Do machines beat humans?
Evidence from mutual fund performance persistence

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Abstract

We study the performance persistence of quantitative actively managed US equity funds. We show that the persistence of quantitative funds originates from poor performers and that there are reversals at the top of the performance scale, which is no different from the widely accepted evidence in the mutual fund literature. When testing for differences in performance persistence between quantitative and non–quantitative funds, we find no differences for poorly performing funds, but we observe significantly more reversals for quantitative funds at the top of the performance distribution. We also find that the differences in performance persistence are not explained by differences in flow–induced incentives to generate alpha, as there is no heterogeneity in investors preferences when allocating capital to these funds. Overall our results are consistent with machines having less skill than their human counterparts.

Keywords: quantitative analysis, mutual fund persistence, management skill, mutual fund industry

JEL Classifications: G11, G23, G40

“The most important quality for an investor is temperament, not intellect.” – Warren Buffet

“You can use all the quantitative data you can get, but you still have to distrust it and use your own intelligence and judgment.” – Alvin Toffler

1. Introduction

Whether there is skill in active fund management, i.e., whether managers add value to fund management in a way that cannot be simply explained by luck, is probably the most debated subject in the mutual fund literature (e.g., Jensen, 1968; Kosowski, Timmermann, Wermers, and White, 2006; Barras, Scaillet, and Wermers, 2010; Busse, Goyal, and Wahal, 2010; Fama and French, 2010; and Berk and Binsbergen, 2015). There is however widespread evidence that active managers do not have the skill to beat the market (e.g., Carhart, 1997). The literature also shows that there is no predictability in mutual fund performance (e.g., Gruber, 1996; Zheng, 1999; and Bollen and Busse, 2001), and that, what little persistence is present, is concentrated among poor–performing funds (e.g., Carhart, 1997; and Fama and French, 2010).[1]

In the past few years, the increasing adoption of quantitative analysis by the asset management industry has introduced a new dimension to this debate.[2] Advances in machine learning and big data analysis have been used in an attempt *“to code a robotic Warren Buffet”* (Financial Times, 2019), and have contributed to the increasing demand for quantitative funds. The growing competition of passively managed funds (index funds) and ETFs has put massive pressure on the

[1] Despite the general consensus that active fund managers lack skill in the aggregate, some studies find evidence of certain types of skill, or at least find skill under certain circumstances: Grinblatt and Titman (1989) document positive alphas for small funds; Grinblatt and Titman (1989), Daniel, Grinblatt, Titman, and Wermers (1997), Chen, Jegadeesh, and Wermers (2000), and Kosowski, Timmermann, Wermers, and White (2006) find superior performance for growth–oriented funds; Coval and Moskowitz (2001) find that funds that invest locally do better; Kacperczyk, Sialm, and Zheng (2005) suggest that funds that concentrate their portfolio in specific industries perform better than funds that do not; Kacperczyk, Nieuwerburgh, and Veldkamp (2014) show that skilled managers pick stocks well in booms, time the market well in recessions, and are able to use their skills differently over the course of a business cycle. Berk and Binsbergen (2015) use the value that a mutual fund extracts from capital markets as a measure of skill and argue that the average fund manager is skilled and that investors reward this skill as better funds collect higher fees and are rewarded with more invested capital.

[2] The beginning of quantitative strategies in asset management is attributed to Harry Markowitz’s seminal work on portfolio theory in 1952.

fund management industry (Cremers, Ferreira Matos, and Starks, 2016), and has contributed to the increasing number of quantitative funds as passive investments have been capitalizing on the lack of skill of active managers by keeping costs low and by eliminating the risk of underperforming a benchmark. Management companies, like BlackRock, are reorganizing their active equity investment and bet more on cheaper strategies based on quantitative computer models. *"The stock market is now run by computers, algorithms and passive managers"* (The Economist, 2019).

While emotions and cognitive errors influence individuals' trading decisions, quantitative investing removes the emotional and cognitive input from the decision process as it relies on objective mathematical and statistical models to select securities (D'Acunto, Phrabhala, and Rossi, 2019). As such, investors expect quantitative funds to overcome the inability of human–managed active funds to beat their benchmarks. However, quantitative strategies are often based on the premise that historical relations among investment factors persist over time and follow flexible strategies (Khandani and Lo, 2011, and Abis, 2020), which is not consistent with the increasing uncertainty observed in financial markets. Also, quantitative trading is vulnerable to overcrowding, as there are too many computer programs trained to exploit too few market anomalies (Abis, 2020, and Beggs, Brogaard, and Hill–Kleespie, 2021). Das (2019) argues that *"While models create an illusion of sophisticated certainty, they can't capture the full range of events that produced a particular outcome and could perform poorly where a paradigm shifts occur. Modern markets may simply be too complex to be modeled accurately."*[3]

In this paper, we study the performance persistence of quantitative actively managed US equity funds. Studying performance persistence holds both practical and theoretical interest: practical,

[3] Chincarini and Kim (2006), and Chincarini (2014) provide a detailed discussion on the advantages and disadvantages of quantitative versus qualitative funds.

because performance persistence is a critical aspect for decision-making and, ultimately, what really matters is whether quantitative funds are able to deliver sustained abnormal performance to investors;[4] theoretical, because examining performance persistence is equivalent to testing the efficient markets hypothesis, and whether or not quantitative funds are increasing financial markets' efficiency is a major question that is yet to be answered.

Despite the rising interest of investors in quantitative funds, very little is known about how quantitative analysis affects the mutual fund industry, and there is virtually no literature on the performance persistence of quantitative funds.[5] Ahmed and Nanda (2005) and Casey and Quark, and Associates (2005) show that quantitative funds outperform fundamental managers, while Wermers, Yao, and Zhao (2012) show that fundamental methods of stock selection are superior to quantitative approaches. Zhao (2006) finds no differences in performance between quantitative and non–quantitative funds, although quantitative funds tend to do better during market downturns, while non–quantitative funds do better during market upturns. Zhao (2006) also conclude that quantitative funds invest in smaller and less liquid stocks, which contributes to higher transaction costs and limited scalability of quantitative strategies. Abis (2020) proposes an equilibrium model that predicts that quantitative funds focus on stock picking, hold more stocks and display pro–cyclical performance, while non–quantitative funds do both stock picking and market timing and focus on stocks with less available information. Beggs, Brogaard, and Hill–Kleespie (2021) show that quantitative investing may result in a more unstable market because quantitative fund fire sales have a much larger impact on market instability than fire sales by traditional mutual funds. The

[4] Performance persistence is also of value to average investors as they use historical performance when making investing decisions (e.g., Sirri and Tufano, 1998). In the U.S. 46% of households own mutual funds, 94% of whom indicated that saving for retirement was one of their financial goals, and 73% said it was their primary financial goal (Investment Company Institute, 2020).

[5] Also some studies employ very small samples of quantitative funds, including Ahmed and Nanda (2005) that use a sample of 22 funds and Casey and Quark, and Associates (2005) who work with 32 quantitative funds.

literature also finds that quantitative funds charge lower fees than their non–quantitative peers (e.g., Ahmed and Nanda, 2005; Zhao, 2006; and Abis, 2020).[6]

There is also ongoing debate on the role of quantitative funds in market efficiency. While recent studies suggest that quantitative models increase market efficiency (Birru, Gokkaya, and Liu, 2019, and D'Acunto, Phrabhala, and Rossi, 2019), Fabbozzi, Focardi, and Jonas (2007 and 2008) argue that the impact of quantitative investing on market efficiency depends on the strategies widely adopted. Quantitative strategies based on trend following models, i.e., those based on past time series of prices and returns, do not improve market efficiency. Different financial periods are characterized by unique conditions that include specific policies, market structures, instruments and investors, and any abnormal return resulting from this information should quickly dissipate. Therefore, it is not only how quantitative models compete with their peers but also how they react to exogenous events and how they differentiate themselves from each other and evolve (Fabbozzi, Focardi, and Jonas, 2008).[7]

The success of quantitative strategies depends on their ability to identify persistent profit opportunities and not merely short-lived inefficiencies. However, there is an inherent contradiction in this process as quantitative strategies are designed to eliminate the same sources of profit they are trying to exploit. If quantitative funds have skill, then we would expect them to learn which investment strategies work well and progressively adopt the best models to consistently earn risk-adjusted excess returns. The presence of performance persistence in quantitative funds would represent a new hope for those investors who have lost faith in actively managed funds and redirected their money to passively managed funds. It would also mean that investors could rely

[6] Some studies analyze the impact of quantitative methods on hedge fund performance, including Khandani and Lo (2011), Chincarini (2014), and Harvey, Rattray, Sinclair, and Van Hemert (2017).
[7] Fabbozzi, Focardi, and Jonas (2007) state that quantitative strategies might actually produce biases of their own, creating new opportunities that can be exploited by other models.

on past performance to predict the future performance of quantitative funds. However, to the extent that persistent abnormal returns represent market inefficiency, finding performance persistence for quantitative funds would also indicate that quantitative models can defy the efficient market hypothesis.

We use the classification provided by Lipper Hindsight to identify quantitative funds. According to Lipper Hindsight, quantitative funds are defined as *"funds that use a rules–based mathematical model in order to initiate buy and sell decisions."*; i.e., funds which rely solely on quantitative models to select stocks.[8] We identify 270 quantitative funds in the 2000–2019 period, representing nearly 6% of the funds in our sample.[9]

We employ two different methods to measure both short– and long–term performance persistence. These methods include the Carhart (1997) approach to measure persistence across fund performance quintiles, and a regression–based approach (Busse, Goyal, and Wahal, 2010). We use the net alpha earned by investors as the performance measure, as we want to test whether there is sufficient skill to produce alpha that covers the investor's costs.[10]

If machines have more skill and consistently outperform their human counterparts, we expect quantitative funds to remain less at the bottom of the performance scale and to stay more at the top of the performance scale, i.e., poor–performing quantitative funds should persist less, while top performers should persist more. Contrarily, if machines do worse, then we anticipate more

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[8] A vast majority of funds use quantitative measures to select stocks. However, many employ quantitative screening to narrow the investment universe and identify those stocks which warrant further investigation before discretionary analysis is used to determine which securities to buy or sell, i.e., final investment decisions are made at the portfolio manager's discretion. According to Lipper Hindsight classification criteria, these are non–quantitative funds. See Section 2.2 for further details.

[9] See Table 1. Section 2 provides detailed information regarding our sample selection.

[10] "*From an investor perspective, "skill" is manager talent in selecting stocks sufficient to generate a positive alpha, net of trading costs and fund expenses.*" (Barras, Scaillet, and Wermers, 2010, p. 180). In robustness tests, we address the concern that our results are driven by differences in fee levels between quantitative and non–quantitative funds by reestimating our models using gross performance.

persistence at the bottom and more performance reversals for quantitative funds at the top of the performance distribution.

Our results show that the performance persistence of quantitative funds originates from bottom–performing funds and that there are reversals at the top of the performance scale. These findings are in line with the widespread consensus that there is no skill in fund management and that quantitative funds lack investment selection ability. We next test differences in performance persistence between quantitative and non–quantitative funds and find no significant differences for poorly–performing funds. However, at the top of the performance distribution, the performance of quantitative funds reverts significantly more, i.e., quantitative funds that do well remain less at the top when compared to their non–quantitative counterparts. The results are the same whether we test short–term or long–term persistence.

Berk and Green (2004) show that the lack of persistence in the portfolio management industry is not inconsistent with management skill. They argue that net alpha is determined in equilibrium by competition between investors and not by managerial skill; and, that there is no persistence in fund management even in the presence of skilled fund managers.[11] Berk and Tonks (2007) test the Berk and Green (2004) model and show that the persistence in the worst performing funds results from an unwillingness of investors to remove capital from these funds. Del–Guercio and Reuter (2014) highlight the need to consider incentives when evaluating mutual fund performance and find that the weaker the sensitivity of investor flows to net alpha, the more funds underperform.[12] Therefore, it is possible that differences in performance persistence between quantitative and non–

[11] There is a two–step mechanism that is responsible for the elimination of persistence: first, capital flows are driven by past performance; and second, because a manager' ability is in short supply and faces decreasing returns to scale, flows into and out of funds eliminate both positive and negative abnormal returns even in the presence of skill. See Berk (2005) for a detailed discussion of the assumptions and predictions of the Berk and Green (2004) model.

[12] Del–Guercio and Reuter (2014) state that fund families will only spend resources to generate alpha if they expect the investment to increase investor flows accordingly.

quantitative funds are not caused by differences in skill between machines and fund managers but are the result of heterogeneity in investor preferences. If this is the case, we should find differences in the sensitivity of investor flows to past performance between quantitative and non–quantitative funds, particularly for funds at the top of the performance scale. More capital invested in top–performing quantitative funds will cause fund size to grow, which in turn will result in less persistent alpha. Likewise, if the sensitivity of investor flows to alpha is weaker for quantitative funds, this will deteriorate performance persistence, as quantitative fund families have less incentive to make alpha–generating investments. However, if we find no differences in the flow–performance sensitivity between quantitative and non–quantitative funds, the documented differences in performance persistence are the result not of how investors allocate capital to funds but of differences in managerial skill.

To test these conjectures, we follow Berk and Tonks (2007) and Del Guercio and Reuter (2014) and examine the sensitivity of flows to raw returns and net alpha for both categories of fund. Our results show no differences in how quantitative and non–quantitative investor flows react to raw returns or risk–adjusted returns for relative or absolute flows. This result indicates homogeneity rather than heterogeneity in investors' preferences and aligns with the view that the observed differences in performance persistence between quantitative and non–quantitative funds arise from machines' lack of ability to beat fundamental managers. In fact, we provide evidence that quantitative funds do worse than non–quantitative funds.

The economic dimension of our results is important. Regardless of the method used to measure performance persistence, we find that reversals for top–performing quantitative funds represent more than two times the reversals for top–performing non–quantitative funds.

We conduct a battery of robustness tests. To alleviate concerns of endogeneity, we use fund fixed effects in our regression–based persistence tests and find consistent results. We address concerns of cross–sectional dependence by running our regression–based persistence tests using the Fama–MacBeth estimation procedure, which is adjusted for autocorrelation to account for the possibility that alphas in adjacent periods are mechanically related. To further address these concerns, we run our regression–based persistence tests using benchmark–adjusted returns. We also examine alternative ways of clustering standard errors. We find that our results are robust. Next, we repeat our regression–based persistence tests controlling for active share and turnover ratio and observe little impact on our main results. To exclude the possibility that our results are driven by differences in fee levels between quantitative and non–quantitative funds, we run our persistence models with gross performance. Our conclusions do not change.

Our work adds to the scarce literature on quantitative funds. To the best of our knowledge, it is the first study to investigate the performance persistence of quantitative mutual funds. Our finding that quantitative funds lack skill has important implications for academic research and practical decision–making. From an academic perspective, the results suggest that the modern portfolio theory and the efficient markets hypothesis are not challenged by quantitative funds. From a practical perspective, our evidence informs investors that quantitative funds' past performance is of little help when predicting future performance.

At a time when investors are moving to index funds, two main factors contribute to the increasing popularity of quantitative funds: (1) the belief that decisions based on quantitative outputs are less susceptible to cognitive errors and emotional bias, and thus quantitative strategies outsmart human minds; and, (2) quantitative funds charge lower fees than other actively managed funds. Our findings inform investors that they can invest in passive investment strategies, keeping costs low and eliminating the risk of underperforming a benchmark, rather than engage in the illusion of the superior performance of funds run by sophisticated computer algorithmics. Moreover, the desperate quest for superior performance may contribute to defrauding investors and lead to unpredictable losses, as most quantitative funds rely on proprietary strategies that lack transparency. This explains fund managers' *"fear that the money gushing into both simple and complex algorithmic trading strategies is making markets both more complex and fragile"* (Financial Times 2018). Therefore, the conclusions of our study are also relevant to policy–making as they suggest that regulators should keep quantitative funds under close scrutiny.[13]

2. Data and variables description

2.1 Data

We use data for US open–end, and actively managed equity funds from the Lipper Hindsight survivorship–bias free database, spanning the period 2000 to 2019.[14] Although Lipper lists multiple share classes as separate funds, they have the same holdings, the same manager, and the same returns before expenses and loads. To prevent double counting of funds, we follow, e.g., Demirci, Ferreira, Matos, and Sialm (2020) and Ferreira, Keswani, Miguel, and Ramos (2019), and use the primary share class as our unit of observation and aggregate fund–level variables across different share classes. Our sample is restricted to domestic funds, i.e., those funds investing primarily in US stocks.

2.2 Quantitative versus non–quantitative funds

[13] The Securities and Exchange Commission already took action against asset managers for concealing errors in their quantitative investment models that caused significant losses to their clients. This includes, AXA Rosenberg (in 2011), and Transamerica (in 2018), that were settled to pay $242 million and $97 million, respectively, to their investors.

[14] This dataset is used in Demirci, Ferreira, Matos, and Sialm (2020), except that we focus in US–domiciled domestic funds only.

We use the classification provided by Lipper Hindsight to identify quantitative and non–quantitative funds, which is done according to the funds' Principal Investment Strategy reported in their prospectus's disclosures. Lipper flags funds which purely rely on quantitative models to select securities as quantitative: *"funds that use a rules–based mathematical model in order to initiate buy and sell decisions."* For example, the *Leuthold Undervalued & Unloved Fund (UGLYX)*, reports in its prospectus that, *"The Fund seeks long–term capital appreciation and dividend income by investing mainly in equity securities traded in the US securities markets. The Fund utilizes a disciplined, unemotional, quantitative investment approach that is based on the belief that there will always be undervalued companies."* Although many funds employ quantitative screening to narrow the investment universe, in many cases investment decisions are made at the portfolio manager's discretion, meaning that ultimately their main stock selection criterion remains the human judgment. *Kopernik International I (KGIIX)* is an example of such funds. The fund's prospectus states that, *"The Adviser's research analysts continually evaluate companies within their defined investable universe based upon a variety of both non–quantitative and quantitative criteria. Quantitative measures include price–to–earnings, price–to–book value, price–to–sales, price–to–net present value, price–to–free cash flow, sustainable dividend yield and price–to–liquidation/replacement value. The non–quantitative analysis assists the research team in producing an understanding of franchise quality, management strength, corporate strategy, barriers–to–entry, shareholder value orientation, operating and industry fundamentals and competitive advantage."* According to Lipper classification criteria, this fund is classified as non–quantitative fund.

To our knowledge, Lipper Hindsight is the unique database providing this classification. Zhao (2006), Abis (2020) and Beggs, Brogaard, and Hill–Kleespie (2021), perform textual analysis of mutual fund prospectuses to identify quantitative funds. The classification criteria in Zhao (2006) is consistent with Lipper Hindsight's classification, as it assumes that quantitative funds are only those funds relying solely on computer models to select securities (*purely quantitative–oriented funds or quant jocks*). Abis (2020) and and Beggs, Brogaard, and Hill–Kleespie (2021) classification process, however, allows the possibility for some hybrid or mixed funds are classified as quantitative funds. *"Over identification resulting from the use of the word "quantitative" may cause funds that use simple value screens to be identified as quantitative funds"* Beggs, Brogaard, and Hill–Kleespie (2021, p.8). Interestingly, these studies have similar sample periods, but display a large difference in the number of funds identified as quantitative funds. At the end of 2015, Abis (2020) identifies 465 quantitative funds, in contrast to 168 quantitative funds that Beggs, Brogaard, and Hill–Kleespie (2021) identify.

At the end of 2019, the Lipper Hindsight database lists a total of 32,058 US equity mutual funds, of which 1,592 funds are quantitative funds. After removing closed–end funds, index–tracking funds, exchanged–traded funds and funds of funds, we get a total of 27,653 funds, 1,397 of which are quantitative funds. We then eliminate non–primary funds, and end–up with 8,749 funds, including 408 quantitative funds. We impose additional filters to construct our final sample:

(1) we exclude non–domestic funds, by removing funds identified by Lipper as international funds (those that invest primarily in stocks domiciled outside the US, including foreign funds, i.e., funds investing in a specific country, regional funds, and global funds); (2) we impose a minimum of 36 continuous monthly observations for each fund, in order to ensure that we have sufficient time series observations to calculate four–factor alphas observations for each fund; and (3) we require mutual funds to have data on all our control variables. This leads to a final sample of 3,915 unique funds, of which 3,698 are non–quantitative funds and 217 are quantitative funds. Figure 1

shows the number of quantitative funds (solid line) and the number of quantitative funds as a percentage of the total number of funds (dashed line) for the 2000–2019 sample period. The number of quantitative funds has increased steadily over the course of our sample period. In the year 2000, we identify 60 funds classified by Lipper Hindsight as quantitative, representing 4% of the total number of funds in our sample. In 2019, the number of quantitative funds climbs to 188 funds, which represents nearly 10% of the total number of funds. Table 1 presents the number of unique funds in our sample and the total assets under management (TNA) at the end of 2019, for both non–quantitative and quantitative funds. We have a sample of 3,698 non–quantitative funds and 217 quantitative funds, representing a TNA of $4,200 million and $173 million, respectively.[15]

2.3 Variables description

Risk–adjusted performance is measured using four–factor alpha (i.e., Carhart,1997, four–factor alpha). To estimate four factor alpha, we run the following regression:

$$R_{i,t} - R_f = \alpha_i + \beta_1 MKT_{i,t} + \beta_2 SMB_{i,t} + \beta_3 HML_{i,t} + \beta_4 MOM_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $R_{i,t}$ is the return net of fees in US dollars of fund *i* in month *t*, R_f is the return on the one–month US Treasury bill rate, $MKT_{i,t}$ (*market)* is the excess return on the market in month *t*, $SMB_{i,t}$ (*small minus big*) is the average return on the small–capitalization stock portfolio minus the average return on the large–capitalization stock portfolio, $HML_{i,t}$ (*high minus low*) is the average return on high book–to–market stock portfolio minus the average return on low book–to–market stock portfolio, and $MOM_{i,t}$ (*momentum*) is the average return on past 12–month winners portfolio minus the average return on past 12–month losers portfolio.[16] We use the previous 36 months of

[15] See Ferreira, Keswani, Miguel, and Ramos (2013), and Cremers, Ferreira, Matos, and Starks (2016) for a detailed description of Lipper's data coverage.
[16] Factors are from AQR Capital Management (https://www.aqr.com/Insights/Datasets). Table IA1reports means and standard deviations of monthly factor returns.

net fund returns to estimate the time series regression of monthly excess returns based on the fund's factor portfolios. We next compare the difference between the expected return and the realized return of the fund and use this difference to estimate the fund's abnormal return (or alpha) in each month. We compound monthly alphas to calculate quarterly and annual alphas (e.g., Ferreira, Keswani, Miguel, and Ramos, 2013).

Table 2, Panel A, presents summary statistics for fund–level characteristics.[17] In Panel B, we present differences in means for these characteristics for quantitative and non–quantitative funds and results of a *t*–test which show whether these differences are statistically significant.

The average quarterly and yearly raw return are higher for quantitative funds, but the differences are not statistically significant. Quantitative funds generate lower alpha, but there are also no significant differences between the alpha produced by quantitative and non–quantitative funds, whether alpha is measured quarterly or yearly. Regarding other mutual fund characteristics, quantitative funds are smaller, younger and belong to smaller families, consistent with the findings in Zhao (2006) and Abis (2020). Consistent with Ahmed and Nanda (2005), Zhao (2006), and Abis (2020), quantitative funds charge significantly lower fees. Quantitative funds charge, on average, an 0.11% lower expense ratio. Additionally, their average loads represent nearly three–quarters of the average loads charged by non–quantitative funds.

Table 2, Panels C and D, present pairwise correlations between fund characteristics for quantitative and non–quantitative funds, respectively. From Table 2, we conclude that using these fund–level variables together in our tests does not raise concerns of multicollinearity.

[17] To ensure that extreme values do not drive our results, we winsorize fund returns, alphas and also other fund characteristics, including flows and fees, at the bottom and top 1% level of the distribution.

3. Measuring performance persistence

To study differences in performance persistence between quantitative and non–quantitative funds, we examine both short– and long–term performance persistence. We test for short–term performance persistence using quarterly measurement periods (e.g., Bollen and Busse, 2005 and Busse, Goyal, and Wahal, 2010). To study long–term performance persistence, we examine persistence at yearly frequency (e.g., Carhart, 1997, Busse, Goyal, and Wahal, 2010, and Elton, Gruber and Blake, 2012).

We use two different approaches to measure mutual fund performance persistence. In the first approach, we follow Carhart (1997) to measure persistence across fund performance quintiles. The second approach uses regression–based persistence tests in the manner of Busse, Goyal, and Wahal (2010).

3.1 Mutual fund persistence across quintiles

To measure persistence across fund performance quintiles, we follow the methodology used in Carhart (1997), and compute persistence quarterly and annually as in Busse, Goyal, and Wahal (2010). We form portfolios performance quintiles during a ranking period and then examine returns over a subsequent post–ranking period. We first sort funds into quintiles based on prior annual raw return. Next, we divide each quintile into quantitative and non–quantitative subcategories and form two equally weighted portfolios from the funds in each of these subcategories. We then follow Busse, Goyal, and Wahal (2010) and record the return for quantitative and non–quantitative funds for each quintile over the following quarter or year, depending on whether we measure persistence quarterly or annually, respectively. Like Busse, Goyal, and Wahal (2010), we roll forward and rebalance the portfolios at the end of every quarter, when the holding period is one quarter, and at the end of every year, when the holding period is one year, producing a non–overlapping set of post–ranking quarterly returns. Finally, we compute the excess return of each quintile and subcategory portfolio in each quarter by subtracting the quarterly return on Treasury Bills from fund raw return, and estimate the following equation:

$$R_{q,t} - R_{f,t} = \alpha_q + \beta_q MKT_t + \delta_q SMB_t + \gamma_q HML_t + \lambda_q MOM_t + \varepsilon_{q,t} \qquad (2)$$

where $R_{q,t}$ is the quarterly net return on the k^{th} quintile portfolio, R_f is the quarterly return on the US Treasury bill rate, MKT_t (*market)* is the excess return on the market, SMB_t (*small minus big*) is the average return on the small–capitalization stock portfolio minus the average return on the large–capitalization stock portfolio, HML_t (*high minus low*) is the average return on high book–to–market stock portfolio minus the average return on low book–to–market stock portfolio, and MOM_t (*momentum*) is the average return on past 12–month winners portfolio minus the average return on past 12–month losers portfolio.[18] To understand whether there is a significant difference between the alpha produced by prior–period winners and losers, we compute the alpha of a portfolio formed by going long quintile 5 (top–performing funds) and short quintile 1 (bottom–performing funds) portfolios (5–1) for quantitative and non–quantitative funds. Finally, for each quintile, we estimate the difference in the alpha estimates between quantitative and non–quantitative funds, which corresponds to the alpha of a portfolio formed by going long quantitative funds and short non–quantitative funds.

3.2 Regression–based persistence tests

In the regression–based persistence tests, we follow Busse, Goyal, and Wahal (2010).[19] We

[18] We use factors from AQR Capital Management as indicated in Equation (1). We compound monthly factors to produce quarterly factors.
[19] The regression based persistence tests allow to control for other fund characteristics that might influence the level of fund performance and fund persistence, including total net assets, which is particularly important in the presence of diseconomies of scale (Busse, Goyal, and Wahal, 2010).

start by regressing current fund performance on prior–period fund performance, using the coefficient on lagged fund performance as our measure of persistence. We estimate the following panel regression:

$$\alpha_{i,t} = \mu + \theta\alpha_{i,t-1} + \eta X_{i,t-1} + \varepsilon_{i,t} \quad (3)$$

where $\alpha_{i,t}$ is fund performance measured using four–factor alpha in a given period (quarter or year), computed as described in Equation (1), and $X_{i,t-1}$ is a set of lagged control variables that the literature has shown to determine future mutual fund performance. A positive and significant coefficient on lagged four–factor alpha (θ) indicates fund performance persistence. If θ is negative and significant, then performance tends to revert. Control variables include fund size, fund family size, flows, age, expense ratio, and loads, all lagged by one period (e.g., Busse, Goyal and Wahal, 2010). Following Abis (2020), we control for fund flows volatility, measured as the standard deviation of monthly fund flows over the past 12 months. Regressions also include time fixed effects and benchmark fixed effects.[20] Because fund style differences might explain differences in the dynamics of persistence, we also control for style fixed effects.[21] To account for cross–sectional correlation and for the time series autocorrelation within funds, we compute robust standard errors clustered by fund and time.[22]

We start by presenting the results of a pooled regression that contains all funds in our sample taken together. To test for differences in performance persistence between quantitative and non–

[20] We follow Cremers, Ferreira Matos, and Starks (2016) and use the Lipper Technical Indicator Benchmark instead of the self–declared Fund Manager Benchmark. This is to avoid concerns that the fund may strategically choose its benchmark. In untabulated results we find similar using the Fund Manager Benchmark.

[21] We follow Hoberg, Kumar, and Prabhala (2018) and, in each period, we double sort funds into three groups based on SMB loadings (low, medium, and high) and, independently, into three groups based on HML loadings. This gives us a 3–by–3 size–by–value grid.

[22] In robustness tests we further address concerns of cross–sectional dependence by running the regression–based persistence tests using Fama–MacBeth regressions. We adjust our Fama–MacBeth estimation for autocorrelation to account for the overlap in alpha estimation. We also examine alternative ways of clustering standard errors.

quantitative funds, we follow Del–Guercio and Reuter (2014), and pool quantitative and non–quantitative funds in a single regression, and present the coefficients separately for: (1) quantitative funds, where the coefficients correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable that takes the value of one if the fund is classified as a quantitative fund; and, (2) non–quantitative funds, where the coefficients correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is not classified as a quantitative fund. We then run a *t*–test to determine the differences in the coefficients on prior–period four–factor alpha (and prior–period control variables) between quantitative and non–quantitative funds.

The literature shows differences in fund performance persistence across the performance scale and that mutual fund persistence in the US originates from bottom–performing funds, while there is evidence of performance reversals for top–performing funds (e.g., Brown and Goetzman, 1995, and Carhart, 1997). Therefore, we might expect differences in performance persistence between quantitative and non–quantitative funds to be different for funds at the bottom and at the top of the performance distribution. To further investigate this, we repeat the regression in Equation (3) allowing the coefficients on lagged four–factor alpha to be different if a fund's lagged alpha is in the bottom 20%, the mid–60%, and the top 20% of funds in the prior period; we do this by using indicator variables for the mid–60% and the top 20% of funds, as in Ferreira, Keswani, Miguel, and Ramos (2019).

4. Empirical results on performance persistence

Table 3 presents the results when we compute mutual fund persistence across quintiles, following the methodology used in Carhart (1997) (see Section 3.1). We report two different post–

ranking horizons: one quarter, to measure short–term persistence, in Panel A of Table 3; and one year, to measure long–term persistence, in Panel B of Table 3. We report alphas in percent per quarter for quintile 1 (bottom–performing funds), for quintiles 2, 3 and 4 aggregated, and for quintile 5 (top–performing funds). We also report 5–1, which is the alpha of a portfolio formed by going long quintile 5 and short quintile 1 portfolios. At the bottom of Panels A and B, for each performance quintile, we compute differences in alphas between quantitative and non–quantitative funds, i.e., the alpha of a portfolio formed by going long quantitative funds and short non–quantitative funds.

Our results indicate performance persistence among poor–performing funds for both quantitative and non–quantitative funds, whether we measure short– or long–term persistence. We also find no statistically significant differences when comparing the alpha produced by bottom–performing quantitative and non–quantitative funds. In the case of best–performing funds, we observe reversals for both types of funds, but the results are only statistically significant for top–performing quantitative funds. There is also evidence that quantitative funds in the best performance quintile generate significantly lower alpha than their non–quantitative peers. The alpha of a portfolio formed by going long quantitative funds and short non–quantitative funds is –0.46% and –0.51% per quarter for short– and long–term persistence, respectively. These differences are economically important as the average quarterly four–factor alphas for quantitative and non–quantitative funds in our sample are –0.33% and –0.30%, respectively (see Table 2). The difference between the top and bottom quintile alphas (5–1) is positive (0.36%) and marginally significant for non–quantitative funds and only for the holding period of one year.

Table 4 shows the results from our regression–based persistence tests (see Equation 3). Panel A presents our findings from the tests for short–term persistence, while Panel B presents the results of our tests for long–term persistence.

Column (1) in Panel A and Panel B, reports the results of a pooled regression, relating performance to lagged performance, containing all funds in our sample, i.e., quantitative and non–quantitative funds. The coefficients in Columns (2) and (3) are estimated in a single regression. The coefficients in Column (2) correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable, which takes the value of one if the fund is classified by Lipper Hindsight as a quantitative fund. Similarly, the coefficients in Column (3) correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is classified as a non–quantitative fund. The coefficients in Columns (2) and (3) are therefore identical to those obtained when estimating a separate regression for quantitative and for non–quantitative funds. In column (4) we test the differences in the coefficients on prior period four–factor alpha between quantitative and non–quantitative funds, obtained in Columns (2) and (3).

The results in Table 4, Panel A, Column (1), are consistent with short–term performance persistence for the full sample of quantitative and non–quantitative funds taken together. However, the coefficients on prior–quarter performance for quantitative (Column 2) and non–quantitative funds (Column 3) show that the performance persistence reported in Column (1) is driven by non–quantitative funds. There is no evidence of short–term persistence for quantitative funds. The difference in short–term performance persistence between quantitative and non–quantitative funds is statistically significant, as indicated in Column (4).

Table 4, Panel B, reports tests for long–term performance persistence and Column (3) shows long–term persistence for non–quantitative funds. For quantitative funds, in Column (2), we observe a statistically significant performance reversal. For tests of coefficients on prior–year performance between quantitative and non–quantitative funds, Column (4) displays the results that show the statistically significant differences between these categories of funds.

To test for differences in performance persistence across the performance scale, we repeat the regression in Equation (3) allowing the coefficients on the lagged four–factor alpha to be different if a fund's lagged alpha is in the bottom 20%, the mid–60%, or the top 20% of funds in the prior–period. We next compute the differences in persistence between quantitative and non–quantitative funds for the three different levels of performance, and test the significance of these differences, in a similar procedure to that described in Table 4. The results are reported in Table 5, Panels A and B, for short–term and long–term performance persistence, respectively.[23]

In Table 5, Column (1) of Panel A presents the results for short–term performance persistence when pooling quantitative and non–quantitative funds and document significant persistence among poor–performing funds and significant reversals for top–performing funds. Columns (2) and (3) present the coefficients on prior–quarter performance for quantitative and non–quantitative funds separately. For both categories of funds, the results are similar to those in Column (1). In Column (4), we find no differences in performance persistence between quantitative and non–quantitative funds for those funds in the bottom–performance quintile; however, it is clear that the performance of top–performing quantitative funds reverts significantly more than that of non–quantitative funds. In Table 5, Panel B presents the results for long–term performance persistence. We find that the results are similar to those presented in Panel A for short–term persistence, i.e., there are no differences in the performance persistence of poorly performing funds but the observed performance reversals of previous winners are much stronger for quantitative funds than for their non–quantitative counterparts. This difference is not only statistically significant but also

[23] The coefficients in our tables reflect the total level of persistence for bottom 20%, mid–60%, and top 20% of funds.

economically meaningful, as reversals in top–performing quantitative funds represent more than two times the reversals observed for top–performing non–quantitative funds.

Overall, regardless of the method used to measure performance persistence, the results show that the performance persistence of quantitative funds is due to poor–performing funds and that there are reversals among winners. These results are no different to that observed for non–quantitative funds in our sample and to the evidence in existing work that suggests that persistence among loser funds is the prevailing form of persistence (e.g., Carhart, 1997). However, our tests show marked statistically and economic differences in the performance persistence of quantitative and non–quantitative funds at the top of the performance scale, as the performance of top–performing quantitative funds reverts substantially more. Therefore, our results are consistent with machines not being able to beat their human counterparts. Actually, we provide evidence of machines having less skill than traditional fund managers, which also suggests that quantitative funds do not challenge the efficient market hypothesis.

5. Investor preferences and fund performance persistence

Berk and Green (2004) shows that there should be no persistence in fund performance even in the presence of managerial skill as the net alpha is determined in equilibrium by competition between investors. Berk and Tonks (2007) show that the persistence amongst the worst performing funds results from an unwillingness of investors to remove capital from these funds. Del Guercio and Reuter (2014) show that investor flows determine the incentive for fund to generate alpha and that a weak sensitivity of investor flows to alpha explains the underperformance of the average actively managed fund. Fund flows are, therefore, one key mechanism that determines performance persistence. One might argue that the documented differences in performance persistence are not caused by different managerial ability between machines and fund managers but are the result of investors preferences. In that case, the flow of capital into and out of quantitative and non–quantitative funds should present different sensitivities to past performance.

To test for these differences, we start by examining flows of funds for bottom and top performance quintiles, like in Berk and Tonks (2007). Table 6 presents the results with performance measured using raw returns. We use quarterly data in Panel A and annual data in Panel B. First, at the end of each period, we sort funds into quintiles based on their raw returns over the previous year. We then compute the average relative and absolute net flow over the period of the quintile formation and test whether it is statistically different from zero. Column (1) shows the results for all funds, Columns (2) and (3), present the results for quantitative and non–quantitative funds, respectively. In Column (4) we compute the differences between the two categories of funds and run a *t*–test to find whether these differences are statistically significant.

Our results show significant net outflows of capital in the bottom performance quintiles and net inflow of capital into top performance quintiles, for both quantitative and non–quantitative funds, which indicates that investors chase past performance and is consistent with the assumptions of the Berk and Green (2004) model. More importantly, the results in Table 6 show no significant differences in the net inflow and net outflow of capital of quantitative and non–quantitative funds. We find identical results in Table 7, when we use four–factor alpha rather than raw returns as our performance measure. This is a first indication that capital flows do not explain the documented differences in performance persistence between the two categories of funds.

We next use a regression–based approach, in the manner of Berk and Tonks (2007) and Del Guercio and Reuter (2014), to further investigate differences in the flow–performance sensitivity between the two categories of funds. We run the following regression:

$$Flows_{i,t} = \mu + \beta Bottom\ performance_{i,t-1} + \delta\ Performance_{i,t-1} + \lambda Top\ performance_{i,t-1} + \theta\alpha_{i,t-1} + \eta X_{i,t-1} + \varepsilon_{i,t}. \tag{4}$$

We regress the relative flows or absolute flows of fund *i* in period *t* on past performance, measured as raw returns. We allow for nonlinearity in the flow–performance sensitivity by including bottom and top relative performance dummies (if fund's *i* performance is in the bottom or the top quintile of funds in period *t–1*, respectively); we also include past period four–factor alpha ($\alpha_{i,t-1}$). Additional control variables include fund size, fund family size, flows, flow volatility, age, total expense ratio, and loads. Regressions also include time fixed effects, benchmark fixed effects, and style fixed effects.

Tables 8 and 9 present the results for relative and absolute flows, respectively. As in our regression–based persistence tests, we start, in Column (1), by running a pooled regression that includes all funds in our sample taken together. To test for differences between quantitative and non–quantitative funds, we next pool quantitative and non–quantitative funds in a single regression and present the coefficients separately for: (1) quantitative funds, where the coefficients, presented in Column (2), correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable that takes the value of one if the fund is classified as a quantitative fund; and (2) non–quantitative funds, where the coefficients, presented in Column (3), correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is classified as a non–quantitative fund. In Column 4, we run a *t*–test to see if there are differences in the coefficients of quantitative and non–quantitative funds.

We find that capital flows are responsive to past performance, which confirms our preliminary results in Tables 6 and 7 and the assumptions in the Berk and Green (2004) model.[24] Our results also show that fund flows are sensitive to both raw returns and four–factor alpha.

If the differences in performance persistence between quantitative and non–quantitative funds, documented in Section 4, occur as the result of differences in the response of capital flows to past performance, the observed differences in column (4) should be statistically significant. In that case, in light of the Berk and Green (2004) model, we should find differences in the sensitivity of investor flows to raw returns, particularly for those funds at the top of the performance scale. More capital into top–performing quantitative funds would cause fund size to increase, which should make generating persistent alpha more difficult for these funds. Similarly, if the sensitivity of investor flows to alpha is weaker for quantitative funds, this might cause quantitative funds to have less incentive to generate alpha and deteriorate persistence. The results in Tables 8 and 9 do not confirm this hypothesis as we find no significant differences on how quantitative and non–quantitative capital flows react to both raw returns and risk–adjusted performance. These results hold whether we use relative or absolute fund flow and whether focusing on quarterly or annual flows.

Overall, our results indicate that the observed differences in performance–persistence cannot be attributed to heterogeneity in the response of investors to past performance.

6. Robustness tests

In this section we run a number of additional tests to check the robustness of our results. The tables are presented in the Internet Appendix.

[24] Different studies show that past performance predicts future fund flows, including Del Guercio and Tkac (2002) and Sirri and Tufano (1998).

The decision to operate a quantitative fund may be related to unobserved fund characteristics that also explain the performance and hence fund performance persistence. We address endogeneity concerns by estimating our regression–based tests, in Equation (3), including fund fixed effects. Table IA2 presents the results of re–estimating Table 5 and shows that our main conclusions remain unchanged.

In our main regression–based persistence tests we account for cross–sectional correlation and for the time series autocorrelation within mutual funds by computing robust standard errors clustered by fund and time. To further address concerns of cross–sectional dependence, we run the results of our regression–based persistence tests using the Fama–MacBeth estimation. Because we use alphas in our regression–based persistence tests that are estimated with three years of past monthly excess returns, it is possible that alphas in adjacent periods are mechanically related and affect our results. To address these concerns, we adjust our Fama–MacBeth estimation for autocorrelation because of the overlap in alpha estimation. Furthermore, we run our regression–based persistence tests using benchmark–adjusted returns (computed as the difference between the fund's return and the return on its benchmark). The results of these tests are presented in Tables IA3 and IA4, for the Fama–MacBeth estimation and for benchmark–adjusted returns. Our main conclusions are preserved. Additionally, we examine alternative ways of clustering standard errors. We follow Hoberg, Kumar, and Prabhala (2018) and, in Table IA5, we cluster standard errors by fund style and time. Fund style is computed based on SMB and HML loadings, as described in Section 3. To allow for the possibility that fund performance is correlated both within mutual fund family and within time, in untabulated results, we also cluster on family and time. We find that our results are robust.

Pastor, Stambaugh, and Taylor (2017), and Hoberg, Kumar, and Prabhala (2018) show that turnover determines performance persistence. Different studies (e.g., Kacperczyk, Sialm, and Zheng, 2005) show that a fund's activity is related to its alpha. Cremers and Petajisto (2009) find that the funds with the highest active share outperform their benchmarks and exhibit strong performance persistence. Therefore, it is important to understand whether our results are affected by the inclusion of these variables. Because Lipper Hindsight does not provide data on fund turnover ratio or active share, we compute these variables using data from the FactSet/LionShares database. We follow Pastor, Stambaugh, and Taylor (2017) and measure fund turnover using the minimum of a fund's total purchases and sales over a year scaled by the average fund NAV over the same period. Active share is computed as the percentage of fund's portfolio holdings that differ from its benchmark index holdings calculated as in Cremers and Petjisto (2009), and Cremers, Ferreira Matos, and Starks (2016).[25] The turnover and the active share data only cover three quarters of the observations in our sample, which explains why we do not include these variables in our main analysis. Also, because turnover and active share are computed at the end of each year, we present the results using annual data only. Tables IA6 and IA7 show that our regression–based persistence tests and flow–performance sensitivity tests do not change, when controlling for turnover and active share, respectively.

Mutual fund fees may determine the persistence observed in fund performance. To alleviate concerns that our results are driven by differences in fee levels between quantitative and non–quantitative funds, we run our persistence models with gross performance. We obtain gross performance by adding back total expense ratio to net performance. Tables IA8 and IA9 present the results for the Carhart (1997) methodology and the regression–based persistence tests, respectively. These tests show that our main conclusions do not change.

[25] We thank Miguel Ferreira and Pedro Pires for providing us with this data.

6. Conclusion

Over the last few years, the increasing adoption of quantitative analysis by the asset management industry has led to a new category of funds: quantitative funds. Quantitative funds select securities using customized algorithms and computer models, and the expectations that these funds might lead to superior performance have contributed to their increasing popularity.

In this paper, we use the classification provided by Lipper Hindsight database to be the first to study the performance persistence of quantitative funds in the US.

Our results show performance persistence for poor–performing quantitative funds, while there is evidence of significant reversals at the top of the performance scale, which is consistent with the main findings in previous work for non–quantitative funds. When testing for differences in performance persistence between quantitative and non–quantitative funds, we find no differences for funds at the bottom tier of the performance scale. However, at the top of the performance scale, we observe important statistically and economic differences, as the performance of top–performing quantitative funds reverts significantly more than the performance of top–performing non–quantitative funds.

We next examine whether these differences are explained by investor preferences, as the literature shows that the sensitivity of investor flows to past performance determines the performance persistence of actively managed funds. We find that this is not the case. Our tests indicate homogeneity rather than heterogeneity in how investors allocate capital flows to quantitative and non–quantitative funds.

Overall, our study shows that, whether looking at short–term or long–term performance persistence, quantitative funds lack skill and do worse that non–quantitative funds. Quantitative funds are therefore failing to meet investor expectations.

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Appendix 1. Variable definitions

Variable	Definition
Raw return	Fund net return in UD dollars (percentage per quarter or year) (Lipper).
Four–factor alpha	Net four–factor alpha (percentage per quarter or year) estimated as indicated in Equation (1).
TNA	Total net assets in millions of US dollars (Lipper).
TNA family	Family total net assets in millions of US dollars of other equity funds in the same management company excluding the own fund TNA (Lipper).
Flow	Percentage growth in TNA in each quarter or year, net of internal growth (assuming reinvestment of dividends and distributions). We follow Chevalier and Ellison (1997) and Sirri and Tufano (1998) and fund flow for fund *i* at period *t* is calculated as: $$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1+R_{i,t})}{TNA_{i,t-1}},$$ where $TNA_{i,t}$ is the total net asset value in US dollars of fund *i* at the end of quarter *t*, and $R_{i,t}$ is fund *i*'s raw return from in quarter *t*. Net annual fund flow is the sum of net quarterly fund flows.
Absolute flow	Change in total net assets adjusted for internal growth due to investment returns: $$Absolute\ Flow_{i,t} = TNA_{i,t} - TNA_{i,t-1}(1+R_{i,t})$$ where $TNA_{i,t}$ is the total net asset value in US dollars of fund *i* at the end of period *t*, and $R_{i,t}$ is fund *i*'s raw return from in period *t*.
Flows volatility	Standard deviation of fund flows, computed using monthly fund flows over the past 12 months.
Age	Number of years since the fund launch date (Lipper).
Total expense ratio	Total annual expenses as a fraction of TNA (Lipper).
Loads	Sum of front–end and back–end loads (Lipper).

Figure 1: Quantitative funds in our sample

This figure shows the number of quantitative funds (solid line) and the number of quantitative funds as a percentage of the total number of funds (dashed line) for the 2000–2019 period. The sample is restricted to US open–end and actively managed domestic equity funds drawn from the Lipper Hindsight database.

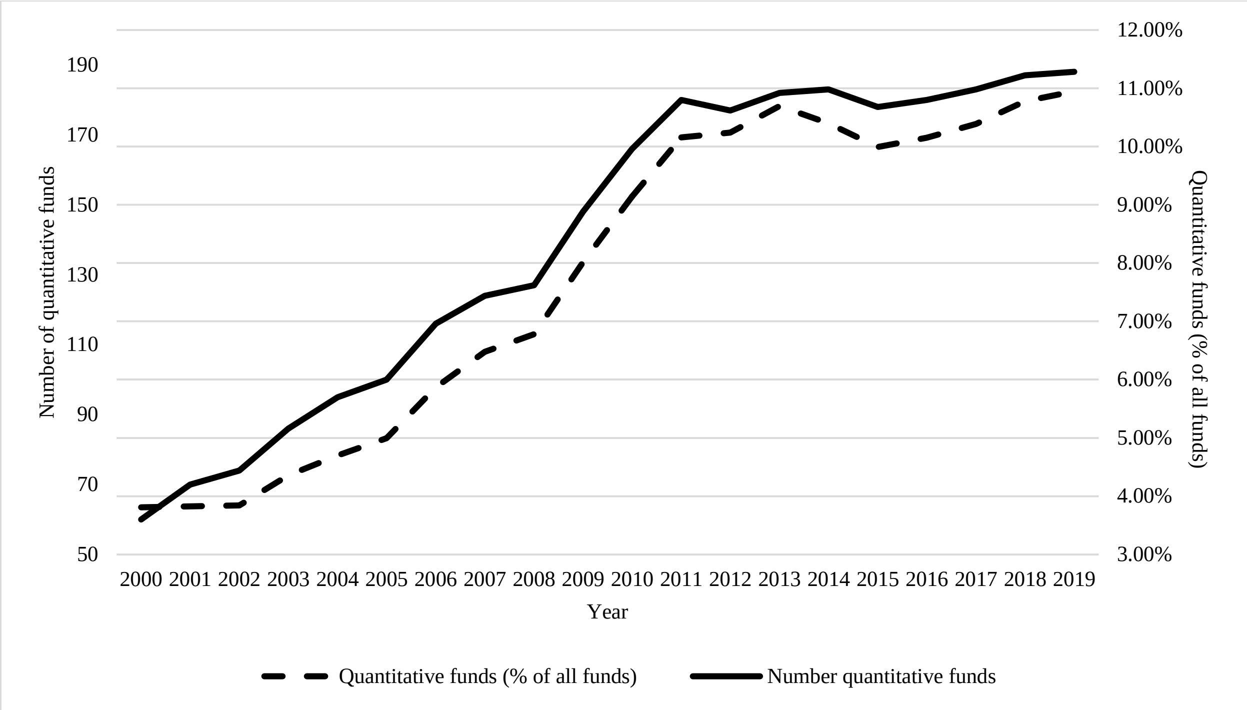

Table 1
Mutual fund industry sample by quantitative and non–quantitative funds

This table presents the number of unique funds in our sample and total net assets (TNA) under management (sum of all share classes in millions of US dollars at the end of 2019) for both quantitative and non–quantitative funds. The sample is restricted to US open–end and actively managed domestic equity funds drawn from the Lipper Hindsight database. The sample period is 2000–2019. See Appendix 1 for variable definitions.

Funds	Number of funds	TNA ($ million)
Quantitative	217	173,062
Non–quantitative	3,698	4,200,469
Total	3,915	4,373,531

Table 2
Mutual fund characteristics for quantitative and non–quantitative funds
This table presents details on mutual fund characteristics for both quantitative and non–quantitative funds. Panel A presents summary statistics for mutual fund characteristics. In Panel B we present differences in means of mutual fund characteristics for quantitative and non–quantitative funds and run a *t*–test, testing whether these differences are statistically significant. Panels C and D present pairwise correlations among fund characteristics for quantitative and non–quantitative funds, respectively. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. The sample is restricted to US open–end and actively managed domestic equity funds drawn from the Lipper Hindsight database. The sample period is 2000–2019. See Appendix 1 for variable definitions.

Panel A: Summary statistics for mutual funds characteristics for quantitative and non–quantitative funds

Variable	Mean	Median	Standard deviation	Percentile 10	Percentile 90	Observations
Quantitative funds						
Raw return (% quarter)	1.89	2.91	8.87	–11.36	12.39	9,086
Raw return (% year)	7.84	9.67	18.48	–23.90	32.06	2,503
Four–factor alpha (% quarter)	–0.33	–0.29	3.10	–4.47	2.99	9,086
Four–factor alpha (% year)	–1.25	–1.19	7.17	–9.78	3.11	2,503
TNA ($ million)	718	170	1,952	20.8	1,684	9,086
TNA family ($ million)	40,266	6,680	183,698	211.4	69,557	9,086
Flow (% quarter)	0.59	–1.71	18.08	–10.53	12.02	9,086
Absolute flow (% quarter)	–5.96	–1.02	55.94	–178.22	243.25	9,086
Flow volatility (% quarter)	9.70	4.46	17.28	1.31	21.68	9,086
Age (years)	13.07	11.17	9.61	4.08	23.08	9,086
Total expense ratio (% year)	1.14	1.11	0.42	0.66	1.66	9,086
Loads (% year)	1.08	0.14	1.51	0.00	3.60	9,086
Non–quantitative funds						
Raw return (% quarter)	1.81	2.86	9.54	–11.52	12.60	150,557
Raw return (% year)	7.71	9.78	20.80	–21.50	32.32	34,278
Four–factor alpha (% quarter)	–0.30	–0.27	3.77	–4.30	3.62	150,557
Four–factor alpha (% year)	–1.20	–1.11	8.20	–9.74	6.83	34,278
TNA ($ million)	1,433	241	5,563	17.5	2,917	150,557
TNA family ($ million)	70,501	9,973	195,268	116.6	153,563	150,557
Flow (% quarter)	0.35	–1.69	18.00	–9.83	9.96	150,557
Absolute flow (% quarter)	–7.97	–1.10	78.09	–181.00	226.97	150,557
Flow volatility (% quarter)	8.45	3.82	16.13	1.08	17.32	150,557
Age (years)	15.18	11.67	12.95	4.17	29.33	150,557
Total expense ratio (% year)	1.24	1.19	0.46	0.76	1.83	150,557
Loads (% year)	1.43	0.72	1.70	0.00	4.23	150,557

Panel B: Differences in mutual funds characteristics: quantitative versus non–quantitative funds

Fund characteristics	Quantitative	Non–quantitative	Quantitative minus Non–quantitative: Difference	(p–value)
Raw return (% quarter)	1.89	1.81	0.08	(0.16)
Raw return (% year)	7.84	7.71	0.13	(0.34)
Four–factor alpha (% quarter)	–0.33	–0.30	–0.03	(0.39)
Four–factor alpha (% year)	–1.25	–1.20	–0.06	(0.28)
TNA ($ million)	718	1,433	–715***	(0.00)
TNA family ($ million)	40,266	70,501	–30,235***	(0.00)
Flow (% quarter)	0.59	0.35	0.24	(0.21)
Absolute flow (% quarter)	–5.96	–7.97	2.02**	(0.02)
Flow volatility (% quarter)	9.70	8.45	1.25***	(0.00)
Age (years)	13.07	15.18	–2.11***	(0.00)
Total expense ratio (% year)	1.14	1.24	–0.11***	(0.00)
Loads (% year)	1.08	1.43	–0.35***	(0.00)

Panel C: Pairwise correlations among fund characteristics (annual data) – Quantitative funds

		1	2	3	4	5	6	7	8	9	10
Raw return	1	1									
Four–factor alpha	2	0.194	1								
TNA	3	–0.095	–0.033	1							
TNA family	4	–0.027	0.038	0.601	1						
Flow	5	–0.018	–0.012	0.016	0.016	1					
Absolute flow	6	0.062	0.057	–0.253	–0.095	0.149	1				
Flow volatility	7	0.025	0.029	–0.234	–0.085	0.094	0.113	1			
Age	8	0.013	–0.004	0.325	0.113	–0.185	–0.205	–0.171	1		
Total expense ratio	9	–0.027	–0.074	–0.388	–0.385	–0.036	0.097	0.057	–0.133	1	
Loads	10	–0.002	–0.028	0.025	–0.013	0.026	0.005	–0.092	0.027	0.407	1

Panel D: Pairwise correlations among fund characteristics (annual data) – Non–quantitative funds

		1	2	3	4	5	6	7	8	9	10
Raw return	1	1									
Four–factor alpha	2	0.295	1								
TNA	3	–0.016	–0.030	1							
TNA family	4	0.018	0.054	0.620	1						
Flow	5	–0.036	–0.016	–0.013	0.001	1					
Absolute flow	6	0.032	0.073	–0.230	–0.120	0.147	1				
Flow volatility	7	0.009	0.011	–0.262	–0.060	0.111	0.107	1			
Age	8	0.067	0.035	0.419	0.232	–0.181	–0.204	0.107	1		
Total expense ratio	9	–0.077	–0.087	–0.431	–0.359	–0.015	0.102	–0.204	0.107	1	
Loads	10	–0.035	–0.039	0.019	0.048	0.006	0.003	0.003	0.367	0.107	1

Table 3
Fund performance persistence across quintiles

This table presents the estimates of performance persistence tests measuring the persistence in mutual funds in our sample across performance quintiles. In Panel A, we measure short–term persistence, while, in Panel B, we measure long–term persistence. We sort funds into quintiles based on prior one–year raw return. Next, we divide each quintile into quantitative and non–quantitative subcategories and form equally weighted portfolios from the funds in each of these subcategories. We then hold the quintile portfolios for post–ranking periods of one quarter, to compute short term persistence, and of one year, to compute long–term persistence. We rebalance the portfolios at the end of every quarter or at the end of every year, when the holding period is one quarter or one year, respectively. Four–factor alphas are estimated by running Equation (2). We present alphas in percent per quarter for quintile 1 (bottom–performing funds), for quintiles 2, 3 and 4 aggregated, and for quintile 5 (top–performing funds). 5–1 is the alpha of a portfolio formed by going long quintile 5 and short quintile 1 portfolios. At the bottom of the table, for each performance quintile, we compute differences in the alpha estimates between quantitative and non–quantitative funds – the alpha of a portfolio formed by going long quantitative funds and short non–quantitative funds. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix 1 for variable definitions.

Panel A: Short–term persistence

	1		2–to–4		5		5–1	
	Coeff.	t–stat	Coeff.	t–stat	Coeff.	t–stat	Coeff.	t–stat
Quantitative	–0.46**	(–2.12)	–0.11	(–0.49)	–0.53**	(–2.37)	–0.07	(–0.24)
Non–quantitative	–0.38*	(–1.84)	–0.09	(–0.41)	–0.07	(–0.32)	0.31	(1.59)
Quantitative minus Non–quantitative	–0.08	(–0.36)	–0.02	(–0.08)	–0.46**	(–2.17)		

Panel B: Long–term persistence

	1		2–to–4		5		5–1	
	Coeff.	t–stat	Coeff.	t–stat	Coeff.	t–stat	Coeff.	t–stat
Quantitative	–0.53**	(–2.23)	–0.17	(–0.71)	–0.62***	(–2.61)	–0.09	(–0.45)
Non–quantitative	–0.47**	(–2.18)	–0.12	(–0.58)	–0.11	(–0.53)	0.36*	(1.67)
Quantitative minus Non–quantitative	–0.06	(–0.26)	–0.05	(–0.22)	–0.51**	(–2.33)		

Table 4

Fund performance persistence: regression–based tests

This table presents the estimates of regression–based persistence tests measuring the persistence in mutual funds in our sample. In Panel A, we use quarterly data, while Panel B presents the results using annual data. Fund four–factor alpha in a given period is regressed on prior–period four–factor alpha and control variables, as presented in Equation (3). Lagged control variables include fund size, fund family size, flows, flow volatility, age, total expense ratio, and loads. Regressions also include time fixed effects, benchmark fixed effects, and fund style fixed effects. Column (1) reports the results of a pooled regression that contains all funds in our sample, i.e., quantitative and non–quantitative funds. The coefficients in Columns (2) and (3) are from a single regression, where the coefficients in Column (2) correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable, which takes the value of one if the fund is classified by Lipper Hindsight as a quantitative fund, and the coefficients in Column (3) correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is not classified by Lipper Hindsight as a quantitative fund. Robust *t*–statistics clustered by fund and quarter (or fund and year) are reported in parentheses. Column (4) presents differences between the coefficients on prior–period four–factor alpha for quantitative and non–quantitative funds, from Columns (2) and (3), respectively, and the results of a *t*–test, testing whether this difference is statistically significant (*p*–values are reported in parentheses). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix 1 for variable definitions.

Panel A: Short–term persistence (quarterly data)

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Performance	0.0423***	0.0091	0.0427***	–0.0336***
	(10.23)	(0.55)	(10.42)	(0.01)
TNA (log)	–0.0007***	–0.0013***	–0.0006***	–0.0007**
	(–9.50)	(–4.95)	(–8.93)	(0.02)
TNA Family (log)	0.0004***	0.0007***	0.0004***	0.0003
	(8.68)	(3.87)	(8.27)	(0.12)
Flows	–0.0002	0.0007	–0.0003	0.0010
	(–0.24)	(0.35)	(–0.40)	(0.64)
Flow volatility	0.0013*	0.0028	0.0012	0.0016
	(1.75)	(1.26)	(1.60)	(0.50)
Age	0.0003*	0.0012*	0.0002*	0.0010
	(1.74)	(1.81)	(1.67)	(0.22)
Total expense ratio	–1.1012***	–1.0319**	–1.1261***	0.0942
	(–8.62)	(–2.31)	(–8.39)	(0.84)
Loads	–0.0696	–0.0226	–0.0980	0.0754
	(–0.54)	(–0.08)	(–0.74)	(0.69)
Adjusted R–squared	0.082			0.083
Number of observations	159,643			159,643

Panel B: Long–term persistence (annual data)

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Performance	0.0298***	–0.0259**	0.0312***	–0.0571***
	(3.37)	(1.97)	(3.51)	(0.00)
TNA (log)	–0.0024***	–0.0047***	–0.0022***	–0.0025**
	(–7.88)	(–4.30)	(–7.21)	(0.03)
TNA Family (log)	0.0017***	0.0026***	0.0017***	0.0009
	(8.25)	(3.51)	(7.81)	(0.26)
Flow	–0.0018***	–0.0000	–0.0019***	0.0019
	(–3.22)	(–0.04)	(–3.20)	(0.19)
Flow volatility	0.0036*	0.0059	0.0035	0.0024***
	(1.70)	(0.95)	(1.59)	(0.00)
Age	0.0010	0.0020	0.0009	0.0011
	(1.56)	(0.96)	(1.45)	(0.64)
Total expense ratio	–0.6542***	–0.9908**	–0.6254***	–0.3654
	(–4.85)	(–2.16)	(–4.43)	(0.44)
Loads	–0.0674**	0.0045	–0.0697**	0.0742
	(–2.45)	(0.04)	(–2.44)	(0.71)
Adjusted R–squared	0.106			0.109
Number of observations	36,781			36,781

Table 5

Fund performance persistence conditioning on past performance: regression–based tests

This table presents the estimates of regression–based persistence tests measuring the persistence in mutual funds in our sample, for the bottom, the mid– and the top levels of the performance scale. In Panel A we use quarterly data to measure short–term persistence, while Panel B presents the results for long–term persistence using annual data. Fund four–factor alpha in a given period is regressed on prior–period four–factor alpha and control variables (not reported), as presented in Equation 3. To allow past performance to influence future performance differently, depending on how well a fund has done in the past, we allow the coefficients on the lagged four–factor alpha to be different for the bottom 20%, the mid–60% and the top 20% of funds in the prior year, and we do so by using indicator variables for the mid–60%, and the top 20% of funds. Lagged control variables include fund size, fund family size, flows, flow volatility, age, total expense ratio, and loads. Regressions also include time fixed effects, benchmark fixed effects, and fund style fixed effects. Column (1) reports the results of a pooled regression that contains all funds in our sample, i.e., quantitative and non–quantitative funds. The coefficients in Columns (2) and (3) are from a single regression, where the coefficients in Column (2) correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable, which takes the value of one if the fund is classified by Lipper Hindsight as a quantitative fund, and the coefficients in Column (3) correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is not classified by Lipper Hindsight as a quantitative fund. Robust *t*–statistics clustered by fund and quarter (or by fund and year) are reported in parentheses. Column (4) presents the difference between the coefficients on prior–period four–factor alpha, for the bottom 20%, the mid–60% and the top 20%, for quantitative and non–quantitative funds, from Columns (2) and (3), respectively, and the results of a *t*–test, testing whether these differences are statistically significant (*p*–values are reported in parentheses). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix 1 for variable definitions.

Panel A: Short–term persistence (quarterly data)

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1	0.0686***	0.0782***	0.0644***	0.0138
	(10.65)	(3.04)	(9.85)	(0.27)
Mid performance t–1	0.0483***	0.0461**	0.0486***	–0.0025
	(5.07)	(2.08)	(5.22)	(0.66)
Top performance t–1	–0.0149**	–0.0496**	–0.0114*	–0.0376**
	(–2.09)	(–2.45)	(–1.72)	(0.02)
Adjusted R–squared	0.083			0.084
Number of observations	159,643			159,643

Panel B: Long–term persistence (annual data)

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1	0.0784***	0.0924**	0.0766***	0.0158
	(6.42)	(2.51)	(6.30)	(0.51)
Mid performance t–1	0.0901***	0.0701**	0.0914***	–0.0213
	(5.17)	(2.49)	(5.11)	(0.41)
Top performance t–1	–0.0523***	–0.1282***	–0.0478***	–0.0812***
	(–4.04)	(–3.21)	(–3.98)	(0.00)
Adjusted R–squared	0.108			0.111
Number of observations	36,781			36,781

Table 6
Fund flows and performance in the bottom and top performance quintiles – raw returns
This table presents the average relative and absolute net flows of the bottom and top performance quintiles, using quarterly data in Panel A and annual data in Panel B. Column (1) reports the results for all funds in our sample, Columns (2) and (3) report the results for quantitative and non–quantitative funds, respectively. At the end of each period, we sort funds into quintiles based on their raw returns over the previous year. We next compute the average relative and absolute net flow over the period of the quintile formation and test whether it is statistically different from zero. Column (4) presents the differences between quantitative and non–quantitative funds, and the results of a *t*–test, testing whether these differences are statistically significant. *p*–values are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix 1 for variable definitions.

Panel A – Quarterly data

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1				
Flow (%)	–3.3912***	–3.1744***	–3.4637***	0.2893
	(0.00)	(0.00)	(0.00)	(0.49)
Absolute flow	–25.0116***	–23.5397***	–25.3186***	1.7789
	(0.00)	(0.00)	(0.00)	(0.41)
Top performance t–1				
Flow (%)	5.3492***	4.9585***	5.4311***	–0.4726
	(0.00)	(0.00)	(0.00)	(0.35)
Absolute flow	15.8794***	13.6457***	16.0646***	–2.4189
	(0.00)	(0.00)	(0.00)	(0.33)
Number of observations	159,643	9,086	150,557	–

Panel B – Annual data

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1				
Flow (%)	–11.7734***	–11.247***	–11.8115***	0.5645
	(0.00)	(0.00)	(0.00)	(0.57)
Absolute flow	–77.9784***	–69.1476***	–78.8504***	9.7028
	(0.00)	(0.00)	(0.00)	(0.68)
Top performance t–1				
Flow (%)	25.7445***	24.7815***	25.8136***	–1.0321
	(0.00)	(0.00)	(0.00)	(0.84)
Absolute flow	40.1879***	39.8405***	41.7914***	–1.9510
	(0.00)	(0.00)	(0.00)	(0.87)
Number of observations	36,781	2,503	34,278	–

Table 7

Fund flows and performance in the bottom and top performance quintiles – four–factor alpha

This table presents the average relative and absolute net flows of the bottom and top performance quintiles, using quarterly data in Panel A and annual data in Panel B. Column (1) reports the results for all funds in our sample, Columns (2) and (3) report the results for quantitative and non–quantitative funds, respectively. At the end of each period, we sort funds into quintiles based on their four–factor alpha over the previous year. We next compute the average relative and absolute net flow over the period of the quintile formation and test whether it is statistically different from zero. Column (4) presents the differences between quantitative and non–quantitative funds, and the results of a *t*–test, testing whether these differences are statistically significant. *p*–values are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix 1 for variable definitions.

Panel A – Quarterly data

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1				
Flow (%)	–3.2201***	–2.6713***	–3.2804***	0.6091
	(0.00)	(0.00)	(0.00)	(0.67)
Absolute flow	–24.3583***	–22.206***	–24.7364***	2.5303
	(0.00)	(0.00)	(0.00)	(0.26)
Top performance t–1				
Flow (%)	4.7643***	4.1631***	4.8223***	–0.6592
	(0.00)	(0.00)	(0.00)	(0.61)
Absolute flow	12.0918***	12.1312***	11.9123***	0.2189
	(0.00)	(0.00)	(0.00)	(0.53)
Number of observations	159,643	9,086	150,557	–

Panel B – Annual data

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1				
Flow (%)	–5.4525***	–6.8791***	–5.0694***	–1.8097
	(0.00)	(0.00)	(0.00)	(0.17)
Absolute flow	–67.7135***	–69.3722***	–66.8994***	–2.4728
	(0.00)	(0.00)	(0.00)	(0.74)
Top performance t–1				
Flow (%)	22.6345***	21.1987***	22.8589***	–1.6602
	(0.00)	(0.00)	(0.00)	(0.41)
Absolute flow	33.9085***	31.674***	34.915***	–3.2410
	(0.00)	(0.00)	(0.00)	(0.69)
Number of observations	36,781	2,503	34,278	–

Table 8
Fund flow–performance sensitivity – relative flow

This table presents the estimates of panel regressions measuring the flow–performance sensitivity for funds in our sample, as presented in Equation (4). We use quarterly data in Panel A and annual data in Panel B. Relative fund flow is regressed on prior–period performance measured using raw returns. We also include dummies for fund's in the bottom and top prior–period performance quintiles, and prior–period four–factor alpha. Lagged control variables include fund size, fund family size, flows, flow volatility, age, tracking error, total expense ratio, and loads. Regressions also include time fixed effects, benchmark fixed effects, and style fixed effects. Column (1) reports the results of a pooled regression that contains all funds in our sample, i.e., quantitative and non–quantitative funds. The coefficients in Columns (2) and (3) are from a single regression, where the coefficients in Column (2) correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable, which takes the value of one if the fund is classified by Lipper Hindsight as a quantitative fund, and the coefficients in Column (3) correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is not classified by Lipper Hindsight as a quantitative fund. Robust *t*–statistics clustered by fund and quarter (or by fund and year) are reported in parentheses. Column (4) presents the difference between the coefficients of independent variables for quantitative and non–quantitative funds, from Columns (2) and (3), respectively, and the results of a *t*–test, testing whether these differences are statistically significant (*p*–values are reported in parentheses). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix 1 for variable definitions.

Panel A – Quarterly data

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom Performance	–0.0116***	–0.0161***	–0.0117***	–0.0044
	(–8.50)	(–2.63)	(–8.37)	(0.37)
Performance	0.3105***	0.2853**	0.3269***	–0.0416
	(8.93)	(2.43)	(9.14)	(0.59)
Top performance	0.0249***	0.0260***	0.0257***	–0.0003
	(16.35)	(4.51)	(16.25)	(0.64)
Four–factor alpha	0.6447***	0.6949***	0.6400***	0.0549
	(18.81)	(4.05)	(18.26)	(0.75)
TNA (log)	–0.0036***	–0.0081***	–0.0033***	–0.0048***
	(–9.75)	(–4.78)	(–8.76)	(0.01)
TNA Family (log)	0.0026***	0.0038***	0.0025***	0.0013
	(10.85)	(3.30)	(10.10)	(0.25)
Flows	0.1413***	0.1359***	0.1404***	–0.0045
	(19.47)	(6.18)	(18.54)	(0.85)
Flow volatility	0.1676***	0.0996***	0.1723***	–0.0727***
	(16.56)	(2.95)	(16.35)	(0.00)
Age	–0.0156***	–0.0121***	–0.0159***	0.0030
	(–22.29)	(–3.57)	(–22.12)	(0.28)
Total expense ratio	–1.4254**	–4.5072**	–1.0943**	–3.4129***
	(2.57)	(–2.39)	(2.03)	(0.00)
Loads	2.1201***	3.0212	2.0176***	1.0036
	(3.89)	(1.50)	(3.59)	(0.30)
Adjusted R–squared	0.201			0.203
Number of observations	159,643			159,643

Panel B – Annual data

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Raw return (Bottom)	–0.0623***	–0.0746**	–0.0602***	–0.0138
	(–5.29)	(–2.42)	(–5.18)	(0.71)
Raw return	0.1753***	0.1995***	0.1698***	0.0297
	(7.74)	(2.01)	(7.41)	(0.84)
Raw return (Top)	0.1198***	0.1114***	0.1148***	–0.0034
	(7.87)	(4.16)	(7.45)	(0.39)
Four–factor alpha	0.4390***	0.4506**	0.4287***	0.0219
	(6.93)	(2.53)	(6.70)	(0.56)
TNA (log)	–0.0271***	–0.0536***	–0.0251***	–0.0286***
	(–8.12)	(–3.40)	(–7.37)	(0.00)
TNA Family (log)	0.0194***	0.0344***	0.0181***	0.0163
	(8.74)	(3.15)	(7.93)	(0.14)
Flow	0.0931***	0.0757*	0.0941***	–0.0184
	(8.85)	(1.79)	(8.74)	(0.67)
Flow volatility	1.0731***	1.1810***	1.0675***	0.1135
	(17.03)	(4.71)	(16.41)	(0.91)
Age	–0.0662***	–0.0605**	–0.0663***	0.0058
	(–10.81)	(–2.03)	(–10.64)	(0.84)
Total expense ratio	–1.3083**	–3.9759**	–1.0243**	–2.9516***
	(–2.12)	(–2.13)	(–1.98)	(0.00)
Loads	1.6035***	1.4500	1.6202***	–0.1702
	(2.95)	(1.17)	(3.01)	(0.60)
Adjusted R–squared	0.175			0.177
Number of observations	36,781			36,781

Table 9
Fund flow–performance sensitivity – absolute flow
This table presents the estimates of panel regressions measuring the flow–performance sensitivity for funds in our sample, as presented in Equation (4). We use quarterly data in Panel A and annual data in Panel B. Absolute fund flow is regressed on prior–period performance measured using raw returns. We also include dummies for fund's in the bottom and top prior–period performance quintiles, and prior–period four–factor alpha. Lagged control variables (no reported in panels) include fund size, fund family size, absolute flows, absolute flow volatility, age, tracking error, total expense ratio, and loads. Regressions also include time fixed effects, benchmark fixed effects, and style fixed effects. Column (1) reports the results of a pooled regression that contains all funds in our sample, i.e., quantitative and non–quantitative funds. The coefficients in Columns (2) and (3) are from a single regression, where the coefficients in Column (2) correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable, which takes the value of one if the fund is classified by Lipper Hindsight as a quantitative fund, and the coefficients in Column (3) correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is not classified by Lipper Hindsight as a quantitative fund. Robust *t*–statistics clustered by fund and quarter (or by fund and year) are reported in parentheses. Column (4) presents the difference between the coefficients of independent variables for quantitative and non–quantitative funds, from Columns (2) and (3), respectively, and the results of a *t*–test, testing whether these differences are statistically significant (*p*–values are reported in parentheses). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix 1 for variable definitions.

Panel A – Quarterly data

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom Performance	–3.5369***	–4.9497**	–3.3951***	–1.5546
	(–3.56)	(–2.05)	(–3.32)	(0.89)
Performance	135.4260***	154.0587**	134.4411***	19.6177
	(5.04)	(2.33)	(4.82)	(0.26)
Top performance	4.9859***	4.5973**	5.3126***	–0.7153
	(4.10)	(1.98)	(4.15)	(0.85)
Four–factor alpha	206.3724***	196.3715***	210.5493***	–14.1778
	(10.94)	(2.95)	(10.80)	(0.59)
Adjusted R–squared	0.425			0.428
Number of observations	159,643			159,643

Panel B – Annual data

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom Performance	–15.0493***	–18.3747*	–16.4405***	–1.9340
	(–4.41)	(–1.86)	(–4.58)	(0.74)
Performance	41.8997**	49.4534*	39.3884**	10.0650
	(2.14)	(1.75)	(2.01)	(0.53)
Top performance	20.8795***	19.2798*	22.0410***	–2.7620
	(4.89)	(1.74)	(4.88)	(0.92)
Four–factor alpha	157.3753***	160.6522**	154.4371***	6.2200
	(8.04)	(2.55)	(7.89)	(0.70)
Adjusted R–squared	0.359			0.365
Number of observations	36,781			36,781

Web Appendix to:
Do machines beat humans?
Evidence from mutual fund performance persistence

António F. Miguel and Yihao Chen

This appendix contains tables that supplement the analysis in the paper "Do machines beat humans? Evidence from mutual fund performance persistence."

Table IA1

Summary statistics of factor returns

This table reports mean and standard deviation of monthly factor returns (percentage per month) of the four–factor model for the 2000–2019 period. MKT (*market*) is the excess return on the stock market, SMB (*small minus big*) is the difference in return between the small and big portfolios, HML (*high minus low*) is the difference in return between the high and low book–to–market portfolios, and MOM (*momentum*) is the difference in return between last year's winner and loser portfolios. Data is downloaded from AQR Capital Management: https://www.aqr.com/Insights/Datasets/Betting–Against–Beta–Equity–Factors–Monthly

Factors	Mean	Standard deviation
MKT	0.53	4.65
SMB	0.22	2.71
HML	0.12	2.77
MOM	0.29	5.25

Table IA2

Fund performance persistence conditioning on past performance: fund fixed effects

This table reports the results from estimating our fund performance persistence tests in Table 5 with fund fixed effects. Panels A and B report the results from reestimating Panels A and B of Table 5, for short–and long–term persistence, respectively. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix 1 for variable definitions.

Panel A: Short–term persistence (quarterly data)

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1	0.0206***	0.0432**	0.0197***	0.0235
	(3.11)	(2.01)	(2.95)	(0.17)
Mid performance t–1	0.0323**	0.0309*	0.0327**	–0.0018
	(2.31)	(1.69)	(2.42)	(0.65)
Top performance t–1	–0.0288***	–0.0601**	–0.0277***	–0.0323**
	(–4.04)	(–2.37)	(–3.83)	(0.04)
Adjusted R–squared	0.100			0.101
Number of observations	159,643			159,643

Panel B: Long–term persistence (annual data)

	All funds	Quantitative	Non–quantitative	Quantitative Minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1	0.0954***	0.0889**	0.0923***	–0.0034
	(6.52)	(2.34)	(6.43)	(0.89)
Mid performance t–1	0.0535***	0.0445*	0.0543***	–0.0098
	(3.05)	(1.67)	(3.14)	(0.72)
Top performance t–1	–0.1106***	–0.1859***	–0.0993***	–0.0869***
	(–8.27)	(–3.75)	(–8.14)	(0.00)
Adjusted R–squared	0.134			0.136
Number of observations	36,781			36,781

Table IA3

Fund performance persistence: Fama–Macbeth regression–based tests

This table reports the results from estimating our regression–based persistence tests, in Equation (3), using Fama–Macbeth cross–sectional regressions with *t*–statistics corrected for autocorrelation. Panels A and B report the results from reestimating Panels A and B of Table 5, for short–and long–term persistence, respectively. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix 1 for variable definitions.

Panel A: Short–term persistence (quarterly data)

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1	0.0797***	0.0849**	0.0794***	0.0055
	(2.78)	(2.48)	(2.65)	(0.68)
Mid performance t–1	0.0582**	0.0659**	0.0555**	0.0104
	(2.44)	(2.13)	(2.37)	(0.43)
Top performance t–1	–0.0172	–0.0522**	–0.0137	–0.0385***
	(–0.72)	(–2.01)	(–0.51)	(0.01)
Adjusted R–squared	0.191			0.194
Number of observations	159,643			159,643

Panel B: Long–term persistence (annual data)

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1	0.0769***	0.0863**	0.0740***	0.0123
	(3.11)	(2.01)	(3.02)	(0.56)
Mid performance t–1	0.0833***	0.0798**	0.0846***	–0.0048
	(3.69)	(2.07)	(3.77)	(0.83)
Top performance t–1	–0.0508**	–0.1135**	–0.0496**	–0.0639**
	(–2.42)	(–2.23)	(–2.38)	(–0.03)
Adjusted R–squared	0.174			0.176
Number of observations	36,781			36,781

Table IA4

Fund performance persistence conditioning on past performance: benchmark–adjusted returns

This table reports the results from estimating our fund performance persistence tests in Table 5 with performance measured as benchmark–adjusted returns. We compute benchmark–adjusted returns as the difference between the fund's return and the return on its benchmark. Panels A and B report the results from reestimating Panels A and B of Table 5, for short–and long–term persistence, respectively. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix 1 for variable definitions.

Panel A: Short–term persistence (quarterly data)

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1	0.0617***	0.0704***	0.0545***	0.0159
	(9.54)	(2.69)	(8.14)	(0.31)
Mid performance t–1	0.0393***	0.0369**	0.0413***	–0.0044
	(4.13)	(1.81)	(4.17)	(0.59)
Top performance t–1	–0.0117*	–0.0422**	–0.0089	–0.0331**
	(–1.79)	(–2.08)	(–1.58)	(0.03)
Adjusted R–squared	0.071			0.073
Number of observations	159,643			159,643

Panel B: Long–term persistence (annual data)

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1	0.0717***	0.0846**	0.0702***	0.0144
	(5.94)	(2.34)	(5.79)	(0.57)
Mid performance t–1	0.0798***	0.0661**	0.0834***	–0.0173
	(4.75)	(2.22)	(4.69)	(0.45)
Top performance t–1	–0.0479***	–0.1198***	–0.0431***	–0.0768***
	(–3.64)	(–2.85)	(–3.51)	(0.00)
Adjusted R–squared	0.095			0.099
Number of observations	36,781			36,781

Table IA5

Fund performance persistence: Regression–base tests clustering on fund style and time

This table reports the results from estimating our regression–based persistence tests, in Table 5, except that we cluster standard errors on both fund style and time. Panels A and B report the results from reestimating Panels A and B of Table 5, for short–and long–term persistence, respectively. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix 1 for variable definitions.

Panel A: Short–term persistence (quarterly data)

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1	0.0686***	0.0782**	0.0644***	0.0138
	(3.25)	(2.12)	(3.03)	(0.34)
Mid performance t–1	0.0483***	0.0461*	0.0486***	–0.0025
	(3.54)	(1.85)	(3.63)	(0.73)
Top performance t–1	–0.0149*	–0.0496*	–0.0114	–0.0376**
	(–1.70)	(–1.93)	(–1.51)	(0.03)
Adjusted R–squared	0.083			0.084
Number of observations	159,643			159,643

Panel B: Long–term persistence (annual data)

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1	0.0784***	0.0924*	0.0766***	0.0158
	(3.03)	(1.92)	(3.07)	(0.69)
Mid performance t–1	0.0901***	0.0701**	0.0914***	–0.0213
	(2.97)	(2.04)	(3.12)	(0.57)
Top performance t–1	–0.0523**	–0.1282**	0.0478**	–0.0812**
	(–2.27)	(–2.51)	(–2.14)	(0.02)
Adjusted R–squared	0.118			0.121
Number of observations	36,781			36,781

Table IA6

Fund performance persistence: Regression–based tests controlling for turnover and active share

This table reports the results from estimating our regression–based tests for long–term persistence, in Panel B of Table 5, except that we add to our control variables fund turnover and fund active share. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix 1 for variable definitions.

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1	0.0563***	0.0685**	0.0546***	0.0139
	(3.65)	(2.17)	(3.53)	(0.35)
Mid performance t–1	0.0669***	0.0511**	0.0682***	–0.0171
	(3.18)	(2.02)	(3.26)	(0.53)
Top performance t–1	–0.0558***	–0.1402**	–0.0529***	–0.0873**
	(–3.63)	(–2.39)	(–3.51)	(0.02)
Active share	0.0197***	0.0015	0.0195***	–0.0180***
	(4.62)	(0.31)	(4.56)	(0.00)
Turnover	–0.0224***	–0.0111	–0.0228***	0.0117
	(–8.21)	(–1.37)	(–7.85)	(0.28)
Adjusted R–squared	0.111			0.095
Number of observations	27,218			27,218

Table IA7

Fund flow–performance sensitivity – controlling for turnover and active share

This table reports the results from estimating our tests in Panel B of Table 8, except that we add to our control variables fund turnover and fund active share. *p*–values are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix 1 for variable definitions.

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Raw return (Bottom)	–0.0536***	–0.0575**	–0.0530***	–0.0045
	(–3.51)	(–2.03)	(–3.43)	(0.82)
Raw return	0.1291***	0.1423*	0.1131***	0.0292
	(3.67)	(1.69)	(3.58)	(0.69)
Raw return (Top)	0.0826***	0.0799***	0.0991***	–0.0192
	(4.68)	(2.88)	(5.36)	(0.24)
Four–factor alpha	0.2838***	0.2940*	0.2772***	0.0168
	(3.60)	(1.66)	(3.43)	(0.63)
Active share	0.1030**	0.0849*	0.1261***	–0.0412
	(2.47)	(–1.93)	(3.05)	(0.15)
Turnover	–0.4720***	–0.5023***	–0.4673***	–0.0350
	(–15.01)	(–4.17)	(–13.92)	(0.41)
Adjusted R–squared	0.185			0.187
Number of observations	27,218			27,218

Table IA8
Fund performance persistence across quintiles – gross performance

This table presents the estimates of performance persistence tests measuring the persistence in mutual funds in our sample across performance quintiles using gross returns. Gross return is computed by adding back total expense ratio to net return. Panels A and B report the results from reestimating Panels A and B of Table 5, for short–and long–term persistence, respectively. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix 1 for variable definitions.

Panel A: Short–term persistence

	1		2–to–4		5		5–1	
	Coeff.	t–stat	Coeff.	t–stat	Coeff.	t–stat	Coeff.	t–stat
Quantitative	–0.18	(–0.86)	–0.07	(–0.32)	–0.26	(–1.33)	–0.08	(–0.35)
Non–quantitative	–0.15	(–0.76)	0.18	(0.84)	0.28	(1.49)	0.43**	(2.32)
Quantitative minus Non–quantitative	–0.03	(–0.13)	–0.24	(–1.04)	–0.54**	(–2.51)		

Panel B: Long–term persistence

	1		2–to–4		5		5–1	
	Coeff.	t–stat	Coeff.	t–stat	Coeff.	t–stat	Coeff.	t–stat
Quantitative	–0.23	(–0.99)	0.05	(0.26)	–0.39*	(–1.71)	–0.16	(–0.71)
Non–quantitative	–0.19	(–0.77)	–0.04	(–0.18)	0.11	(0.56)	0.30	(1.42)
Quantitative minus Non–quantitative	–0.04	(–0.17)	0.09	(0.41)	–0.50**	(–2.28)		

Table IA9

Fund performance persistence conditioning on past performance: gross performance

This table reports the results from estimating our fund performance persistence tests in Table 5 using before fee four–factor alpha rather than after–fee four–factor alpha. Gross four–factor alpha is computed by adding back total expense ratio to net four–factor alpha. Panels A and B report the results from reestimating Panels A and B of Table 5, for short– and long–term persistence, respectively. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix 1 for variable definitions.

Panel A: Short–term persistence (quarterly data)

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1	0.0648***	0.0743***	0.0627***	0.0116
	(9.40)	(2.89)	(9.18)	(0.31)
Mid performance t–1	0.0501***	0.0479**	0.0498***	–0.0019
	(5.51)	(2.19)	(5.32)	(0.69)
Top performance t–1	–0.0157**	–0.0509**	–0.0126*	–0.0374**
	(–2.14)	(–2.52)	(–1.91)	(0.02)
Adjusted R–squared	0.081			0.082
Number of observations	159,643			159,643

Panel B: Long–term persistence (annual data)

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1	0.0761***	0.0982**	0.0746***	0.0236
	(5.76)	(2.56)	(5.49)	(0.44)
Mid performance t–1	0.0821***	0.0584**	0.0848***	–0.0264
	(4.60)	(2.06)	(4.62)	(0.35)
Top performance t–1	–0.0411***	–0.1197***	–0.0361***	–0.0837***
	(–3.86)	(–3.01)	(–3.45)	(0.00)
Adjusted R–squared	0.101			0.103
Number of observations	36,781			36,781