Kacperczyk et al. (2016) (KVV). They propose a static general equilibrium model in which skilled and unskilled Bayesian agents invest in multiple assets, which are subject to a common aggregate shock and to idiosyncratic shocks. Unskilled investors learn about assets' payoffs from prices, skilled investors can additionally allocate a limited capacity to learning from private signals. Hence, before making investment decisions, skilled investors optimally allocate their limited learning capacity to maximize the benefit of learning. KVV show that skilled investors optimally shift from learning about idiosyncratic shocks in expansions to learning about the aggregate shock in recessions, when its marginal benefit of learning increases.[19] This leads to differences in both strategy and returns across the business cycle.

I chose this framework as skilled investors seem to accurately represent discretionaries, for which investment decisions are predominantly determined by the judgment of an asset management team. Indeed, the limited capacity for processing information reflects humans' limited cognitive abilities. While the ability to seamlessly shift to learning about aggregate or idiosyncratic shocks implies a

[19] Studies have shown that aggregate stock market volatility (Hamilton and Lin (1996); Campbell et al. (2001); Engle and Rangel (2008)) and aggregate risk aversion (Dumas (1989); Chan and Kogan (2002); Garleanu and Panageas (2015)) rise in recessions. KVV show that the marginal benefit of learning about a shock increases with its supply and volatility.

flexible investment approach; likely not grounded in fixed-rules or pre-determined models. These key features of KVV might differ for quants.

We have little guidance from the academic literature on the behavior of quant mutual funds. From industry reports (e.g., Becker and Reinganum (2018)) we gather that they are predominantly based on the premises of the academic literature on factor investing and anomalies. They utilize factor models and other stock-specific quant measures (fixed-rules) to identify mis-priced securities, which they overweight or underweight in their portfolios relative to the weight they have in a pre-determined benchmark. Table 5 provides some suggestive evidence in support of this view. Models (1)–(2) regress funds' excess return on the Fama and French (2015) 5 factor model plus momentum ($ff6$), for quants (1) or discretionaries (2). The factor model has a 5% higher explanatory power (R^2) over the variation in the excess return of quants.[20] This suggests a greater reliance of quants on factor models. Models (3) and (4) check differences in idiosyncratic volatility ($IVol - ff6$).[21] All regression specifications are equivalent to those described for Eq. 1:

$$ln(IVol - ff6)_{j,t} = \alpha + \beta_1 Quant_{j,t} + \beta_2 Quant_{j,t} \times Recession_t + \gamma X_{j,t} + \eta_t + \epsilon_{j,t} \qquad (2)$$

The average 24-months rolling idiosyncratic volatility of quants is 13.15% ($(e^{-0.141} - 1) * 100$) lower than that of discretionaries–β_1 significant at 1% level, Model (3).[22]. Indicating a larger variance in discretionary returns not explained by the factor model, potentially pointing to less reliance on similar fixed-rules. The difference is attenuated in recessions, likely indicating differences in behavior across the business cycle—β_2 positive and significant at 1% level.

These arguments lead to hypothesize that quants might face different constraints than discretionaries. For instance, limited cognitive ability might not be a primary bottleneck for them–i.e., they should be able to utilize quant methods and computing power to construct factors and analyze stock characteristics for the universe of securities. Conversely, reliance on factor

[20] Through bootstrapping with 1,000 repetitions I obtain 95% confidence intervals for the R^2s: [82.91%, 83.90%] for Model (1) and [78.24%, 78.77%] for Model (2); hence the difference is statistically significant.

[21] $IVol - ff6$ is the volatility of the residual of regressing funds' excess returns on the $ff6$ model over the prior 24 months or 36 months; $ln(.)$ indicates the natural logarithm.

[22] Results are similar when using 36-months rolling windows, Model (4)–12.98% lower ($(e^{-0.139} - 1) * 100$)

models and fixed-rules might make them less capable of flexibly adapting their strategy across the business cycle. It is an empirical question whether KVV's findings extend to quant mutual funds. In what follows, I formulate hypotheses of how KVV's predictions might differ for quants; I then test them empirically utilizing the classification developed in Section 2.2.

4 Development and Testing of Predictions

4.1 Skill

KVV's main prediction is that capacity constrained investors, discretionaries, focus their attention on macroeconomic shocks in recessions and on stock-specific shocks in expansions. If quant equity mutual funds mostly rely on traditional factor models and other fixed-rules in determining their asset allocation, they might not be able to flexibly shift to learning about macroeconomic shocks in recessions. If this conjecture was correct, we should observe a greater ability of discretionaries to time macroeconomic shocks in recessions. In expansions, a clear prediction cannot be made. On the one hand, quants might be less constrained in the quantity of information they can process—i.e. they might not need to choose which assets to focus on but should be able to construct factors/fixed-rules based on the universe of securities. For that reason, we might expect their stock picking ability to be greater than that of discretionaries. On the other hand, quants might not be able to collect as much information as discretionaries about any given security. Particularly if discretionaries were to focus on stocks for which relatively more soft information was available.

Prediction 1. *Skilled discretionaries shift their attention to learning about macroeconomic shock in recessions; skilled quants do not. Hence, in recessions, discretionaries display a higher ability to time macroeconomic shocks and a lower stock picking ability than quants.*

Measurement: As in KVV, I measure Stock-Picking (SP) and Macro-Timing (MT) abilities as the covariance between the weight allocated by fund j to each stock i (in excess of the market weight) and next-period's stocks-specific (z_{it}) or aggregate (z_{nt}) shocks respectively. Timing is constructed over a 12-months rolling window. These measures imply that holdings should reflect managers'

information set. Hence, the holdings of skilled managers should covary with innovations in *future* stock-specific or aggregate shocks; depending on the ones about which they have private information.

$$MT_{jt} = \frac{1}{TN^{jt}} \sum_{i=1}^{N^j} \sum_{\tau=0}^{T-1} (w^j_{i(t+\tau))} - w^m_{i(t+\tau))})(b_{i(t+\tau)} z_{n(t+\tau+1)}); \; SP_{jt} = \frac{1}{N^{jt}} \sum_{i=1}^{N^j} (w^j_{it} - w^m_{it})(z_{i(t+1)}) \quad (3)$$

where N^{jt} denotes the number of stocks held by fund j at time t; w^j_{it} the weight (in percentage of TNA) of stock i in the portfolio of fund j at t, and w^m_{it} the weight (in percentage of market capitalization) of stock i at t in the CRSP universe. I measures stock-specific shocks with earnings surprises (SUE); the aggregate shock with innovations in the change in industrial production or non-farm payrolls.[23] I then measure funds' ability to time exposures to the size, book-to-market and momentum factors (Characteristic-Timing, CT), as in Daniel et al. (1997) (DGTW).

Finally, for each recession I select all observations belonging to the top q% of the MT or CT distribution, and for each expansion belonging to the top q% of the SP distribution (i.e., the high-ability sample). Then, for each recession/expansion I calculate how frequently each fund belongs to the high-ability sample; measured as the number of months (relative to number it is alive) that it is among the top timers or pickers. Finally, I construct dummy variables identifying high-ability funds– i.e., the top q% of funds that most frequently display, high stock-picking ability in the *precvious* expansion ($TopPickers^E_q$) or high market-timing ability in the *previous* recession ($TopTimers^R_q$).[24]

Testing: I test Prediction 1 by running the following regressions, whose specifications are equivalent to those described for Eq. 1, for $Tim = [MT, \; CT]$, conditioning on recession (R) or expansion (E) periods. Regression outcomes are shown graphically in Table 6.

$$Tim_{jt} = \alpha + \beta_1 Quant_{jt} + \beta_2 TopPickers^E_{qj} + \beta_3 TopPickers^E_{qj} \times Quant_{jt} + \gamma X_{jt} + \eta_t + \epsilon_{jt} | R; \quad (4)$$

$$SP_{jt} = \alpha + \beta_4 Quant_{jt} + \beta_5 TopPickers^E_{qj} + \beta_6 TopPickers^E_{qj} \times Quant_{jt} + \gamma X_{jt} + \eta_t + \epsilon_{jt} | R; \quad (5)$$

[23] To construct the latter I fit a 36-months rolling AR(1) process to changes in industrial production or non-farm payroll (Δy_t) to obtain a predicted change ($\hat{\Delta y_t}^{(t-1,t-36)}$). I then construct surprises as: $z_{nt} = \Delta y_t$ - $\hat{\Delta y_t}^{(t-1,t-36)}$. The sensitivity of the return of stock i to the aggregate shock (β_t) is obtained through 12-months rolling regressions of the excess return on the stock (r_{it}) on macro surprises: $r_{it} = \alpha + \beta_t z_{nt}$.

[24] The utilized cutoffs (q) are all quantiles from the top 10% to the top 25% of high ability funds.

$$Tim_{jt} = \alpha + \beta_7 Quant_{jt} + \beta_8 TopTimers^R_{qj} + \beta_9 TopTimers^R_{qj} \times Quant_{jt} + \gamma X_{jt} + \eta_t + \epsilon_{jt}|E \quad (6)$$

Equation 4 tests whether high-ability funds switch from stock picking in expansions to macro-timing in recessions. Measuring macro-timing with shocks in industrial production (Panel 1), discretionaries with high stock picking ability in expansions also have high macro-timing ability in recessions ($\beta_2 > 0$). For quants this effect roughly cancels out ($\beta_3 \approx -\beta_2$)–i.e., quants do not switch between stock picking and macro-timing across the business cycle, while high-ability discretionaries do so. The effect is more pronounced for $q = 10\%$ but still significant up to $q = 25\%$. Results are consistent when measuring macro-timing with shocks to non-farm payrolls (Panel 2). There is no evidence of switching when looking at characteristic-timing (Panel 3) indicating that, as hypothesized, differences come from the timing of macroeconomic shocks. Eq. 5 tests for whether some funds specialize in stock picking across the business cycle. Panel 4 shows that top discretionary pickers in expansion are *not* top pickers in recessions ($\beta_5 < 0$), for quants this effect is reversed ($\beta_6 \approx -\beta_5$). Eq. 6 tests for whether some funds specialize in market timing across the business cycle. Panels (5)-(7) show that top timers in recessions are not top timers in expansions ($\beta_8 = 0$), the effect is not different for quants ($\beta_9 = 0$). Hence, there is no evidence that any fund specializes in market timing across the business cycle.

Finally, I test for differences in average abilities of quants or discretionaries, for $Ability = [SP,\ MT,\ CT]$. All regression specifications are equivalent to those described for Eq. 1.:

$$Ability_{jt} = \alpha + \beta_1 Quant_{jt} + \beta_2 Quant_{j,t} \times Recession_t + \gamma X_{jt} + \eta_t + \epsilon_{jt} \quad (7)$$

Prediction 1 implies a positive (negative) and significant ($\beta_1 + \beta_2$) for stock-picking (macro timing) in recessions; it does not provide predictions for characteristic timing or for expansions. Table 7 reports regression outcomes. The average stock picking ability of quants in recessions is higher than that of discretionaries of 0.5779 ($-0.089 + 0.6669$); that is 31.42% (0.5779/1.839) higher–β_1 and β_2 significant at 1% level, Model (1). The average macro-timing ability (measured with innovations in industrial production) of quants in recessions is lower than that of discretionaries of 0.4957; that is 40.53% ($-0.4957/1.223$) lower–β_2 significant at 1% level, Model (2). Results are

similar when measuring macro timing with innovations in non-farm payrolls, Model (3). There are no differences in characteristic-timing ability, Model (4). These results confirm Prediction 1: quants and discretionaries differ in stock-picking and macro-timing abilities across the business cycle.

4.2 Portfolio Diversification

If quants are less constrained in the amount of information they can analyze before making an investment decision, we might expect them to hold a larger number of securities. Holding a more diversified portfolio should then yield diversification benefits, such as a lower volatility of returns.

Prediction 2. *Quants hold a larger number of securities than discretionaries and display a lower volatility of returns.*

Measurement: I measure diversification with the natural logarithm ($ln(.)$) of the number of stocks held ($NStocks_{jt}$), and of the 24 or 36 months rolling volatility of returns ($RetVol_{jt}$).

Testing: I test Prediction 2 by running the following regressions, whose specifications are equivalent to those described for Eq. 1, for $Div = [NStocks,\ RetVol]$:

$$ln(Div_{jt}) = \alpha + \beta_1 Quant_{jt} + \beta_2 Quant_{jt} \times Recession_t + \gamma X_{jt} + \eta_t + \epsilon_{jt} \tag{8}$$

Prediction 2 implies a positive (negative) and significant β_1 for the number of stocks held (return volatility). Table 8 reports regression outcomes. Quants hold 36.89% ($(e^{0.314} - 1) * 100$) more stocks than discretionaries–β_1 significant at 1% level, Model (1). Results are similar when controlling for funds' cash holdings–$(e^{0.291} - 1) * 100 = 33.78\%$ more, Model (2). Quants have 3.15% ($(e^{-0.032} - 1) * 100$) less 24-months rolling volatility of returns than discretionaries–β_1 significant at 1% level, Model (3).[25] The effect is less pronounced in recessions: $\beta_2 < -\beta_1$ positive and significant. These results confirm Prediction 2: quants display greater portfolio diversification than discretionaries.

[25] Results are similar for the 36-months rolling volatility specification–$(e^{-0.035} - 1) * 100 = 3.44\%$ less.

4.3 Information Availability

Quants and discretionaries might also differ in the type of information they are able to consume and hence in the characteristics of their holdings. In fact, some information available for human consumption might not be machine-processable and vice versa. For instance, less machine-processable information might be available about relatively younger or smaller firms, yet discretionaries could obtain soft information about those companies through discussions with management or other informal channels.

That is relevant given the substitution effect highlighted by KVV: for discretionaries the marginal benefit of learning about a stock increases when relatively fewer other investors learn about it. In the presence of quants, then, discretionaries have an incentive to learn about stocks for which relatively less machine-processable information is available, since quants would not learn much about them. Additionally, discretionaries could have an advantage relative to quants on those assets if they were able to collect soft information about them.

Prediction 3. *Quants hold securities for which more information is available.*

Measurement: I constructs proxies for the TNA-weighted average of information availability of the stocks a fund holds. Machine-processable information should be more abundant for stocks for which more overall information is available. I proxy for the information availability stock i at time t (I_{it}) with: market capitalization, the number media mentions in Dow Jones news articles every month, age (in months), and the number of IBES unique analysts following the stock.[26] For those stocks there should be a greater gap in the information consumed by quants or discretionaries, the former being less constrained in their learning capacity. I measure that information gap as:

$$InfoGap_{jt}^{wd} = \sum_{i=1}^{N^j} \left[w_{it}^j I_{it} \right] \tag{9}$$

[26] Media mentions are measured using Ravenpack news. For each stock-month I count the number of news articles which mention it, weighted by their relevance with respect to the stock of interest. Size and media mentions are log-transformed as their distributions are skewed.

Testing: I test Prediction 3 running the following regressions:

$$InfoGap_{jt} = \alpha + \beta_1 Quant_{jt} + \beta_2 Quant_{jt} \times Recession_t + \gamma X_{jt} + \eta_t + \epsilon_{jt}; \tag{10}$$

where all regression specifications are equivalent to those described for Eq. 1, with the addition of the average illiquidity of stocks held as a control—constructed as one-year rolling Amihud ratios. Prediction 3 implies a positive and significant β_1. Table 9 shows regression outcomes.

When excluding from the vector of controls the size style control, the average market capitalization of stocks held by quants is 26.24% ($(e^{0.233} - 1) * 100$) more than that of stocks held by discretionaries–β_1 significant at 1% level, Model (1). When including it (Model 2), the effect is lower in magnitude but persists–9.64% ($(e^{0.092} - 1) * 100$) more, β_1 significant at 5% level–indicating that quants not only belong to larger size styles, but also that they hold larger stocks than those held by discretionaries in the same styles.

The average age of stocks held by discretionaries is 26 years (312.077/12), that of stocks held by quants is 27.48 years ((312.077 + 17.644)/12), 5.65% (17.644/312.077) more–β_1 significant at 1% level, Model (3). When additionally controlling for the natural logarithm of the average market capitalization of stocks held–$ln(MktCap)$ (Model (4)), the effect remains significant–average age of stocks held by quants 27.10 ((312.077 + 13.182)/12) years, 4.22% (13.182/312.077) more, β_1 significant at 1% level. These are residual effects after controlling for the size style and the average size and illiquidity of stocks held. Age differences are relevant as quants usually base their investments on historically back-tested models, when a sufficiently long time-series is not available, it might be difficult to obtain statistically significant predictions.

Quants also hold stocks that have 7.57% ($(e^{0.073} - 1) * 100$) more media mentions per month than the stocks held by discretionaries–β_1 significant at 1% level, Model (5). Model (5) controls for both the size style of the fund and the average illiquidity of stocks held, it does not control for $ln(MktCap)$. When controlling for $ln(MktCap)$, β_1 remains positive but loses significance, indicating that within their size style funds choose stocks with more media mentions, those same stocks have a higher market capitalization, Model (6).

Stocks held by both quants and discretionaries are followed on average by 8.03 analysts, Model (7). When controlling for $ln(MktCap)$ the average number drops to 7.888 (8.03 − 0.142) for quants, 1.77% (−0.142/8.03) less–β_1 significant at 1% level, Model (8). This indicates that, given a certain size of stocks held, discretionaries prefer stocks followed by more analysts. This can have a learning interpretation, in fact analysts summarize large amounts of information into reports and recommendations, this service should be particularly useful to capacity constrained investors.

Taken together, these results confirm Prediction 3: quants hold stocks for which relatively more information is available.

4.4 Dispersion of Opinion

KVV derive the determinants of dispersion of opinion among discretionaries; which translates in dispersion in portfolio allocations. Dispersion increases with the total precision of private signals: the greater the total precision of private signals the more weight is given to the heterogeneous private signals as opposed to common priors in determining posteriors. Additionally, dispersion of opinion increases with the cumulative difference in the attention allocated by investors to each asset with respect to the attention allocated to the same assets by the average investor of their type.

The above two forces might play out differently for quants. The first effect would likely determine a higher dispersion of opinion among quants than among discretionaries, given their relatively higher capacity for processing information. The second effect would likely go in the opposite direction, due to the above mentioned substitution effect. Having to optimally allocate their limited learning capacity, discretionaries might choose to learn about different shocks from each other, increasing the difference between the attention that each investors allocates to a given shock and that allocated by the average discretionary. For quants that might matter less, as information processing capacity is likely a lesser bottleneck; leading to more homogeneous information consumption and hence a greater commonality in holdings. Moreover, if indeed their investment approach is guided by academic research and likely similar fixed-rules, we would expect them to process information more similarly, increasing portfolio commonality. I hypothesize that the second force should prevail, as quant mutual funds are not considered to be among the most sophisticated investors.

Prediction 4. *There exists a greater dispersion in portfolio allocation among discretionaries than among quants.*

Measurement: I construct two basic measures: the natural logarithm of the cumulative squared difference in the weight allocated by each fund and the average weight allocated by funds of the same type to each stock ($ln(Disp)$); and the TNA-weighted average of the percentage of funds of the same type who hold the same stocks as fund j at time t ($Comm$):

$$ln(Disp^F_{jt}) = ln\left(\sum_{i=1}^{N^j_t}\left(w^j_{it} - \bar{w}^F_{it}\right)^2\right); \quad Comm^F_{jt} = \sum_{i=1}^{N^j_t}\left[w^j_{it}\left(\frac{F_{it}}{F_t}\right)\right] \tag{11}$$

for $F = (Q,\ D)$, where: $\bar{w}^F_{it}$ is the average weight allocated by quants (discretionaries) to stock i at time t; Q_t (D_t) is the number of quants (discretionaries) at time t; Q_{it} (D_{it}) is the number of quants (discretionaries) who hold stock i at time t.

I construct another measure that captures commonality in the stocks that investors most actively learn about. I define "active-weights" as the standardized deviation of the weight allocated by funds to each stock and the stocks' weight in the market $(w^j_{it})^A$. For each fund-month I then identify the "active set" as stocks in the top 25% of the funds' active-weight distribution. Finally, I construct active commonality as the active-weighted average of the percentage of funds of the same type who are most active on the same stocks as fund j at t:

$$AComm^F_{jt} = \sum_{i=1}^{N^j_t}\left[(w^j_{it})^A\left(\frac{F^A_{it}}{F_t}\right)\right]; \quad where: \quad (w^j_{it})^A = \frac{|w^j_{it} - \bar{w}^m_{it}|}{\sum_i |w^j_{it} - \bar{w}^m_{it}|} \tag{12}$$

for $F = (Q,\ D)$, where: Q^A_{it} $\left(D^A_{it}\right)$ is the number of quant (discretionary) funds for whom stock i belongs to their "active set" at time t.

Finally, I measure "overcrowding" by multiply commonality measures by the sum of TNA of same-type funds in trillions of \$s, such that: $(A)Comm\_TNA^F_{jt} = (A)Comm^F_{jt} \times TNA_{F_t}$ for $F = (Q, D)$. These measures should be interpreted as the total amount of capital managed by funds of the same type who (are active on) hold the same stocks.

Testing: I test Prediction 4 by running the following regressions, whose specifications are equivalent to those described for Eq. 1, for $D = [Comm,\ AComm,\ ln(Disp)]$:

$$D_{jt} = \alpha + \beta_1 Quant_{jt} + \beta_2 Quant_{jt} \times Recession_t + \gamma X_{jt} + \eta_t + \epsilon_{jt} \tag{13}$$

Prediction 4 implies a negative (positive) and significant β_1 when the dependent variable is dispersion (commonality). Table 10 reports regression outcomes. The average commonality in holdings among discretionaries is 11.592%, among quants it is 16.189% (11.592 + 4.597), 39.66% (4.597/11.592) more–β_1 significant at 1% level, Model (1). Results are similar when using active commonality (2.418/6.341 = 38.13% more, Model (2)). The average holdings dispersion of quants is 11.57% ($(e^{-0.123} - 1) * 100$) less than that of discretionaries–β_1 significant at 1% level, Model (3). These are average effects, Figure 9 displays the distribution of dispersion (Row 1, Panel 1) and of commonality (Row 2, Panel 1) for the two fund types. Commonality displays a two-peaked distribution, particularly pronounced for quants, indicating that funds polarize between a low and high common portfolio ownership. Panel 2 (Panel 3) displays commonality (overcrowding) over time for discretionaries (Row 1) or quants (Row 2). Commonality has been declining over time, but it has has consistently been higher for quants. Overcrowding is always higher for discretionaries, as they represent a higher total share of the market. Trends in overcrowding, though, are quite different. At the end of 2017 discretionaries experience a similar overcrowding as in 2000. Quants' overcrowding, instead, is 6-times higher. These results confirm Prediction 4: quants display a lower dispersion of opinion and hence in holdings than discretionaries.

4.5 Active Returns

Finally, KVV show that active returns (returns in excess of a benchmark) are an increasing function of the precision of the private signals on the risk factors that investors choose to learn about, in proportion to the marginal benefit of learning about them. Active returns decrease with increases in the average precision of private signals across all investors in the market. They show that for capacity constrained investors it is optimal to learn about the aggregate shock in recessions, given

that it is the time when its marginal benefit of learning is the highest (higher aggregate shock volatility), and it is the shock in largest supply.

Given quants' inability to timely switch to macro timing (Prediction 1), we should expect them to deliver lower risk-adjusted returns than discretionaries when the benefit of macro timing is the highest–i.e., in recessions. Additionally, quants' greater diversification (Prediction 2), and lower idiosyncratic volatility (Table 5), imply a less dispersed distribution of active returns.

Prediction 5. *The active return distribution of quants is less dispersed than that of discretionaries. In recessions, quants display lower active returns than discretionaries.*

Measurement: To measure active returns (AR) I run the following regression for each fund over 24 and 36 months rolling windows–i.e., for each fund j and window W I run:

$$R_{j\tau} = a^W + \beta_1^W MKT_\tau + \beta_2^W SMB_\tau + \beta_3^W HML_\tau + \beta_4^W RMW_\tau + \beta_5^W CMA_\tau + \beta_6^W UMD_\tau + \zeta_{j\tau} \quad (14)$$

where $R_{j\tau}$ is the gross of fees return of fund j at time τ, in excess of the risk free rate. The active return of fund j at time t (the final date of each estimation window) is then:

$$\begin{aligned} AR_{jt} = R_{jt} - \left(\hat{\beta}_1^W MKT_t + \hat{\beta}_2^W SMB_t + \hat{\beta}_3^W HML_t + \hat{\beta}_4^W RMW_t + \hat{\beta}_5^W CMA_t + \hat{\beta}_6^W UMD_t\right) \\ = \hat{a}^W + \zeta_{jt} \quad (15) \end{aligned}$$

Finally, I average active returns within quarters, in order to reduce measurement noise. Such that $\overline{AR}_{jq}$ indicates the average monthly active return of fund j in quarter q.

Testing: To test Prediction 5, I run the following regressions:

$$\overline{AR}_{jq} = \alpha + \beta_1 Quant_{j(q-1)} + \beta_2 Quant_{j(q-1)} \times Recession_q + \gamma X_{j(q-1)} + \eta_q + \epsilon_{jq}. \quad (16)$$

where all fund-level explanatory variables are lagged, so to relate average active return in quarter q to fund-characteristics at the end of quarter $(q-1)$. $Recession_q$ is an indicator variable equal to 1 if

at least 2 of the 3 months in quarter q are categorized as recessions by the NBER, 0 otherwise. All other regression specifications are equivalent to those described for Eq. 1. Differences in mean are estimated through OLS, differences in the pth percentile are estimated with quantile regressions.[27] The first part of Prediction 5, predicting a less dispersed active return distribution for quants, implies a positive and significant β_1 for $p < 50\%$ and a negative and significant β_1 for $p > 50\%$. The second part, predicting a lower active returns of quants in recessions, implies a negative and significant $(\beta_1 + \beta_2)$. Figure 10 shows results graphically for $p = [1, 5, 10, 20, 30, 40, 50, 60, 70, 80, 90, 95, 99]$, utilizing 95% confidence intervals; Table 11 provides a quantification for the mean and for $p = [25, 50, 75]$.

Panel (1) of Figure 10 shows that for $p < 50\%$ quants' active return is significantly higher than that of discretionaries, for $p > 50\%$ it is significantly lower. The magnitude of $|\beta_1|$ increases for percentiles further from the median. Similarly, in Table 11, for the 24-months specification, quants' active return is on average 1.9 *bps* higher per month than that of discretionaries at the 25th percentile, Model (2), and 5.1 *bps* lower at the 75th percentile, Model (4)–β_1 significant at 5% and 1% levels respectively. Results are similar for the 36-months specification, Models (6) and (8). Panel (2) of Figure 10 illustrates β_2. The OLS and quantile estimates are all negative, statistically significant, and not statistically different from each other. Similarly, in all specifications of Table 11, β_2 is negative and statistically significant. For the 24-months specification (Models (1–4)), the average (median) quant has an $\overline{AR}$ lower than that of the average (median) discretionary of 17.8 (14.5) *bps* per recession month, that is 4.3 (6.3) times lower, $-0.178/0.041$ $(-0.145/0.023)$. In annualized terms that corresponds to a 2.14% (1.74%) lower active return. Results are similar for the 36 months specification. These results confirm Prediction 5: quants' active return distribution is less dispersed than that of discretionaries, and it is significantly lower in recessions.

4.6 Robustness

Switching Funds: Looking at the documented growth in quants (Figure 5), one might worry that the portion due to switching funds might be driven by the inclusion of more typically quantitative

[27] Quantile regressions have the same specification as OLS by: using the STATA command *robreg q*, adding time dummies, clustering standard errors by fund and time through bootstrapping with 1000 repetitions.

terms in funds' prospectuses, as it becomes more in fashion. To verify that changes in language correspond to change behavior, I run the following regressions:

$$D_{jt} = \alpha + \beta_1 Quant_{jt} + \beta_1 Quant_{jt} \times Recession_t + \gamma X_{jt} + \eta_t + \iota_j + \epsilon_{jt} | Switcher = 1 \qquad (17)$$

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 quant in month t. *Switcher* is an indicator variable identifying funds that at any point in time change classification. Since all funds in this sample have multiple classifications, I also include fund fixed-effects (ι_j).[28] All other regression specifications are equivalent to those described for Eq. 1.

Fund and month fixed-effects allow assessing for the same fund in the same month what is the impact of a quant assignment on the similarity of their holdings to those of all other quants. If changes in classification did not correspond to changes in behavior, we would expect β_1 to be non-significant. Alternatively, we would expect a fund's holdings to be closer to those of other quants when they are classified as such–i.e. β_1 positive (negative) and significant when the dependent variable is commonality (dispersion).

Table 12 reports regression outcomes. Switchers have a 4.87% higher commonality (Model (1), 0.741/15.222) a 5.31% higher active commonality (Model (2), 0.444/8.362), and a 18.7% lower dispersion (Model (3), $(e^{-0.207} - 1) * 100$) with respect to quants when they are classified as such–β_1 significant at 1% level in Models (1) and (3) and at 5% level in Model (2). Leading to conclude that changes in classification reflect changes in behavior.

Placebo Classifications: I construct two placebo classifications. The first captures mechanical effects due to the persistence of the Quant classification for any given fund. It takes as input the overall percentage of observations classified as quant (12.15%), then randomly selects 12.15% of funds from the overall sample (386 funds) and it permanently assigns a value of 1 to those funds (0 otherwise). The second captures mechanical effects due to the upwards trend in the share of

[28] Fund fixed-effects cannot be added to other specifications as they would be collinear with the *Quant* dummy for all funds that never change type.

quants during the sample period. This variable is constructed by randomly assigning a value of 1 every month to as many observations as those classified as Quant in that month (0 otherwise). All predictions are tested using these placebos in place of the random forest classification. Results are reported in Section C of the Internet Appendix. As expected when running many regressions using a dummy as explanatory variable, a few coefficients are significant. Reassuringly, in most regressions the coefficients on the two placebos are not significant, and when significant they have a small economic magnitude; there are no clear patterns of significance. This further validates the measure's construction and excludes that simple mechanical effects are driving results.

5 Conclusion

This paper demonstrates that there exist significant differences between quant and discretionary equity mutual funds, driven by differences in their learning. The traditional fixed-rules approach to quant investment determines a trade-off between learning capacity and flexibility, which allows humans to more easily adapt their strategies and maintain greater active returns in recessions. Quants display better portfolio diversification and risk management throughout the business cycle, with a lower dispersion of active returns. It's important to understand these trade-offs as they could foretell future developments. Indeed, increases in the availability and use of big data could accentuate the capacity advantages of quants, but could also worsen overcrowding. Moreover, recent developments in AI could provide a foundation for overcoming the limited flexibility of quant equity models based on fixed-rules. This paper provides a framework to think about those issues.

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Figure 1: **Training Sample - Inter-rater Agreement:** Pairwise agreement among the 12 classifiers who were asked to categorize a randomly selected sample of 500 PIS sections. Agreement is calculated as: observed agreement (Panel 1), Gwet's gamma (Panel 2), and Fleiss' Kappa (Panel 3).

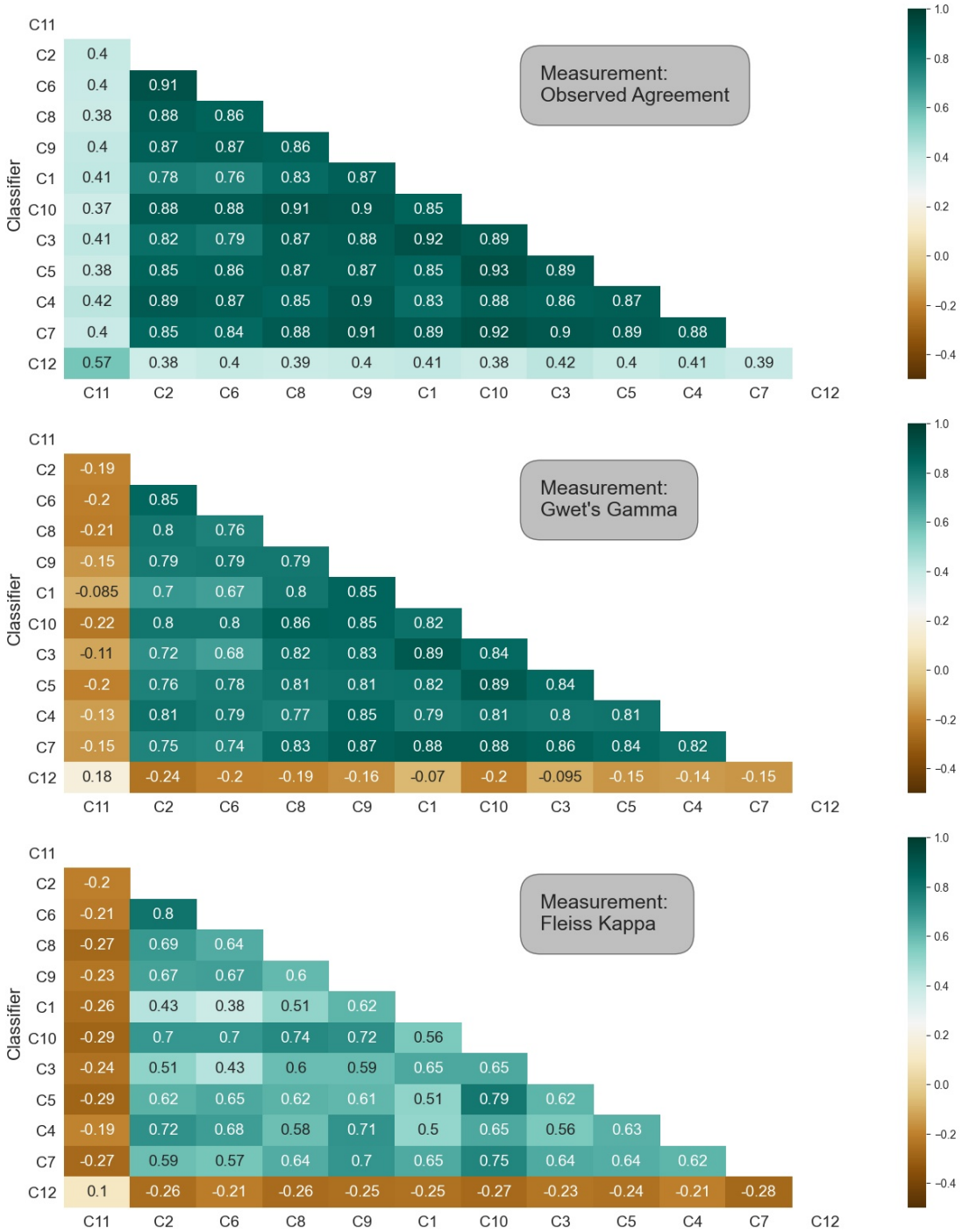

Figure 2: **Random Forest - Features Importance:** Top 15 features used by the random forest algorithm, ranked by informativeness. Informativeness is measured as: the average reduction in classification impurity (measured with entropy) when splitting the sample according to each feature (Panel 1); or mean SHAP values (Panel 2).

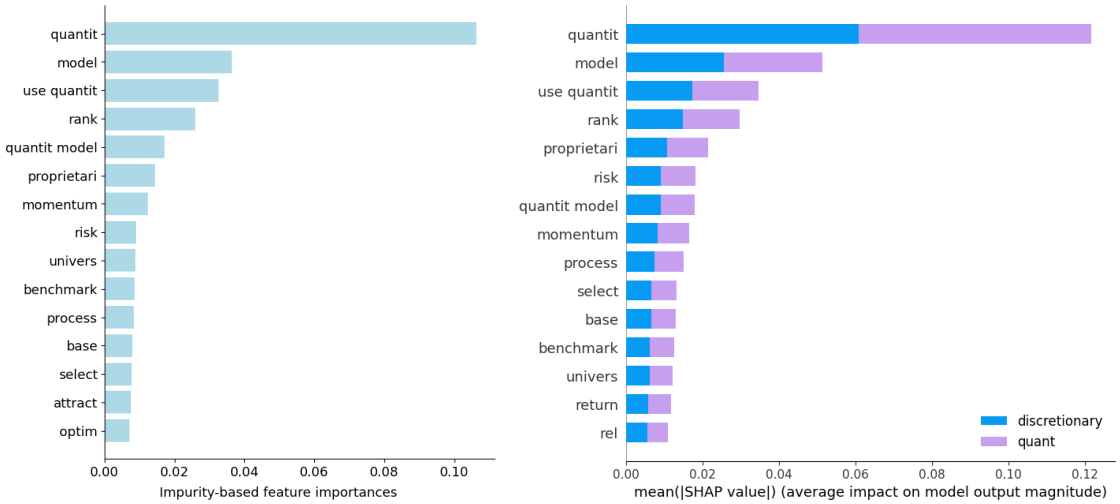

Figure 3: **Random Forest - Decision rule:** Per-feature distribution of SHAP values for the quant class across all classified PIS sections. Dots represents the SHAP value for a feature in a given section. A greater absolute SHAP value indicates a greater importance of the feature in classifying the section. A lighter color indicates a greater relative frequency (tf-idf) of the feature in the section.

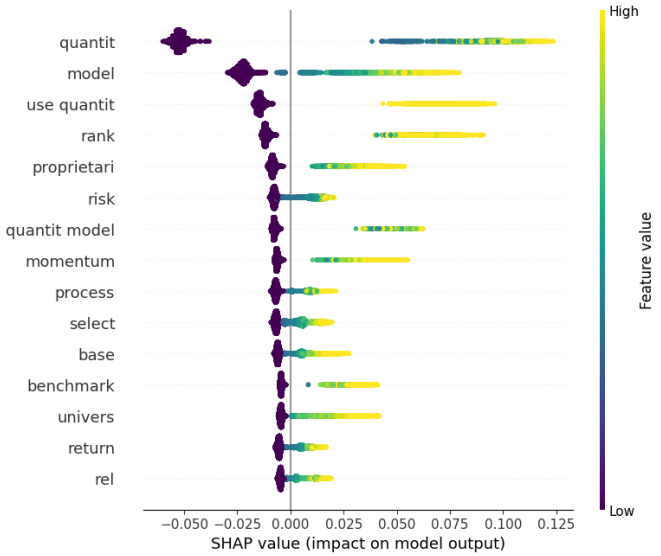

Figure 4: **Random Forest - Dependence plots:** Panels represent the dependence plot for each of the 15 most informative features in determining a quant classification, as measured by SHAP values. In each Panel, dots displays sections, the x-axis the feature's relative frequency (tf-idf), the y-axis its SHAP value; color indicates frequency (tf-idf) of the term "quantit", as read off Panel 1.

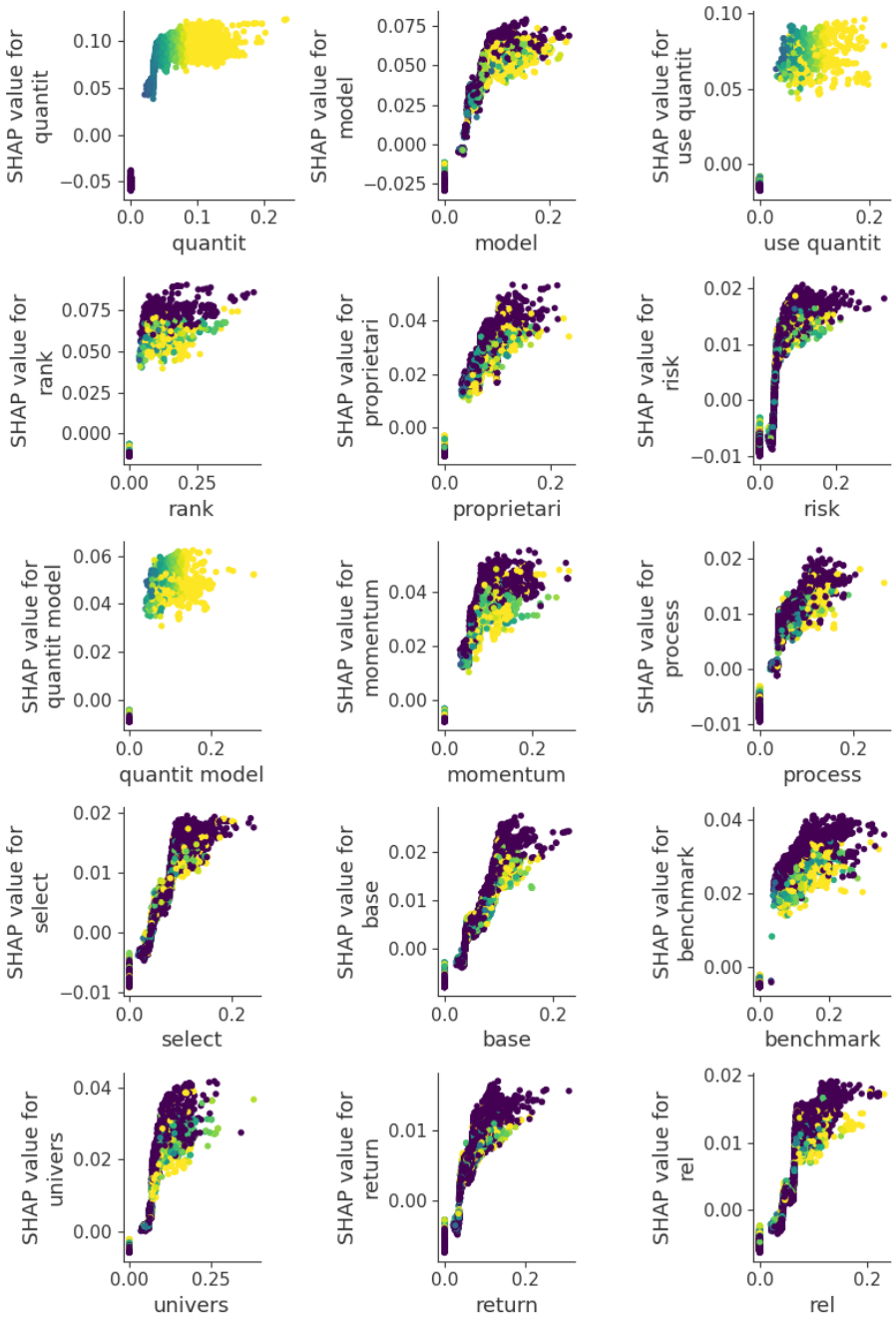

Figure 5: **Random Forest - Switching Behavior:** Number of funds classified as quantitative by the random forest algorithm in a given month; split between funds that were classified as quantitative at inception and funds that were classified as discretionary at inception and switched to a quantitative classification afterwards.

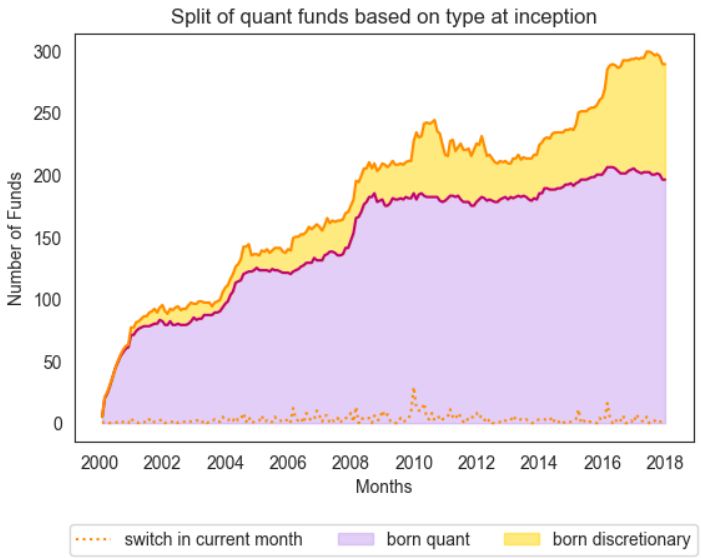

Figure 6: **Random Forest - PIS Similarity:** Panel 1 displays the distribution in cosine similarity among PIS sections of the same fund at different prior lags. Panel 2 zooms into the distribution among consecutive prospectuses of the same fund (i.e., lag -1 in Panel 1); split between months in which funds switch type and months with no classification change.

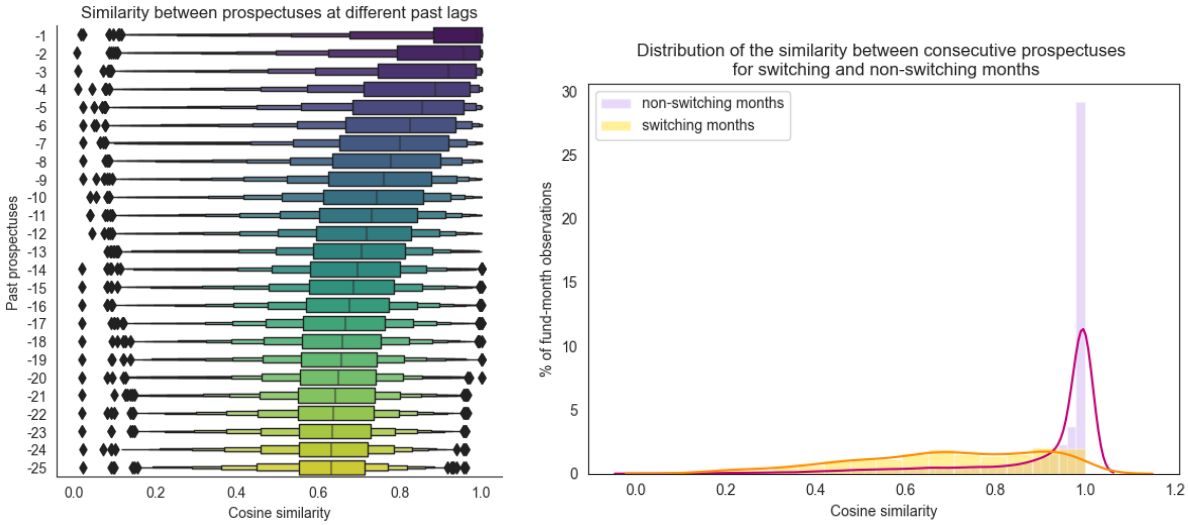

Figure 7: **Funds Growth:** Growth in the number and TNA of quants and discretionaries by month (Panel 1); and TNA and number of quants, as a percentage of overall market TNA and total number of funds respectively (Panel 2). Shaded areas indicate NBER recessions.

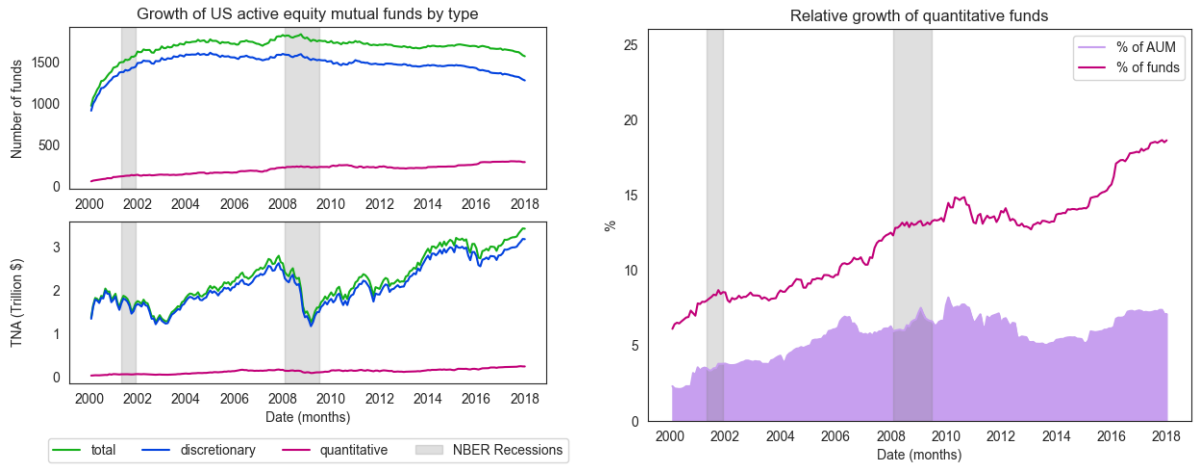

Figure 8: **Style deciles:** Distribution of quantitative and discretionary funds sorted into deciles based on the average exposure of the stocks they hold to the market (Row 1, Panel 1), size (Row 1, Panel 2), book-to-market (Row 1, Panel 2), momentum (Row 2, Panel 1), investment (Row 2, Panel 2) and profitability (Row 2, Panel 3) factors.

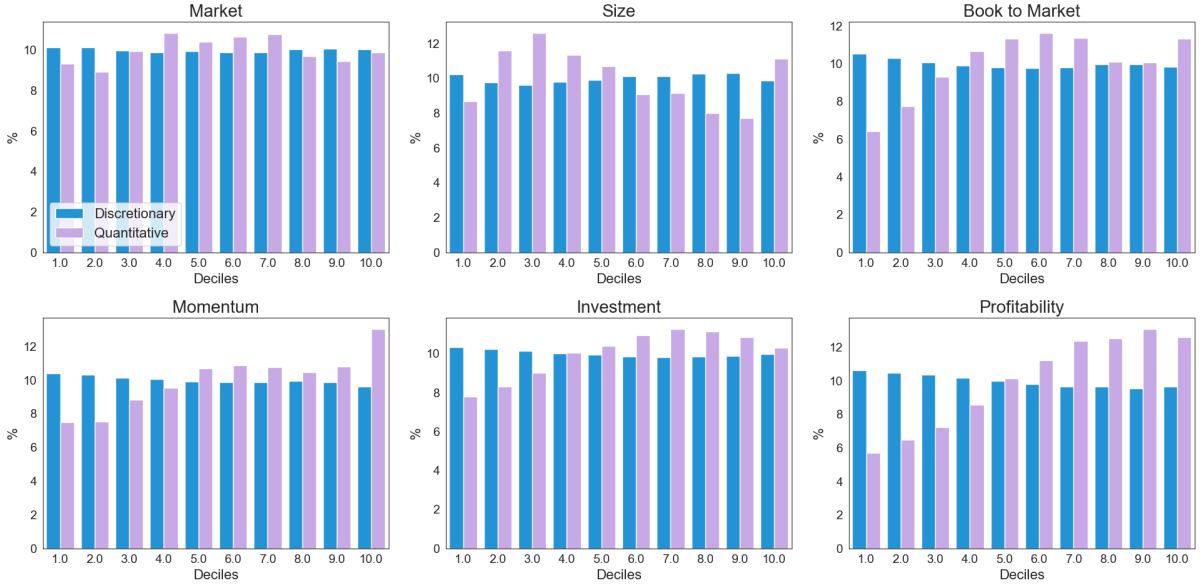

Figure 9: **Portfolio overlap:** Distribution of dispersion and commonality by fund type (quant or discretionary)–Panel 1, Rows 1 and 2 respectively; and distribution of commonality and overcrowding over time (Panels 2 and 3) for discretionaries (Row 1) or quants (Row 2). Variables construction is detailed in Section 4.4.

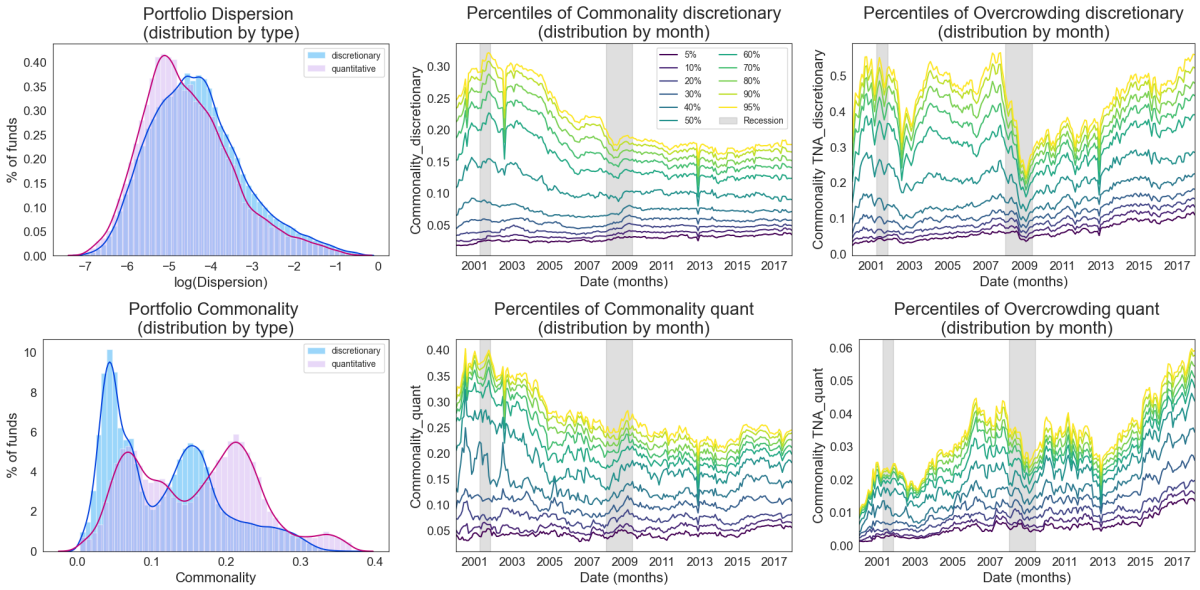

Figure 10: **Active Return:** Estimated β_1 (Panel 1) and β_2 (Panel 2) from Eq. 16, for the mean, and for the following percentiles of active return ($\overline{AR}$): $p = [1, 5, 10, 20, 30, 40, 50, 60, 70, 80, 90, 95, 99]$. Shaded areas indicate 95% confidence intervals (CI). OLS estimates are included as a constant across all quantiles. Variables are constructed as detailed in Section 4.5.

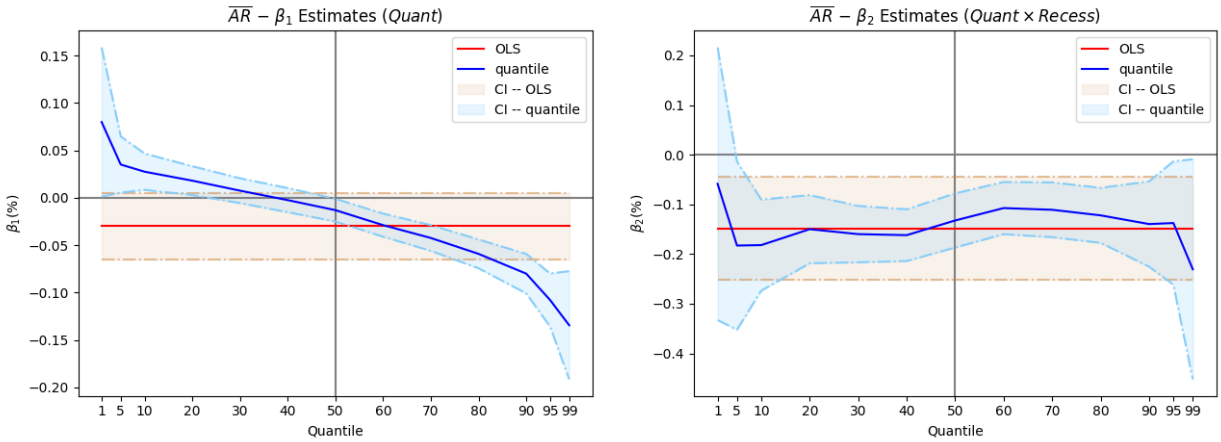

Table 1: **Variables Description:** Description of all fund-level variables utilized in subsequent tables. Common principles: all variables that present large outliers are winsorized at the 1% level (aside for active returns and TNA), all skewed variables that can only have positive values are log-transformed and all ratios representing a percentage are multiplied by 100. Other selected variables are rescaled or transformed for interpretability.

$Quant$	Dummy variable identifying quantitative funds. Details in Section 2.2.
$Recess$	Dummy variable identifying NBER recession months. In quarterly regressions $Recess = 1$ if at least 2 of the 3 months in a quarter are categorized as recessions.
$ln(Age)$	The natural logarithm of the number of months since fund inception.
TNA	Total Net Assets in Millions of $s.
$ln(TNA)$	The natural logarithm of TNA.
$Expenses$	Ratio of total investment that shareholders pay for the fund's operating expenses annually; winsorized at the 1% level and multiplied by 100.
$Turnover$	Minimum of aggregated sales or aggregated purchase of securities, divided by the average 12-month Total Net Assets; winsorized at the 1% level and multiplied by 100.
$FlowGrowth$	Monthly percentage change in TNA not determined by returns; winsorized at the 1% level and multiplied by 100.
$FlowVol$	12–months rolling volatility in net fund flow growth ($FlowGrowth$); winsorized at the 1% level.
$Loads$	Total fund loads: sum of average front and read loads across all share classes of a fund. Set to zero when none is reported, and winsorized at the 1% level.
$Style$	TNA-weighted sensitivity (beta) of stocks held with respect to the market ($Market$), size ($Size$), book-to-market ($Value$), momentum (Mom), profitability ($Profit.$) and investment ($Invest.$) factors; winsorized at the 1% level. Betas are obtained using 24–months rolling regressions of stock returns, in excess of the risk-free rate, on the above-mentioned factors.
$Cash$	Amount of cash held in percentage of TNA, winsorized at the 1% level.
$Mgmt$	Annual management fees, winsorized at the 1% level (can be negative due to reimbursements).
$12b1$	Ratio of total assets attributed to marketing and distribution costs annually, multiplied by 100.
R	Total monthly gross of fees return per share, in excess of the risk-free rate, multiplied by 100. Obtained by adding $\left(\frac{Expenses}{12} - r_f\right)$ to monthly net-of-fees fund returns.
$ln(IVol - ff6)$	Natural logarithm of idiosyncratic volatility, multiplied by 100. Obtained as the volatility of the residual of regressing R, on the market, size, book-to-market, momentum, profitability and investment factors over 24– or 36–months rolling windows.

$ln(NStocks)$	Natural logarithm of the number of stocks held.
$ln(RetVol)$	Natural logarithm of the 24– or 36–months rolling volatility of fund returns, multiplied by 100.
Characteristics Timing (CT)	Funds' ability to time their exposures to the size, book-to-market and momentum factors, multiplied by 100 and winsorized at the 1% level (CT_DGTW). Constructed following Daniel et al. (1997).
Stock Picking (SP), Macro Timing (MT)	Covariance of portfolio weights (in excess of the market weight) with future earning surprises (SP_SUE) and innovations in industrial production (MT_IndPro) or non-farm payrolls (MT_NFPay). Variables are multiplied by 10,000 and winsorized at the 1% level. Details in Section 4.1.
$TopAbility$	For each expansion (recession): Top q% of funds that belong to the top q% of the distribution of timing (picking) ability in the previous recession (expansion), i.e., $TopT\_R$ (TopP_E). Measures are constructed using high-ability cut-offs of q = 10% to q = 25%. Top timing ability is measured using CT_DGTW, MT_IndPro or MT_NFPay. Top picking ability is measured using SP_SUE. Details in Section 4.1.
$InfoGap$	TNA-weighted average of characteristics of stocks held. The natural logarithm is taken when the measure is highly skewed. Stock characteristics: market capitalization ($ln(MktCap)$), age (Age), number of analysts following the stocks ($Analysts$) and the number of Dow Jones news articles, weighted by relevance–Source Ravenpack–($ln(News)$). Details in Section 4.3.
$Illiquidity$	One year rolling Amihud ratio; multiplied by 1,000,000.
$Commonality$	TNA-weighted average of the percentage of same-type-funds holding the same stocks ($Comm$) or active in the same stocks ($AComm$); multiplied by 100 and winsorized at the 1% level. Details in Section 4.4.
$Overcrowding$	OC (AOC): product of $Comm$ ($AComm$) with the sum of TNA of same-type-funds in a given month. Where the sum of TNA is expressed in trillions of $s.
$ln(Disp)$	Natural logarithm of the cumulative squared difference in the weight allocated by each fund and the average weight allocated by same-type-funds to each stock, multiplied by 100. Details in Section 4.4.
AR	Active return of a fund, measured as a fund's gross-of-fees return in excess of the risk-free rate (R), minus its benchmark return. Benchmark returns are obtained by regressing R against the Fama-French 6 factor model (market, size, value, momentum, investment and profitability factors) over 24– or 36–months rolling windows. Monthly active returns are then averaged within each quarter ($\overline{AR}$), and multiplied by 100. Details in Section 4.5.

Table 2: **Summary Statistics:** Number of observations, mean, standard deviation (sd), minimum (min), maximum (max) and 25th, 50th and 75th percentiles of the distribution of all utilized fund-level variables. Variables averaged within each quarter are marked with (∗).

	number	mean	sd	min	25th	50th	75th	max
				Control Variables				
$ln(Age)$	360090	4.80	0.88	0.00	4.26	4.88	5.38	7.02
$ln(TNA)$	360642	5.52	1.84	1.61	4.16	5.48	6.83	12.22
$Expenses$	356116	1.22	0.39	0.29	0.97	1.18	1.43	2.45
$Turnover$	355559	80.95	68.04	4.00	34.00	63.00	105.00	380.00
$FlowGrowth$	359798	0.08	4.46	-14.45	-1.47	-0.40	0.87	23.18
$FlowVol$	344005	0.04	0.07	0.00	0.01	0.02	0.04	0.49
$Loads$	360642	0.01	0.01	0.00	0.00	0.00	0.02	0.04
$Market$	351997	0.73	0.49	0.00	0.00	0.99	1.07	1.51
$Size$	351997	0.16	0.35	-0.31	-0.04	0.00	0.30	1.20
$Value$	351997	0.04	0.25	-0.72	-0.04	0.00	0.16	0.83
Mom	351997	-0.02	0.18	-0.70	-0.08	0.00	0.02	0.61
$Profit.$	351997	-0.04	0.26	-1.09	-0.11	0.00	0.05	0.77
$Invest.$	351997	-0.06	0.29	-1.30	-0.13	0.00	0.05	0.69
				Other Variables				
$Cash$	336861	3.04	3.90	-2.21	0.45	1.90	4.16	21.27
$Mgmt$	355649	0.70	0.36	-1.11	0.57	0.74	0.90	1.50
$12b1$	239587	0.25	0.25	0.00	0.00	0.25	0.42	1.01
R	355271	0.55	5.10	-46.33	-1.99	0.99	3.53	59.35
$ln(IVol - ff6\_24m)$	317221	-0.06	0.53	-3.18	-0.40	-0.08	0.27	2.28
$ln(IVol - ff6\_36m)$	295676	0.04	0.51	-2.85	-0.28	0.03	0.36	2.30
$ln(NStocks)$	351997	4.45	0.79	2.30	3.93	4.34	4.81	8.18
$ln(RetVol\_24m)$	317221	1.49	0.40	-0.60	1.20	1.48	1.76	3.24
$ln(RetVol\_36m)$	295676	1.53	0.37	-0.41	1.27	1.53	1.78	3.13
$ln(MktCap)$	351993	9.71	1.82	2.97	7.98	10.43	11.33	12.67
Age	351997	315.65	130.15	0.00	211.54	319.90	409.30	849.02
$ln(News)$	351821	4.37	1.21	-7.78	3.36	4.51	5.31	7.23
$Analysts$	351997	8.03	4.44	0.00	4.81	7.25	10.47	60.48
$Illiquidity$	351997	0.01	0.16	0.00	0.00	0.00	0.00	16.84
$Comm$	351997	12.13	7.61	1.28	5.23	11.34	17.18	31.28
$AComm$	351997	6.59	6.30	0.48	2.19	4.60	7.63	27.46
$ln(Disp)$	351993	0.25	1.13	-4.53	-0.56	0.15	0.91	5.01
OC	351997	21.22	15.38	0.06	7.75	17.32	34.33	97.17
AOC	351997	11.18	11.03	0.04	3.31	6.95	15.14	59.10
SP_SUE	351530	-0.18	2.65	-15.37	-0.32	0.06	0.42	9.78
MT_IndPro	308581	0.03	1.47	-3.90	-0.45	-0.10	0.14	7.93
MT_NFPay	308581	0.28	1.90	-4.25	-0.44	-0.01	0.53	10.72
CT_DGTW	351997	0.19	2.68	-10.48	-0.63	0.15	1.07	9.39
$*AR\_24m$	106812	0.01	0.81	-16.65	-0.39	-0.01	0.37	11.09
$*AR\_36m$	99657	-0.01	0.84	-17.27	-0.42	-0.02	0.37	13.47

Table 3: **Age, Size and Style:** Dependent variables: funds' age ($ln(Age)$), size ($ln(TNA)$), turnover ratio ($Turnover$), amount of cash held in percentage of TNA ($Cash$), and 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. Regression statistics are reported at the bottom of the table: $Adjusted\ R^2$, number of observations (Obs), mean of the dependent variable for discretionaries ($\bar{y}^D$). 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).

	$ln(Age)$ (1)	$ln(TNA)$ (2)	$Turnover$ (3)	$Cash$ (4)	$Market$ (5)	$Size$ (6)	$Value$ (7)	Mom (8)	$Invest.$ (9)	$Profit.$ (10)
$Constant$	4.00***	3.86***	58.16***	3.80***	0.73***	-0.15***	0.01	0.11***	0.21***	0.10***
	(54.90)	(17.30)	(7.40)	(9.86)	(97.88)	(-3.54)	(0.55)	(5.06)	(4.89)	(3.85)
$Quant$	-0.10***	-0.33***	29.53***	-0.73***	0.00	-0.04***	0.02***	0.02***	0.02***	0.04***
	(-3.36)	(-5.15)	(10.97)	(-7.47)	(1.62)	(-3.09)	(3.44)	(4.97)	(3.55)	(7.54)
$Quant \times Recess$	-0.05	-0.01	-5.25	-0.52***	0.01*	0.00	0.01	0.01	0.01	-0.01
	(-1.44)	(-0.21)	(-1.63)	(-3.46)	(1.73)	(0.38)	(0.71)	(1.54)	(0.98)	(-1.04)
$Adjusted\ R^2$	0.28	0.32	0.14	0.08	0.94	0.15	0.35	0.18	0.16	0.30
Obs	334,821	334,821	334,821	317,247	334,821	334,821	334,821	334,821	334,821	334,821
$\bar{y}^D$	4.899	5.659	77.262	3.141	0.734	0.161	0.034	-0.019	-0.065	-0.052
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cl: Month+Fund	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Table 4: **Flows and Fees:** Dependent variables: growth in net fund flows (*Flow Growth*), volatility of net fund flows growth (*Flow Vol*), funds' expense ratio (*Expenses*), management fees (*Mgmt*), Actual 12b1 fees (12*b*1) and fund loads (*Loads*). Variables construction is detailed in Table 1; summary statistics are reported in Table 2. Regression statistics are reported at the bottom of the table: *Adjusted* R^2, number of observations (*Obs*), mean of the dependent variable for discretionaries ($\bar{y}^D$). Independent variables and all regression specifications are the same as described in Table 3. Control variables are omitted for brevity.

	Flow		*Fees*			
	Growth (1)	*Vol* (2)	*Expenses* (3)	*Mgmt* (4)	12*b*1 (5)	*Loads* (6)
Constant	2.743***	0.134***	1.645***	0.639***	0.473***	-0.025***
	(13.74)	(29.35)	(41.70)	(17.08)	(12.98)	(-16.59)
Quant	-0.067	0.001	-0.078***	-0.033**	0.021	-0.000
	(-1.04)	(0.91)	(-5.52)	(-2.60)	(1.49)	(-0.21)
Quant × *Recess*	-0.573***	0.007**	-0.022	-0.021	-0.013	0.000
	(-4.33)	(2.01)	(-1.40)	(-1.29)	(-1.09)	(0.35)
Adjusted R^2	0.06	0.09	0.35	0.07	0.31	0.19
Obs	334,821	334,821	334,821	334,481	228,769	334,821
$\bar{y}^D$	-0.073	0.039	1.221	0.721	0.243	0.009
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 5: **Investment Style:** Dependent variables: funds' gross of fees excess return (R), 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 3 (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. Regression statistics are reported at the bottom of the table: *Adjusted* R^2, number of observations (*Obs*), mean of the dependent variable for quants in Model (1) ($\bar{y}^Q$) and for discretionaries in all other models ($\bar{y^D}$).

	R		$ln(IVol - ff6)$	
	Quant	*Discretionary*	24*m*	36*m*
	(1)	(2)	(3)	(4)
Constant	-0.055	0.013	-0.380***	-0.288***
	(-1.51)	(0.33)	(-6.50)	(-4.51)
Quant			-0.141***	-0.139***
			(-8.33)	(-8.13)
Quant × *Recess*			0.058***	0.063***
			(2.65)	(2.91)
MKT	1.018***	1.013***		
	(68.89)	(65.65)		
HML	0.029	0.007		
	(1.05)	(0.30)		
SMB	0.187***	0.214***		
	(8.17)	(10.67)		
UMD	0.039***	0.011		
	(3.44)	(0.83)		
RMW	0.076***	0.018		
	(3.59)	(0.97)		
CMA	-0.044	-0.025		
	(-1.49)	(-0.86)		
Adjusted R^2	0.834	0.785	0.47	0.50
Obs	42,888	312,383	307,996	287,174
$\bar{y}^Q$	0.625			
$\bar{y}^D$		0.544	-0.044	0.063
Controls	No	No	Yes	Yes
FE: Month	No	No	Yes	Yes
Cl: Month+Fund	Yes	Yes	Yes	Yes

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

Table 6: **Prediction 1: High Ability Funds:** Graphical representation of regression coefficients. Dependent variables: macro-timing in recessions with respect to innovations in industrial production ($IndPro$ (R), Panel 1) or non-farm payrolls ($NFPay$ (R), Panel 2); characteristic-timing in recessions ($DGTW$ (R), Panel 3); stock picking in recessions ($Picking$ (R), Panel 4); characteristic-timing in expansions ($DGTW$ (E), Panel 5); and macro-timing in expansions with respect to innovations in industrial production ($IndPro$ (E), Panel 6) or non-farm payrolls ($NFPay$ (E), Panel 7). Independent variables: a dummy identifying quantitative funds ($Quant$), dummy variables identifying the top $q\%$ of funds with the highest timing ability in the previous recession ($TopT\_R$) or picking ability in the previous expansion ($TopP\_E$); and the interaction between the $Quant$ dummy (in interactions abbreviated with: Q) and the high-ability dummies ($TopP\_E \times Q$, $TopT\_R \times Q$). Variables construction is detailed in Table 1; summary statistics are reported in Table 2. Coefficients are estimated using high-ability cut-offs of $q = 10\%$ to $q = 25\%$. Bars indicate 95% confidence intervals. Control variables and all regression specifications are the same as described in Table 3. Control variables are omitted for brevity.

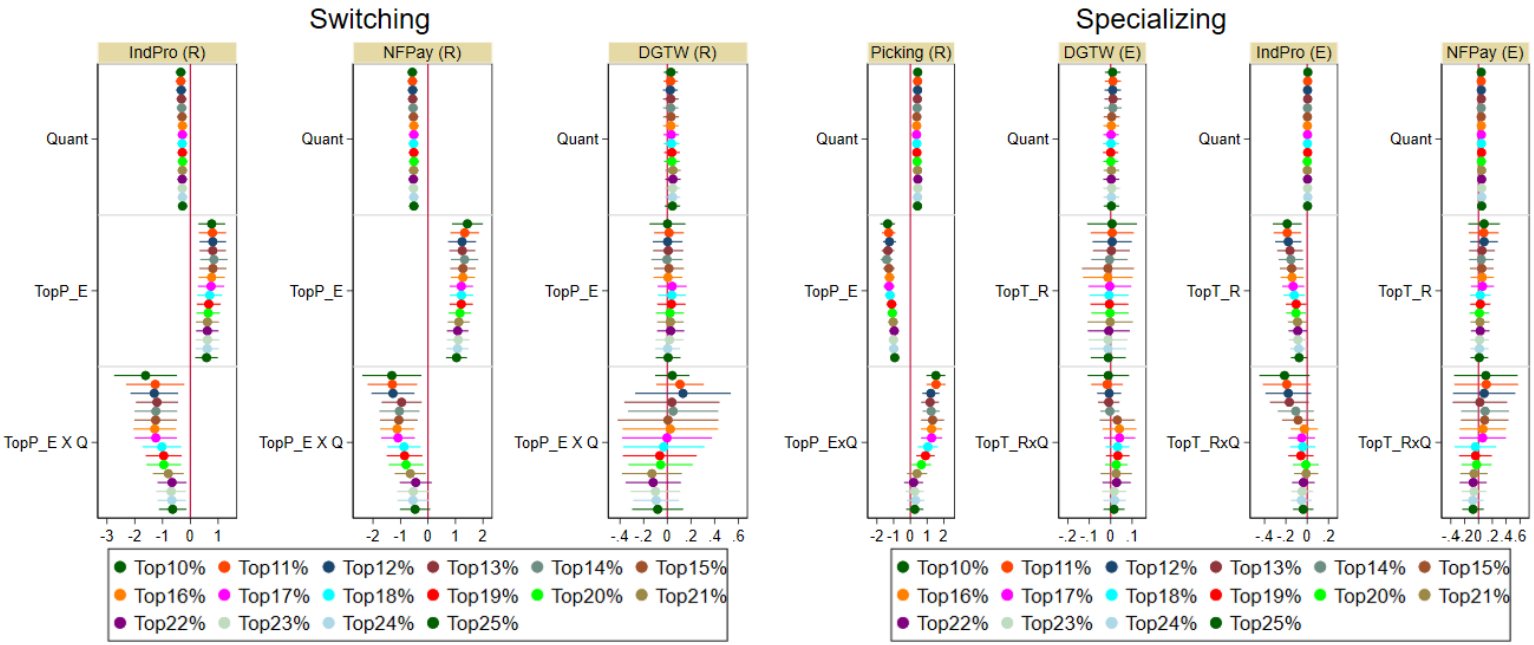

Table 7: **Prediction 1: Average Picking and Timing Abilities:** Dependent variables: stock picking (SP_SUE), macro-timing (MT_IndPro, MT_NFPay) and characteristics-timing (CT_DGTW) abilities. Variables construction is detailed in Table 1; summary statistics are reported in Table 2. Independent variables and all regression specifications are the same as described in Table 3. Control variables are omitted for brevity. Regression statistics are reported at the bottom of the table: *Adjusted* R^2, number of observations (*Obs*), the mean of the dependent variable for discretionaries (y^D) in recessions (R) and expansions (E).

	SP_SUE (1)	MT_IndPro (2)	MT_NFPay (3)	CT_DGTW (4)
Constant	0.0570	0.3009***	-0.0815	-0.1031
	(0.34)	(3.41)	(-0.65)	(-0.82)
Quant	-0.0890***	0.0198	0.0554**	0.0234
	(-2.81)	(0.97)	(2.07)	(1.12)
Quant × *Recess*	0.6669***	-0.4957***	-0.7932***	-0.0794
	(5.50)	(-4.09)	(-7.83)	(-1.62)
R2	0.18	0.37	0.38	0.57
Obs	334,374	293,325	293,325	334,821
$\bar{y}^{D,E}$	0.044	-0.131	0.046	0.259
$\bar{y}^{D,R}$	-1.839	1.223	1.996	-0.385
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 8: **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 3; control variables are omitted for brevity. Model (2) also controls for the percentage of cash held ($Cash$). Variables construction is detailed in Table 1; summary statistics are reported in Table 2. Regression statistics are reported at the bottom of the table: *Adjusted* R^2, number of observations (Obs), mean of the dependent variable for discretionaries ($\bar{y}^D$).

	$ln(NStocks)$		$ln(RetVol)$	
			$24m$	$36m$
	(1)	(2)	(3)	(4)
Constant	4.477***	4.590***	1.246***	1.304***
	(42.49)	(42.11)	(50.36)	(49.16)
Quant	0.314***	0.291***	-0.032***	-0.035***
	(9.76)	(9.01)	(-4.66)	(-5.06)
Quant × *Recess*	0.029	0.019	0.020**	0.029***
	(0.83)	(0.52)	(2.25)	(3.19)
Cash		-0.017***		
		(-7.61)		
Adjusted R^2	0.19	0.20	0.77	0.77
Obs	334,821	317,247	307,996	287,174
$\bar{y}^D$	4.413	4.419	1.495	1.534
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 9: **Prediction 3: Information Gap:** 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 3, 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 3. Variables construction is detailed in Table 1; summary statistics are reported in Table 2. Regression statistics are reported at the bottom of the table: *Adjusted* R^2, number of observations (Obs), mean of the dependent variable for discretionaries ($\bar{y}^D$).

	Stock Characteristics							
	$ln(MktCap)$		Age		$ln(News)$		$Analysts$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	10.165***	9.527***	342.449***	-120.231***	3.858***	-1.882***	5.882***	-7.326***
	(38.60)	(67.99)	(27.28)	(-7.96)	(36.55)	(-16.71)	(20.26)	(-10.13)
Quant	0.233***	0.092**	17.644***	13.182***	0.073***	0.016	-0.015	-0.142***
	(2.88)	(2.29)	(5.66)	(5.67)	(2.66)	(1.13)	(-0.21)	(-3.40)
Quant × *Recess*	-0.084	-0.065	-3.167	0.010	-0.055*	-0.014	-0.113	-0.023
	(-1.13)	(-1.47)	(-0.71)	(0.00)	(-1.70)	(-0.67)	(-1.36)	(-0.34)
Illiquidity	-0.944***	-0.317***	7.233**	22.648***	-0.049***	0.142***	-0.427***	0.013
	(-3.05)	(-4.36)	(2.43)	(5.36)	(-2.68)	(3.48)	(-4.43)	(0.18)
Size		-3.985***	-200.302***	-6.744	-2.300***	0.103**	-6.358***	-0.832**
		(-126.28)	(-51.95)	(-1.31)	(-66.98)	(2.17)	(-26.16)	(-2.37)
Stock_Size				48.566***		0.603***		1.386***
				(42.39)		(61.17)		(18.98)
Adjusted R^2	0.11	0.60	0.50	0.69	0.52	0.85	0.63	0.76
Obs	334,817	334,817	334,817	334,817	334,652	334,652	334,817	334,817
$\bar{y}^D$	9.690	9.690	312.077	312.077	4.363	4.363	8.030	8.030
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 10: **Prediction 4: Commonality:** Dependent variables: holdings commonality ($Comm$), active commonality ($AComm$), and the natural logarithm of dispersion ($Log(Disp)$). Independent variables and all regression specifications are the same as described in Table 3. Control variables are omitted for brevity. Variables construction is detailed in Table 1; summary statistics are reported in Table 2. Regression statistics are reported at the bottom of the table: *Adjusted* R^2, number of observations (Obs), mean of the dependent variable for discretionaries ($\bar{y}^D$).

	$Comm$ (1)	$AComm$ (2)	$ln(Disp)$ (3)
Constant	8.312***	2.594***	0.162
	(12.96)	(4.14)	(1.24)
Quant	4.597***	2.418***	-0.123***
	(22.61)	(16.40)	(-3.62)
Quant × *Recess*	0.221	0.410*	-0.048
	(0.82)	(1.75)	(-1.09)
Adjusted R^2	0.59	0.55	0.16
Obs	334,821	334,821	334,817
$\bar{y}^D$	11.592	6.341	0.270
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 11: **Prediction 5: Active Return:** Dependent variables: 24–months (Models $(1-4)$), and 36–months (Models $(5-8)$) Fama-French 6 Active Return (AR); constructed monthly and averaged within quarters. Independent variables are the same as described in Table 3, but they are lagged of one quarter. Controls are omitted for brevity. Variables construction is detailed in Table 1. Models $(1,5)$ are estimated with OLS. Models $(2,3,4,6,7,8)$ are estimated with quantile regressions for the 25th ($q25$), 50th ($q50$), and 75th ($q75$) percentiles. At the bottom of each panel is reported the mean (or the relevant quantile), of the dependent variable for discretionaries (y^D) in recessions (R) and expansions (E). All regressions are run at the quarterly frequency and include quarter fixed–effects; standard errors are clustered at the quarter and fund level.

	$\overline{AR}_{ff6}$							
	$24m$ OLS (1)	$24m$ $q25$ (2)	$24m$ $q50$ (3)	$24m$ $q75$ (4)	$36m$ OLS (5)	$36m$ $q25$ (6)	$36m$ $q50$ (7)	$36m$ $q75$ (8)
Constant	0.157**	0.535***	1.112***	1.806***	0.121*	0.358***	0.925***	1.629***
	(2.24)	(11.05)	(19.60)	(24.10)	(1.68)	(6.02)	(16.23)	(19.92)
Quant	-0.030*	0.019**	-0.013**	-0.051***	-0.027	0.016**	-0.012*	-0.041***
	(-1.71)	(2.54)	(-2.18)	(-6.88)	(-1.56)	(2.11)	(-1.81)	(-5.33)
Quant × *Recess*	-0.148***	-0.159***	-0.132***	-0.109***	-0.135**	-0.105***	-0.114***	-0.132***
	(-2.84)	(-5.10)	(-4.78)	(-4.13)	(-2.44)	(-3.41)	(-4.13)	(-4.46)
$\bar{y}^{D,E}$	0.018	-0.374	-0.009	0.369	-0.002	-0.402	-0.021	0.369
$\bar{y}^{D,R}$	-0.041	-0.573	-0.023	0.487	-0.054	-0.582	-0.035	0.481

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

Table 12: **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. Control variables are omitted for brevity. Regression statistics are reported at the bottom of the table: *Adjusted* R^2, number of observations (*Obs*), mean of the dependent variable for discretionaries ($\bar{y}^D$).

	(1) $Comm^Q$	(2) $AComm^Q$	(3) $ln(Disp^Q)$
Constant	7.478***	-0.486	0.264
	(3.31)	(-0.19)	(0.73)
Quant	0.741***	0.444**	-0.207***
	(4.41)	(2.31)	(-5.88)
Quant × *Recess*	0.148	0.252	-0.036
	(0.76)	(1.27)	(-0.72)
$AdjustedR^2$	0.86	0.77	0.44
Obs	84,279	84,279	84,279
$\bar{y}^D$	15.222	8.362	0.344

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

APPENDIX

A Random Forest Classification

Once obtained a pre-classified training sample, I categorize all strategy sections as quantitative or discretionary following the steps below.

First, I pre-process all sections using the "bag of words" approach: (1) I remove stop-words (e.g. is, the, and) and financial stopwords (e.g. S&P, Russel). (2) I stem words using the Porter stemmer (thus, e.g.: quantitative, quantitatively, ... = quantit). (3) I compile a list of all features mentioned in the pre-classified training sample. I exclude features appearing in more than 60% or less than 5% of the files, as unlikely to be informative in distinguishing between the two categories. (4) I transform each section into a vector of features, this contains a 1 (resp., 0) when the section does (resp., does not) mention the feature. (5) I adjust features weights by within-section frequency versus the frequency in all samples (tf-idf).

Second, I use the random forest to classify all section: (1) I use stratified sampling to split the pre-classified sample into training (75%) and test (25%) samples.[29] (2) I train a random forest classifier with an ensemble of $1,000$ trees and an entropy-based impurity measure using the training sample and check the model's accuracy in the test sample; obtaining 97.67% accuracy.[30] This corresponds to 100% recall and 96% precision for *Discretionary* sections and 94% recall and 100% precision for *Quantitative* ones (Confusion matrix in Table B.1).[31] (3) I use that model to classify all $24,732$ unique strategy sections.

Table A.1: **Confusion Matrix:** Rows indicate Random Forest assignments, columns indicate human assignments; 0 indicates *Discretionary* assignments, 1 *Quantitative*.

		Human	
		0	1
Random Forest	0	26	0
Random Forest	1	1	16

[29] This ensures a balanced split of categories when one is less prevalent.

[30] The Internet Appendix contains additional details about the random forest algorithm.

[31] *Accuracy* is the percentage of total observations classified correctly. *Recall* is the percentage of observations belonging to a given category that are correctly assigned to it. *Precision* is the percentage of observations assigned to a given category that correctly belongs to it.

B 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.[32] 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 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 250 sections, maintaining balance among the two classes.[33]

All students agreed on a *Discretionary* assignment for 128 sections, 121 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 81.53% Fleiss Kappa, and an 81.67% Gwet's gamma with respect to the summary classification.[34] That corresponds to a 88% precision and a 95% recall (94% precision and a 87%

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

[33] The final selection contains 137 Discretionary sections and 113 Quantitative ones.

[34] Here Fleiss Kappa and Gwet's gamma have a similar score as there is no skewness in the classification distribution by construction.

recall) for the *Discretionary* (*Quantitative*) assignments (confusion matrix in Panel 1 of Table B.1). Utilizing Method (2) the random forest classification displays an 85.6% level of observed agreement (Accuracy), a 70.52% Fleiss Kappa, and a 71.85% Gwet's gamma with respect to the summary classification. That corresponds to a 92% precision and a 83% recall (78% precision and a 89% recall) for the *Discretionary* (*Quantitative*) assignments (confusion matrix in Panel 2 of Table B.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 conclude that the accuracy of the classification in the full sample is comparable to that obtained in the training sample.

Table B.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 1) and utilizing method (2) (Panel 2). 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	121	16	*Random Forest*	0	126	11
Random Forest	1	7	106	*Random Forest*	1	25	88

C PIS Examples

This section includes the most informative excerpts from a selection of PIS sections.[35] Examples were selectively chosen to emphasize a variety of cases based on the top features included in the text and their quant probability.[36] For each example are reported: the fund name, the prospectus year, the quant probability, a PIS excerpt, and an image representing the random forest's decision rule, obtained using SHAP. The top axis of each image represents the quant probability, each segment of the red (blue) bar underneath it indicates the positive (negative) contribution of a feature to the quant assignment. Contributions are measured using SHAP values and have an additive property towards the computation of the overall probability. The most informative features for each example are highlighted below the bar segment which corresponds to their contribution, for those features is also reported their tf-idf frequency in the section's text.

[35] Excerpts are presented for brevity, the full text was utilized for the classification.

[36] In the corpus the average quant probability is 64% for quants and 25% for discretionaries (st.dev. 10%).

Figure C.1: **Quant: Credit Suisse Large Cap Growth Fund, 2009**. Quant probability: 83%.
The fund invests substantially all of its assets in equity securities of large cap U.S. companies. The fund uses proprietary quantitative models designed to: (1) forecast the expected relative return of stocks by analyzing a number of fundamental factors, including a company's relative valuation, use of capital, balance sheet quality, profitability, realized and expected growth potential and earnings and price momentum (2) identify stocks likely to suffer price declines if market conditions deteriorate and limit the fund's overall exposure to such low quality stocks and (3) help determine the fund's relative exposure to different industry sectors by analyzing sector performance under different market scenarios. The fund maintains investment attributes similar to those of the Russell 1000 Growth Index and intends to limit its divergence from that index in terms of market, industry and sector exposures.

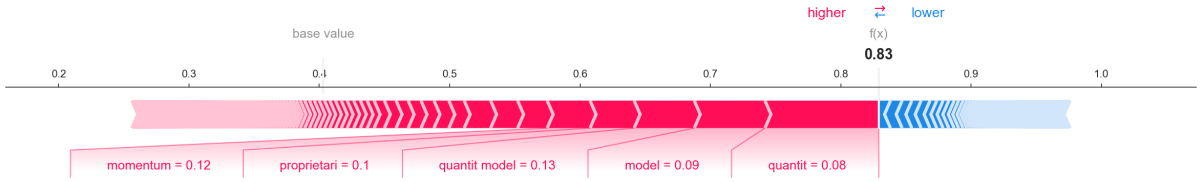

Figure C.2: **Quant: American Century Quantitative Equity Funds, Inc—Disciplined Growth Plus Fund, 2013**. Quant probability: 96%.
The managers use quantitative models to construct the portfolio of equity securities for the fund. The fund invests approximately 130% of its assets in long positions, while 30% of its assets are sold short. (...) The portfolio managers initially identify an eligible universe of growth stocks and then buy, or take long positions in, equity securities that they have identified as the most attractive and take short positions in equity securities that they have identified as the least attractive using a multi-factor quantitative model in a two-step process. In the first step, the managers rank stocks, primarily large capitalization, publicly traded U.S. companies with a market capitalization greater than $2 billion, from most to least attractive based on an objective set of measures, including each stock's value, quality, growth, and momentum. In the second step, the managers use a quantitative model to build a portfolio that provides the optimal balance between risk and expected return.

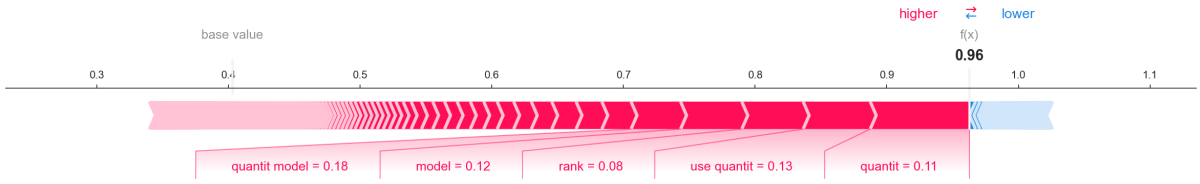

Figure C.3: **Quant: MainStay Funds Trust—MainStay Growth Equity Fund, 2011**. Quant probability: 85% (despite *quantit* absent).
The Subadvisor uses a "bottom-up" investment approach when selecting investments for the Fund. This means it bases investment decisions on company-specific factors, and not general economic conditions. In selecting stocks for the Fund, the Subadvisor uses a model that attempts to gain maximum exposure to attractive fundamentals that it believes drive U.S. large and mid-cap growth stocks in a disciplined, risk-controlled framework. The model ranks stocks based on traditional value measures, earnings quality and technical factors.

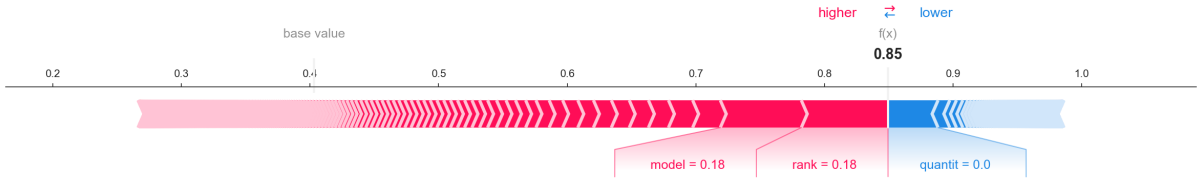

Figure C.4: **Discretionary: MFS Series Trust VII—MFS Capital Opportunities Fund, 2007**. Quant probability: 34% (despite *quantit* present).
MFS uses a bottom-up investment approach in buying and selling investments for the fund. Investments are selected primarily based on fundamental analysis of issuers and their potential in light of their current financial condition and industry position, and market, economic, political, and regulatory conditions. Factors considered may include analysis of earnings, cash flows, competitive position, and management ability. Quantitative analysis of these and other factors may also be considered.

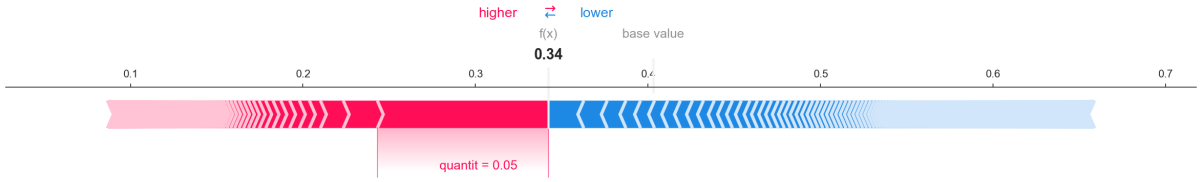

Figure C.5: **Discretionary: Royce Fund—Royce Micro-Cap Opportunity Fund, 2016**. Quant probability: 17%.

Royce & Associates, LP ("Royce"), the Fund's investment adviser, invests the Fund's assets primarily in a limited number (generally less than 100) of equity securities of micro-cap companies with stock market capitalizations up to $1 billion in an attempt to take advantage of what it believes are opportunistic situations for undervalued securities. Such opportunistic situations may include turnarounds, emerging growth companies with interrupted earnings patterns, companies with unrecognized asset values, or undervalued growth companies.

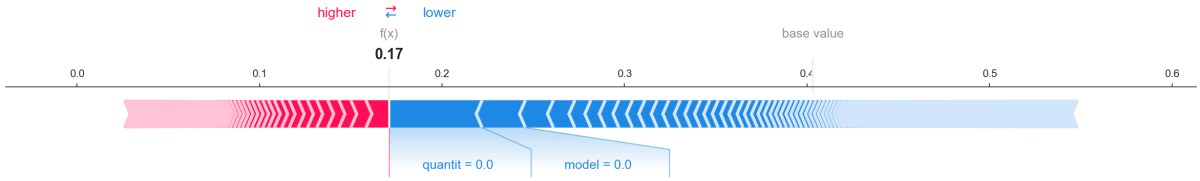

Figure C.6: **Discretionary: Ivy Funds— Ivy Small Cap Value Fund, 2008**. Quant probability 19%.

In selecting securities for the Fund, IICO, the Fund's investment manager, emphasizes a bottom-up approach that focuses on securities that, in IICO's opinion, have favorable prospects but low to moderate expectations implicit in the stock price. IICO may look at a number of factors in its consideration of a security, such as: the "intrinsic value" of the company in comparison to its stock price historical and projected financial performance free cash flow generation industry characteristics and potential competitive strategy management history. "Intrinsic value" is the perceived realizable market value, determined through IICO's analysis of a company's financial statements and an estimate of the present value of future cash flows.