



How active is your (nominally) actively managed quantitative fund?

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ABSTRACT

We study the *Active Share* (AS) of quantitative actively managed US equity funds (quants). Our results suggest that closet indexing is a common practice among these funds, with 50 % of the assets in quants managed by closet indexers by the end of 2019. This fraction significantly exceeds that observed among human-managed funds (non-quants). Our analysis indicates that AS is associated with lower performance for quants, in contrast to the positive relationship observed for non-quants. We incorporate *Tracking Error* (TE) alongside AS to further categorize funds based on their level of active management. We find that, after fees, quants tend to underperform their benchmarks across all categories. This result is particularly pronounced among stock pickers, with quants notably trailing non-quants, and for factor bets, which emerge as the poorest performing category. Our findings also challenge the common belief that quants charge lower fees. Although this is generally true for strategies characterized by low AS, it does not hold for those with high AS. Overall, our work documents the prevalence of closet indexing among quants and suggests that significant progress is needed before algorithms can effectively substitute human expertise in strategies that require extensive discretionary decision-making.

1. Introduction

Quantitative funds, which rely on automated algorithms for portfolio-decision making, are gaining prominence in the mutual fund industry. Initially employed by hedge funds, quantitative approaches have been increasingly adopted by mutual funds to overcome managerial skill

constraints and enhance cost efficiency.²³ Prior research has primarily focused on whether quantitative models outperform their human-managed counterparts; however little attention has been paid to the level of active management employed by quants and the strategies they utilize.^{4,5}

This paper seeks to address this gap by examining the AS of

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² Compared to mutual funds, hedge funds are more effective at fully leveraging quantitative models, as their structure allows for sophisticated strategies, including the use of derivatives and market-neutral approaches. Features such as longer lock-up periods and fewer liquidity constraints provide flexibility for complex or infrequent trades. In contrast, mutual funds, catering to broader retail audiences, face stricter regulations, higher transparency requirements, and a benchmark-relative focus, limiting the adoption of some advanced strategies. However, their cost efficiency and scalable management goals make systematic models valuable for factor investing and rules-based decision-making, optimizing portfolios and reducing human biases.

³ The literature on quantitative hedge funds is sparse and limited in scope. Chincarini (2014) shows that quantitative hedge funds outperform peers, attributing this to superior market timing ability. Harvey, Rattray, Sinclair, and Van Hemert (2017) highlight the cost efficiency and scalability of quantitative strategies, while noting potential underperformance during unforeseen market shifts. Khandani and Lo (2011) analyze the 2007 "quant meltdown," revealing vulnerabilities to crowded trades and liquidity crises, which can negatively impact quantitative approaches.

⁴ Studies on the trading behavior of quants are scarce and, like the literature on hedge funds, focus on the impact of investment strategies during periods of market instability. Abis (2022) presents a theoretical framework suggesting that quants possess unlimited learning capacity but are less adaptable to changing market conditions than non-quants. Supporting these hypotheses, she observes that quants hold more stocks, favor stocks with greater information availability, and engage in crowded trades, explaining why they underperform non-quants during recessions. Beggs, Brogaard, and Hill-Kleespie, 2023 show that quants' fire sales increase market instability more than those of non-quants. Using AS to calculate portfolio overlap, they find that quants experiencing fire sales show higher portfolio and sale overlap, exacerbating their effects on the market. Other studies, such as Birru, Gokkaya, and Liu (2024) and D'Acunto et al. (2019), have explored the impact of the disciplined nature of quantitative models on market efficiency.

⁵ With respect to the performance of quants vis-à-vis non-quants, previous work yields mixed results: Miguel and Chen (2021) find lower performance persistence for quants, while Ahmed and Nanda (2005) and Casey and Associates (2005) report that quants outperform non-quants. Abis (2022) concludes that quants underperform during recessions, while Zhao (2006) shows that they perform worse in market upturns but better in downturns.

quantitative (nominally) active US equity funds.⁶ Through this analysis, we aim to shed light on whether these funds truly deviate from or simply mimic their benchmark index. While the literature shows that many nominally active funds merely track an index, i.e., closet index (Cremers and Curtis, 2016; Cremers and Petajisto, 2009), whether and to what extent quants engage in this form of misconduct remains an open question. Studying the AS of quants also provides insights into their ability to generate value for investors. At its core, value creation relies on the fund manager's skill to deviate from the benchmark in ways that yield positive returns relative to it. Furthermore, analyzing AS enhances our understanding of the fees quants charge and allows for meaningful comparisons with their counterparts. Although quants are widely perceived as offering lower fees – a perception contributing to their growing popularity (Abis, 2022 and Miguel and Chen, 2021) – a comprehensive assessment of fees, considering the extent of active management employed by these funds, has not yet been conducted.

While both quants and non-quants face limitations in the type of information they can process, these funds can make rational choices about which information to focus on.⁷ The information that a fund consumes and how it processes it plays a crucial role in determining its investment decisions and ultimately its performance (Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016).

Quants benefit from access to vast amounts of data and extensive computing power, enabling them to process a larger volume of information than their counterparts. Consequently, this reduced constraint on information processing helps to mitigate uncertainty, expands the investment universe for quants, and potentially leads to deviations from the benchmark. However, certain information, such as soft information, may not be easily processable by machines, rendering it inaccessible to quants.⁸ Therefore, while traditional fund managers might choose to allocate their limited learning capacity to gain insights on stocks that only a fraction of investors are aware of, thus increasing their focus on stock picking, quants tend to concentrate on stocks for which more hard information is available.⁹ This more homogeneous information consumption, combined with the use of similar investment processes, may contribute to quants closely tracking the benchmark, i.e., focusing on low AS strategies. This expectation aligns with the fact that quants operate on a rule-based approach, relying on traditional factor models and fixed rules, which may explain why they are more likely to hold and trade the same securities (Abis, 2022 and Beggs, Brogaard, and Hill-Kleespie, 2023).¹⁰ Our tests provide evidence supporting this pattern, showing that quants exhibit an average AS that is 5 % lower than that of their non-quant counterparts. Moreover, we also observe a significant prevalence of closet indexing among these funds. Throughout our sample period, an average of 35 % of assets in nominally active quants

are managed by closet indexers, a figure that raises to 50 % by the end of 2019. These numbers are economically significant, exceeding those for non-quants by 11 % and 12 %, which stand at 24 % and 38 %, respectively.

Incorporating *TE* into our analysis and categorizing funds by their levels of active management using the framework in Cremers and Petajisto (2009), we find results consistent with the observed passive behavior of quants.^{11,12} Specifically, quants exhibit lower levels of active management than non-quants, regardless of the type or category of active management examined.

Next, we examine the relationship between AS and performance of both types of funds. Cremers and Petajisto (2009) show that AS is indicative of performance.¹³ However, they acknowledge that while AS is a necessary ingredient for outperforming the benchmark – since funds must deviate from the benchmark to beat it –, AS is not sufficient on its own. AS is only beneficial when fund managers are able to deviate from the benchmark in a way that yields positive returns relative to it. For less skilled managers, AS can adversely affect future performance.

Non-quants rely on the manager's personal judgment and fundamental analysis for stock selection. While this approach involves emotional and cognitive input, it also offers flexibility in the decision-making process.¹⁴ This flexibility may enable non-quants to deviate significantly from the benchmark and potentially capitalize on unique insights and opportunities for generating alpha. In contrast, the systematic and rule-based nature of quantitative strategies allows quants to make unemotional decisions and eliminate cognitive biases from the decision-making process, ensuring a consistent and disciplined approach (D'Acunto, Prabhala, and Rossi, 2019). However, this inherent discipline also limits the flexibility of these funds. Rule-based algorithms are programmed using historical data and predefined rules, lacking adaptability to unforeseen events or changing market conditions. Therefore, we anticipate that quants may be less able to implement high AS strategies. As for low AS strategies, by deviating slightly from the benchmark within a controlled range, these funds could exploit mispricing, market efficiencies, and quantitative signals to enhance performance. Low AS strategies are typically more scalable because they involve fewer discretionary decisions, allowing quants to more efficiently manage large amounts of capital. However, the systematic nature of quantitative strategies may also lead to overcrowding, potentially limiting the ability of quants to deviate from the benchmark in ways that create value for investors: “*These [quantitative] strategies are becoming better and better known, so the alpha is disappearing.*” (Financial Times, 2020).

We find empirical evidence that is consistent with our predictions.

⁶ Introduced by Cremers and Petajisto (2009), AS is a widely used tool for assessing and comparing active management levels within investment portfolios. AS is reported by platforms like Morningstar, and since 2018, major mutual fund families, including BlackRock and Vanguard, have disclosed AS for their actively managed funds to retail investors.

⁷ The theory of rational inattention (Sims, 2003) states that agents cannot process all available information, but they can make rational choices about what information to attend to. Agents then act based on the chosen information.

⁸ Soft information includes opinions, ideas, and other information obtained through different informal channels. It is mostly communicated as text, and hence it is difficult to collect, store, and machine-process. Hard information is mostly numbers, including returns and financial statements, which is easier to collect, store, and machine-process.

⁹ The substitution effect (e.g. Kacperczyk et al., 2016), suggests that, in the presence of quants, the incentive for non-quants to learn about stocks for which less machine-processable information is available should increase, as the marginal benefit of learning about a stock increases when there are relatively fewer others learning about it. The results in Abis (2022) confirm that quants invest in stocks for which more information is available, including larger stocks, and stocks with a longer history and greater media coverage.

¹⁰ Our results indicate that quants, relative to non-quants, pursue significantly more exposure to risk factors, which aligns with their response to similar return signals during their investment process. See Section 2.3 for further details.

¹¹ While both AS and *TE* are measures of how different an active manager is from an appropriate passive benchmark, they capture different aspects of portfolio activity. AS is a measure of the level of stock selection and is calculated by using portfolio and benchmark holdings. *TE* measures the volatility of the differences in returns between the investment portfolio and its benchmark. As such, it is strongly influenced by factor exposures and can be used as a proxy for factor bets. We also observe a lower average *TE* for quants, as it represents only nearly 80 % of that of non-quants.

¹² Following Cremers and Petajisto (2009), we identify five categories of funds, separately for quants and non-quants: (1) closet indexers; (2) moderately active funds; (3) factor bets; (4) concentrated stock pickers; and (5) diversified stock pickers. See Section 2.2 for further details.

¹³ The positive effect of AS on performance is shown in other studies, including Petajisto (2013), Cremers and Pareek (2016), Cremers et al. (2016), Cremers (2017), Keswani, Mamdough, Miguel, and Ramos (2020), Cremers et al. (2022), and Cline and Gilstrap (2021). Other work showing that the empirical relation between deviations from the benchmark and fund alpha is reliably positive includes Kacperczyk, Sialm, and Zheng (2005), Kacperczyk, van Nieuwerburgh and Veldkamp (2014), and Doshi, Elkamhi, and Simutin (2015).

¹⁴ The literature shows that even highly experienced fund managers are susceptible to behavioral biases that impact their decision-making (Brown, Wei, and Wermers, 2014 and Chevalier and Ellison, 1999).

Like Cremers and Petajisto (2009), our results suggest a positive association between AS and the performance of non-quants.¹⁵ However, notable differences emerge when examining quants. Quants with high AS tend to exhibit poorer performance compared to closet indexers (both before and after fees) and generally underperform non-quants. Conversely, we observe that quants generally do better than their counterparts in low AS strategies, although the differences in alpha never reach statistical significance. Regarding *TE*, our analysis suggests a negative effect on the performance of both types of funds, with no significant differences in how *TE* affects quants versus non-quants. This result suggests that factor bets are not rewarded in the market, aligning with the findings of Cremers and Petajisto (2009) and Petajisto (2013). In fact, we observe that funds concentrating on factor bets have eroded the most value for investors for both types of funds, suggesting quants are also not superior to non-quants in implementing these strategies. There is also evidence indicating that, after fees, quants underperform their benchmarks across all active management categories.

The economic implications of our results are important. On average, a 10 % increase in AS is associated with a 0.24 % increase in net four-factor alpha for non-quants over the subsequent year. In contrast, the same increase in AS corresponds to a 0.20 % decrease in alpha for quants. Notably, the average annual net alpha of quant diversified stock pickers is 1.64 % lower than that of non-quants, underscoring the negative impact of AS on the performance of quants.

We investigate the reasons behind the low AS of quants relative to non-quants. The literature highlights the role of incentives in the mutual fund industry, suggesting that funds typically raise AS to attract investor flows (e.g., Cremers, Ferreira, Matos, and Starks, 2016 and Del Guercio and Reuter, 2014). To explore this, we examine whether investor flow responses to AS differ between quants and non-quants. The results indicate that non-quants with higher AS attract significantly greater flows, particularly top-performing funds. In contrast, quants exhibit a negative relation between AS and fund flows. These findings suggest that the lower AS in quants may stem from a lack of investor-driven incentives, as investors likely perceive quants as relying on systematic strategies. High AS may be seen as counterproductive, potentially signaling a deviation from the expected approach and undermining confidence in the fund's methodology.

Finally, we examine differences in fees charged by quants and non-quants. The literature suggests that quants typically charge lower fees due to the automated nature of their strategies, which reduce the need for costly research teams and analysts (Abis, 2022; Miguel and Chen, 2021). However, similar to other actively managed funds, the fees charged by quants are expected to vary across different categories of active management. Low AS strategies involve few discretionary decisions and offer scalability, whereas high AS strategies require greater complexity and resource, justifying higher fees due to the use advanced models and extensive research efforts.

Consistent with the literature, our findings suggest that the total expense ratio (*TER*) charged by quants is 10 bps lower than that charged by non-quants. When examining fee differences within categories of active management, we observe significant differences only for funds closely tracking or deviating moderately from the benchmark. For instance, in the case of closet indexers, quants charge a substantial 23 bps less in *TER*. Conversely, for diversified and concentrated stock picking strategies, these differences are not statistically significant.¹⁶

Our work provides valuable contributions to the literature. Firstly, we document that nominally active quants largely engage in closet indexing. Closet indexing is a major phenomenon within the mutual

fund industry, which has garnered attention and raised concerns among regulators and policymakers (Cremers and Curtis, 2016 and Cremers, Fulkerson, and Riley, 2022). Despite these concerns, no regulatory measures have been implemented to address the mismatch between funds' marketing claims and their actual strategies, leaving investors potentially misled. Our finding that quants closely align with their benchmarks suggests a potential need for regulatory intervention to ensure transparency and protect investor interests, particularly given the increasing prominence of quantitative strategies in the fund industry. These strategies often rely on proprietary, rule-based approaches that lack transparency, complicating effective regulatory oversight. Furthermore, advancements in artificial intelligence and machine learning add to this complexity, enabling funds to process diverse information and adapt strategies dynamically, further blurring the distinction between active and passive management. These developments also highlight the need for regulatory standards to evolve in response to the increasing sophistication of investment strategies. Beyond disclosing traditional active management metrics like AS, greater transparency regarding the use of proprietary algorithms by quants may help safeguard investors and preserve market integrity.

Secondly, we extend the literature on the performance of quants (Abis, 2022; Ahmed and Nanda, 2005; Miguel and Chen, 2021 and Zhao, 2006). Different from previous research, we study the performance across various types and categories of active management strategies employed. This approach enables us to document the constraints faced by quants in formulating investment strategies that add value for investors, particularly those involving higher levels of *TE* or AS. It also allows for a thorough comparison with their non-quant counterparts.

Thirdly, our study is the first comprehensive analysis of the fee structures within quantitative investment strategies. By examining fees across different categories of active management, we show that the prior evidence that quants entail lower fees compared to their human-managed counterparts (Abis, 2022 and Miguel and Chen, 2021) may not be universally applicable. Although quants generally exhibit lower fees in portfolios with lower levels of AS, this advantage seems to fade in portfolios characterized by higher AS.

Lastly, our research also contributes to the growing literature on automation in the asset management industry (Cao, Jiang, Wang, and Yang, 2024 and D'Acunto et al., 2019). Our findings indicate that the systematic, rules-based nature of quantitative strategies aligns well with indexed investment approaches, offering low-cost exposure to broad market indices. However, these strategies face significant challenges in implementing approaches that require intensive discretionary decision-making and scalability. This suggests that these strategies have not yet fully matured into a viable alternative to traditional fund management. However, since the sample period covered in our analysis, the field of quantitative investing has likely evolved, driven by rapid advancements in machine learning and artificial intelligence. These developments are expected to enhance the ability of quantitative strategies to process soft information, adapt more dynamically to shifting market conditions, and broaden their investment scope. As these technologies continue to progress, they may further influence the patterns of AS and performance documented in our study.

2. Data and variables description

2.1. Data

Our study uses data from two primary databases: *Lipper Hindsight* and *FactSet*. We obtain individual fund characteristics, such as fund name, returns, size, expenses, and benchmark from the *Lipper Hindsight* database, which is free of survivorship-bias. We focus on US open-end and

¹⁵ Our findings show a positive link between AS and performance for non-quants; nevertheless, in contrast to Cremers and Petajisto (2009), there is no evidence indicating that non-quants with the highest AS significantly outperform their benchmarks after accounting for fees.

¹⁶ We obtain consistent results when using alternative fee proxies such as the Active fee (AF) measure from Cremers and Curtis (2016) or Total Shareholders Costs (TSC).

Table 1

Mutual fund industry sample by quants and non-quants.

Funds	Number	TNA (\$ million)
Non-quants	3126	4038
Quants	204	168
Total	3330	4206

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 quants and non-quants. The sample is restricted to US open-end and actively managed domestic equity funds drawn from the *Lipper Hindsight* database for which holdings are available in *Factset*. The sample period is 2000–2019. See Appendix B for variable definitions.

actively managed equity funds for the 2000–2019 period.¹⁷ 11F *Lipper* lists multiple share classes as separate funds, but these funds have the same holdings, the same manager, and the same returns before expenses and loads. Therefore, to avoid double-counting of funds, we follow *Demirci, Ferreira, Matos, and Sialm (2022)*, and use the primary share

class as our unit of observation and aggregate fund-level variables across different share classes. F Because *Lipper* does not provide data on funds' AS, we follow *Cremers et al. (2016)* and use portfolio equity holdings data from the *FactSet* database to compute this variable.¹⁸

To identify quants, we follow *Miguel and Chen (2021)* and use the classification provided by *Lipper*, which relies on the Principal Investment Strategy reported in funds' prospectus. *Lipper* flags as quantitative: “funds that use a rule-based mathematical model in order to initiate buy and sell decisions.” i.e., funds that rely solely on quantitative models to select stocks to buy and sell. Appendix A provides a detailed description of how we classify quants and of our final sample selection. The final sample contains 3330 unique funds with a TNA of \$4206 million, of which 204 are quants and 3126 are non-quants, with a TNA of \$168 million and \$4038 million, respectively (see *Table 1*). *Fig. 1* shows both the absolute number of quants and their proportion as a percentage of the total number of funds for the sample period. The number of quants increased steadily throughout our sample period. In 2000, there were 35 funds classified by *Lipper* as quants, representing 4.6 % of the total number of funds in our sample. In 2019, this number increased to 163, representing

**Fig. 1.** Quants in our sample by year.

This figure shows the absolute number of quants (solid line) and the number of quants 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 for which holdings are available in *Factset*.

¹⁷ This dataset is used in *Demirci et al. (2022)*, except that we focus on US-domiciled domestic funds only. See *Ferreira et al. (2013)* for a detailed description of *Lipper's* data coverage.

¹⁸ *Lipper* and *Factset* databases are matched by *CUSIP*, *ISIN*, or fund name.

Table 2
Identifying different categories of active management.

Category	Label	Quintiles	
		Active Share	Tracking Error
5	Stock pickers	5	1 to 4
4	Concentrated	5	5
3	Factor bets	1 to 4	5
2	Moderately active	2 to 4	1 to 4
1	Closet indexers	1	1 to 4

This table presents details on how we classify funds into different active management categories. We follow [Cremers and Petajisto \(2009\)](#) and [Petajisto \(2013\)](#) and, at the end of each year, we use a 5×5 grid of AS and TE quintiles (5 represent high and 1 low) to identify five categories of funds, separately for quants and non-quants in our sample: (5) diversified stock pickers are funds that combine a very high AS with low TE; (4) concentrated stock pickers combine high AS and high TE; (3) factor bets combine low AS and high TE; (2) moderately active funds fall in the middle in terms of both AS and TE; (1) closet indexers score low on both dimensions of active management. See Appendix B for variable definitions.

nearly 10 % of the total number of funds.¹⁹

2.2. Measuring active management

Our measures of active management include AS and TE.²⁰ Following [Cremers and Petajisto \(2009\)](#), AS is defined as the percentage of a fund's portfolio holdings that differs from its benchmark index holdings, calculated as follows:

$$\text{Active Share} = \frac{1}{2} \sum_{i=1}^n |w_{i,\text{fund}} - w_{i,\text{index}}| \quad (1)$$

where $w_{i,\text{fund}}$ and $w_{i,\text{index}}$ are the portfolio weights of stock i in the fund and its benchmark index, respectively, and the sum is taken over the universe of all stocks in the fund.^{21 22}

AS captures the portion of a fund's holdings (based on position weights) that is different from its benchmark index. Therefore, AS represents the fraction of a fund's holdings that drives performance as an active manager can only add value relative to the index by deviating from it. The more a fund's holdings overlap with those of its index, the closer the fund's returns will be to the index's returns, meaning that investors could achieve similar gross returns (at lower fees) just by investing in explicitly index funds. TE represents the volatility of the difference between a portfolio's return and its benchmark index's return. It is measured as the time-series standard deviation of the difference between the fund's return ($R_{\text{fund},t}$), and its benchmark adjusted return ($R_{\text{index},t}$):

$$\text{Tracking error} = \text{Stdev} [R_{\text{fund},t} - R_{\text{index},t}]. \quad (2)$$

A low TE indicates that the fund closely tracks its benchmark, while a

high TE indicates that the fund deviates from the benchmark, i.e., it is more volatile.

While both AS and TE are measures of active management, they emphasize different aspects of it. AS measures the degree of differentiation between a fund's portfolio and its benchmark and is therefore a proxy for stock selection. On the other hand, a fund's TE measures the degree of dispersion between a fund's returns and its benchmark and is a proxy for systematic factor risk (factor bets).²³ Thus, we need both measures to capture a fund management's efforts in the two dimensions. Following [Cremers and Petajisto \(2009\)](#) and [Petajisto \(2013\)](#), we divide funds into different categories based on a 5×5 grid of AS and TE quintiles, separately for quants and non-quants. We identify five categories of funds (see [Table 2](#)): (5) diversified stock pickers are funds that combine a very high AS with low TE; (4) concentrated stock pickers combine high AS and high TE; (3) factor bets are those funds with low AS and high TE; (2) moderately active funds fall in the middle in terms of both AS and TE; while (1) closet indexers score low on both dimensions of active management.

[Table 3](#) presents summary statistics for our two measures of active management for the two types of funds. It shows that both AS and the TE are lower for quants. The observed differences in AS and TE are both statistically and economically relevant. On average, the holdings of quants deviate 4.14 % less from their benchmarks than their peers. The average TE for quants and non-quants is 4.92 % and 5.99 %, respectively, indicating that the average TE for quants represents about 80 % of that of their counterparts. These differences seem to persist across funds in all five active management categories identified in [Table 2](#). [Figs. 2 and 3](#) show the average AS and TE, respectively, by year for both types of funds. They indicate that the AS and TE of quants remain higher than those observed for non-quants throughout our sample period.

The literature shows that active funds vary considerably in the degree to which their portfolio holdings differ from the holdings of their benchmark indexes. In fact, the distinction between active and passive investing is not always clear-cut as many funds marked as active are largely passively managed using so-called “closet indexing” strategies ([Cremers and Petajisto, 2009](#)). Therefore, we go further in our analysis to understand whether nominally active quants behave similarly to their counterparts by closely mirroring a benchmark index. To do so, we start by using the cutoff established in [Cremers and Petajisto \(2009\)](#) and define *closet indexers* as funds with an AS of less than 60 %. Thus, truly active funds are those with an AS equal to or greater than 60 %.

[Figs. 4 and 5](#) depict the market share (as a percentage of TNA) of fund assets by AS group over the period 2000–2019 for quants and non-quants, respectively. The bottom group of funds, with AS below 60 %, consists of closet indexers, leaving truly active funds in four categories: funds with AS between 60 % and 70 %; between 70 % and 80 %; between 80 % and 90 %; and between 90 % and 100 %. [Figs. 4 and 5](#) document the general trend toward lower AS over time for both quants and non-quants, as in [Cremers and Petajisto \(2009\)](#) and [Cremers \(2017\)](#). However, our results indicate notable differences between the two types of funds. From 2000 to 2019, the share of assets in closet indexers increased by 22 % (from 28 % to 50 %) for quants, compared to 13 % (from 25 % to 38 %) for non-quants. We also observe that, relative to their counterparts, quants have a larger fraction of assets in closet indexers and a smaller percentage of assets in funds with an AS above 80 %. On average, 35 % of the assets in nominally active quants are managed by closet indexers, exceeding non-quant closet indexers (24 %) by 11 %. In contrast, the average percentage of assets in funds with an AS above 80 % is 21 % for quants and 33 % for non-quants, reflecting a substantial difference of 12 % between the two types of funds.

Next, in [Figs. 6 and 7](#), for quants and non-quants, respectively, we plot the market share of fund assets across the five categories in [Table 2](#).

¹⁹ Our sample is identical to that in [Miguel and Chen \(2021\)](#), with the additional exclusion of funds for which holdings are not available in *Factset*.

²⁰ In robustness tests, we also use the R^2 from the four-factor regression model as a proxy active management as in [Amihud and Goyenko \(2013\)](#).

²¹ We thank Miguel Ferreira and Pedro Pires for providing us with the AS data.

²² *Lipper* independently assigns the ‘*Lipper Technical Indicator Benchmark*’ funds in the database according to its assessment of the fund's investment strategy. To mitigate concerns that funds may strategically select their benchmarks, we use the “*Lipper Technical Indicator Benchmark*” instead of the self-declared “*Fund Manager Benchmark*”, as in [Cremers et al. \(2016\)](#). [Cremers et al. \(2021\)](#) find that benchmark discrepancies are common, with the prospectus benchmark often underestimating risk when such discrepancies occur. As a result, funds tend to outperform their prospectus benchmarks on average, but they underperform the benchmarks that more accurately reflect their portfolios. However, in untubulated results, we find consistent results when using the “*Fund Manager Benchmark*”.

²³ See [Cremers and Petajisto \(2009\)](#) and [Petajisto \(2013\)](#) for further discussion of the differences between AS and TE.

Table 3
Summary statistics for measures of active management for quants and non-quants.

Category	Label	Quants						Non-quants						Difference in means	
		Mean	Median	Standard deviation	Percentile 10	Percentile 90	Observations	Mean	Median	Standard deviation	Percentile 10	Percentile 90	Observations	(1)–(7)	(p-value)
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Active share (%)															
5	Stock pickers	93.75	93.82	2.52	90.73	96.44	192	97.36	97.01	1.45	94.79	98.69	2935	–3.61***	(0.00)
4	Concentrated	95.29	95.26	2.28	91.88	97.85	269	98.58	98.41	1.57	95.37	99.68	2995	–3.29***	(0.00)
3	Factor bets	77.96	81.95	13.61	54.32	90.48	192	82.37	86.75	11.89	65.43	93.32	2936	–4.41***	(0.00)
	Moderately														
2	active	76.00	76.70	9.31	63.58	88.09	1243	80.86	82.02	8.58	68.56	92.05	15,177	–4.87***	(0.00)
1	Closet indexers	51.10	52.99	11.59	30.38	58.87	449	54.21	56.87	10.98	37.21	63.87	5662	–3.11***	(0.00)
All		75.59	77.29	17.09	51.88	94.36	2345	79.73	82.99	16.45	56.39	97.24	29,705	–4.14***	(0.00)
Tracking error (%)															
5	Stock pickers	6.02	4.50	2.69	3.72	9.89	192	6.64	5.63	3.10	3.98	11.16	2935	–0.62***	(0.00)
4	Concentrated	9.25	7.72	3.79	5.22	14.34	269	10.99	9.01	6.08	5.82	19.70	2995	–1.74***	(0.00)
3	Factor bets	8.19	6.07	4.51	4.61	12.93	192	10.31	8.36	5.71	5.44	18.58	2936	–2.12***	(0.00)
	Moderately														
2	active	4.18	3.12	2.32	2.17	6.69	1243	4.99	4.28	2.65	2.66	8.10	15,177	–0.81***	(0.00)
1	Closet indexers	2.50	1.79	1.32	1.24	4.32	449	3.47	2.97	2.10	1.55	5.94	5662	–0.97***	(0.01)
All		4.92	3.48	3.41	1.95	9.43	2345	5.99	4.79	4.29	2.46	10.93	29,705	–1.07***	(0.00)

This table presents summary statistics for fund AS, calculated as in Eq. (1), and fund TE, calculated as in Eq. (2), for all quants and for all non-quants and for the five types of active management categories identified in Table 2. Columns (1)–(6) present the numbers for quants, Columns (7)–(12) for non-quants, and Columns (13)–(14) present differences in means between quants and non-quants and the results of a *t*-test, testing whether these differences are statistically significant. *, **, 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 for which holdings are available in *Faciset*. The sample period is 2000–2019. See Appendix B for variable definitions.

These figures show that closet indexers and moderately active funds represent by far the largest share of assets under management and that only a small fraction of assets is allocated to funds in the top three categories of active management. On average, closet indexers represent 25 % and 18 % of the assets managed by quants and non-quants, respectively. Concentrated and stock-picking categories represent 10 % of assets in non-quants, but only 6 % in quants. It is also clear that, even in the case of factor bets, the percentage of assets managed by quants is much smaller than that managed by non-quants (3 % and 7 %, respectively).

Overall, our results suggest that closet indexing is common among quants and that the fraction of assets in quants following closet indexing strategies is much higher than that observed for non-quants. Additionally, we document that quants are generally less active than their counterparts, irrespective of the type and degree of active management observed.

2.3. Measuring fund performance

We measure fund performance using risk-adjusted returns (i.e., Carhart, 1997, four-factor alpha). To estimate four-factor alpha, we run the following regression:

$$R_{i,t} - R_f = \alpha_i + \beta_1 MKT_{i,t} + \beta_2 SMB_{i,t} + \beta_3 HML_{i,t} + \beta_4 MOM_{i,t} + \varepsilon_{i,t}; \quad (3)$$

where $R_{i,t}$ is the US dollar return net of fees of fund *i* in month *t*, R_f is 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 of 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.²⁴ We use the previous 36 months of net fund returns to estimate the time series regression of monthly excess returns based on the fund's factor portfolios. Next, we compare the difference between the expected return and the realized return to compute the fund's abnormal return (or alpha) for each month. We compound the monthly alphas to calculate the annual alphas (Ferreira, Keswani, Miguel, and Ramos, 2013).

Table 4 reports summary statistics on factor loadings and R^2 from the four-factor alpha estimation and on fund characteristics, separately for both types of funds. We observe that quants exhibit greater exposure to risk factors relative to their peers, as reflected in the larger coefficients on all four factor loadings observed for these funds. The lower standard deviation of the coefficients for quants suggests that they are more homogeneous in their trading criteria. The higher R^2 observed for quants indicates a stronger reliance on factor models and lower stock selectivity. These results align with our priors that quants respond to similar return signals in their investment process, which may contribute to lesser deviations from their benchmarks. From Table 4, we also note that the average annual raw returns are 8.15 % and 8.24 %, while the average four-factor alphas are –1.24 % and –1.26 %, for quants and non-quants, respectively. The negative risk-adjusted returns, for both types of funds, are consistent with the results in Miguel and Chen (2021).

2.4. Control variables

Other mutual fund characteristics include size and family size, fees, age, flow and flow volatility, the number of stocks held, and tenure of fund management. Table 4 shows that quants are smaller and younger, charge lower fees, as in Abis (2022), and Miguel and Chen (2021), and belong to smaller fund families. Quants hold a larger number of stocks,

²⁴ Factors are from AQR Capital Management (<https://www.aqr.com/Insights/Datasets>).

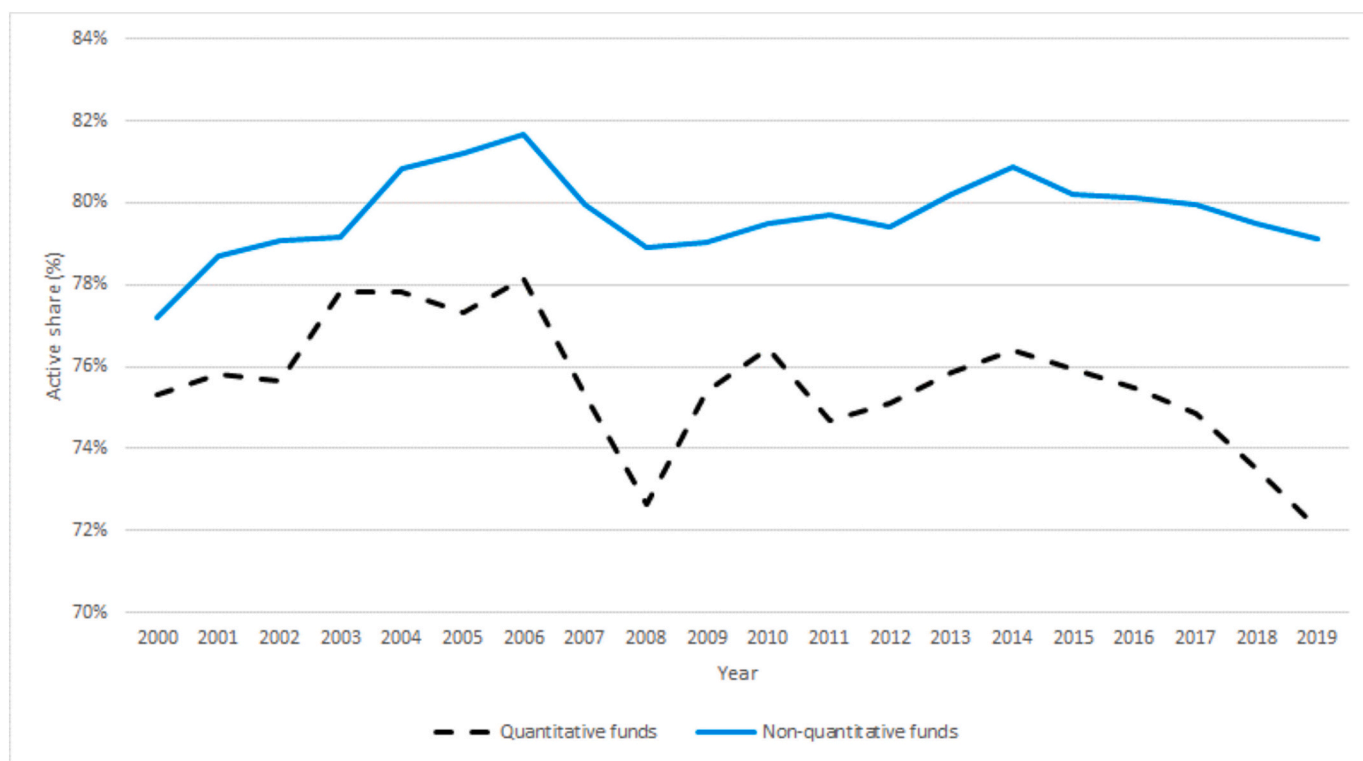


Fig. 2. Average Active Share by year for quants and non-quants.

This figure shows the average AS by year for quants (dashed line) and non-quants 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 for which holdings are available in *Factset*. See Appendix B for variable definitions.

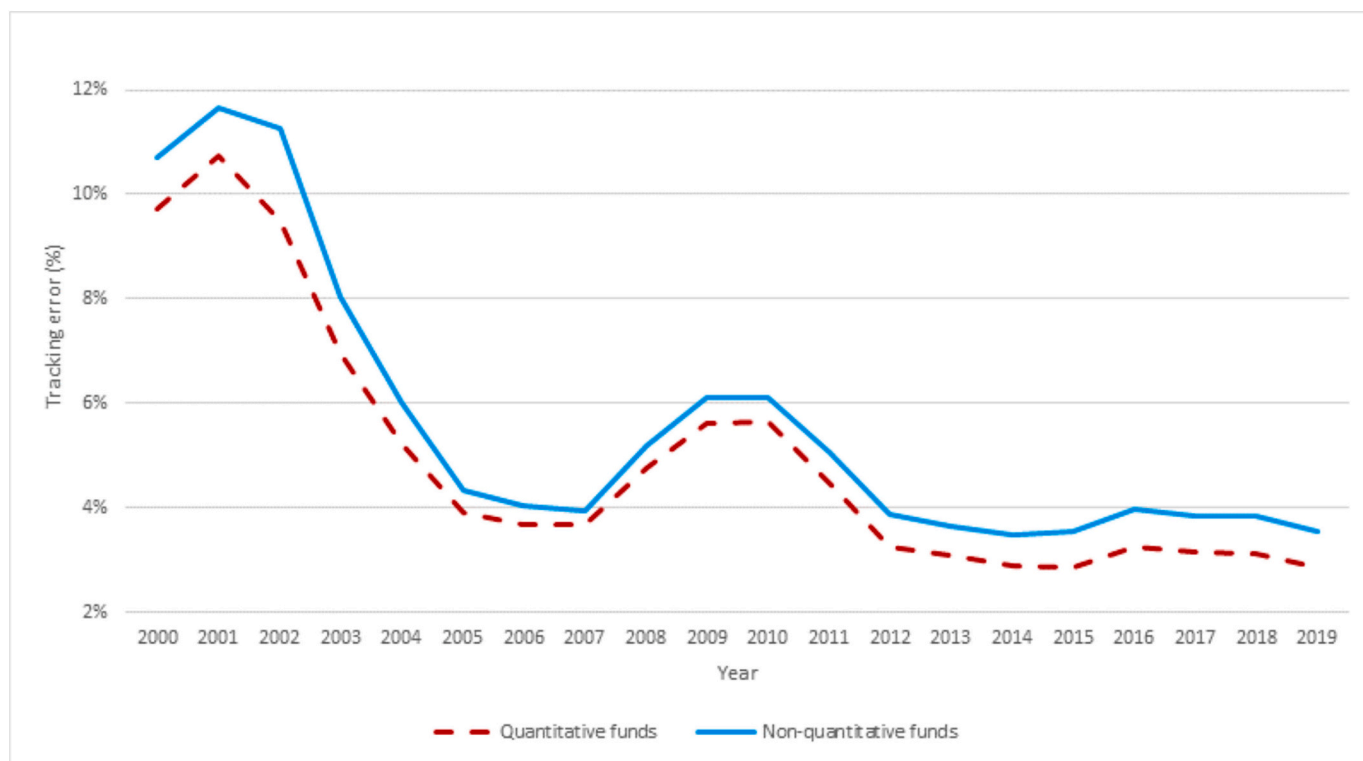


Fig. 3. Average Tracking Error by year for quants and non-quants.

This figure shows the average TE by year for quants (dashed line) and non-quants 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 for which holdings are available in *Factset*. See Appendix B for variable definitions.

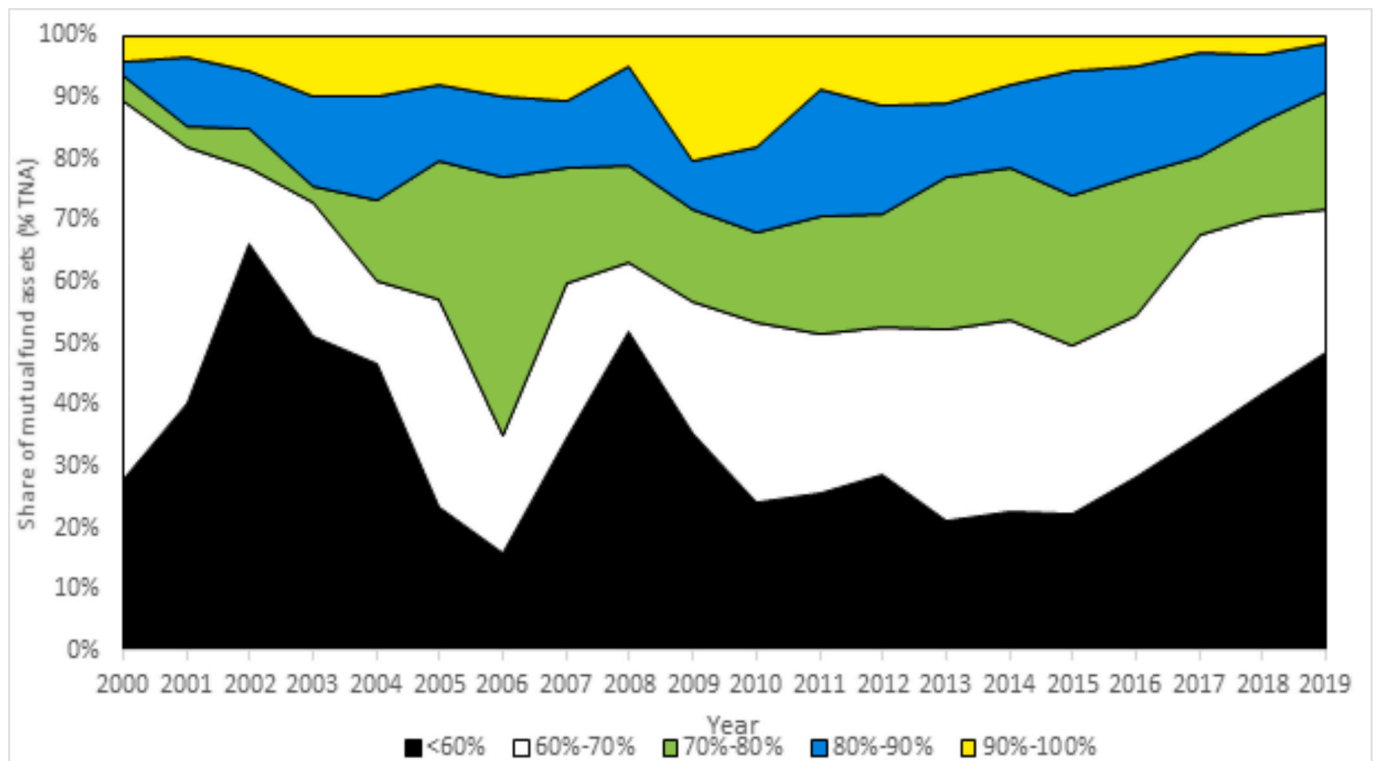


Fig. 4. Assets by active share group for quants by year.

This figure shows the fraction of mutual fund assets (% TNA) by AS group for quants for the 2000–2019 period. The AS groups are distinguished as follows: below 60 % (Closet indexers); between 60 % and 70 %; between 70 % and 80 %; between 80 % and 90 %; and between 90 % and 100 %. The sample is restricted to US open-end and actively managed domestic equity funds drawn from the *Lipper Hindsight* database for which holdings are available in *Factset*. See Appendix B for variable definitions.

averaging 30 % more than non-quants, due to reduced constraints in information processing (Abis, 2022). We also observe that quants attract more flows, experience greater flow volatility, and shorter management tenures.

3. Explaining active management for quants and non-quants

Our preliminary results in Section 2.2 indicate significantly less active management for quants, both in terms of lower AS and lower TE. In this section, we aim to understand whether the specific characteristics of quants and non-quants explain the observed differences. To do so, we run the following panel regression:

$$\text{Active management}_{i,t} = \alpha + \beta \text{Quantitative}_i + \gamma X_{i,t-1} + \varepsilon_{i,t}; \quad (4)$$

where *Active management* is proxied by AS or by TE, calculated as in Eqs. (1) and (2), respectively, *Quantitative* is a dummy variable that takes the value of one if the fund is classified by *Lipper* as a quant and zero otherwise, and $X_{i,t-1}$ is a set of lagged fund-specific variables that the literature has shown to determine AS (Cline and Gilstrap, 2021; Cremers and Petajisto, 2009 and Petajisto, 2013). These variables comprise TE or AS, when the dependent variable is AS or TE, respectively, as they capture different aspects of portfolio activity. We include Total Shareholder Cost (TSC), because we expect more active funds to charge more

fees, fund size and fund size squared, to account for the nonlinear relationship between AS and fund size. We add performance, flow, flow volatility, age, and the number of stocks in a fund's portfolio, and also control for management tenure. Regressions include time fixed effects, as a fund's active management may be meaningfully different at different points in time, depending on the opportunities in the market.²⁵ We account for cross-sectional correlation and time-series autocorrelation within funds by computing robust standard errors clustered by fund and year.

The results are reported in Table 5. In Columns (1)–(4) and (5)–(8) active management is proxied by AS and TE, respectively. Across various specifications, we observe consistently lower levels of active management among quants, whether in terms of stock selection or tracking-error volatility. In economic terms, the differences in AS and TE reported in Columns (4) and (8) are -5.03% ($-0.0401/0.7973$) and -16.19% ($-0.0097/0.0599$), respectively.^{26,27} Overall, these findings lend support to our preliminary results, indicating that quants tend to exhibit lower deviations from their benchmarks compared to their

²⁵ The literature also shows that AS can vary depending on a fund's market-capitalization group and its benchmark (Cohen, Leite, Nielson, and Browder, 2014; Cremers, 2017; Cremers and Curtis, 2016; Frazzini, Friedman, and Pomorski, 2016 and Petajisto, 2013). In robustness tests, we further address these concerns by estimating differences in AS between quants and non-quants within market capitalization groups (see Table IA3). In untabulated results, we also re-estimate our tests by including benchmark fixed effects.

²⁶ The average non-quant has as AS and a TE equal to 79.73 % and 5.99 %, respectively (see Table 4).

²⁷ To examine whether fund characteristics affect active management differently for quants and non-quants, we remove the *Quantitative* dummy variable from Eq. (5) and re-estimate the regressions allowing for different sensitivities to fund-specific characteristics between the two types of funds. The results are presented in Table IA1 and show that the differences in the coefficients of control variables between quants and non-quants are either not significant or have a very small economic impact.

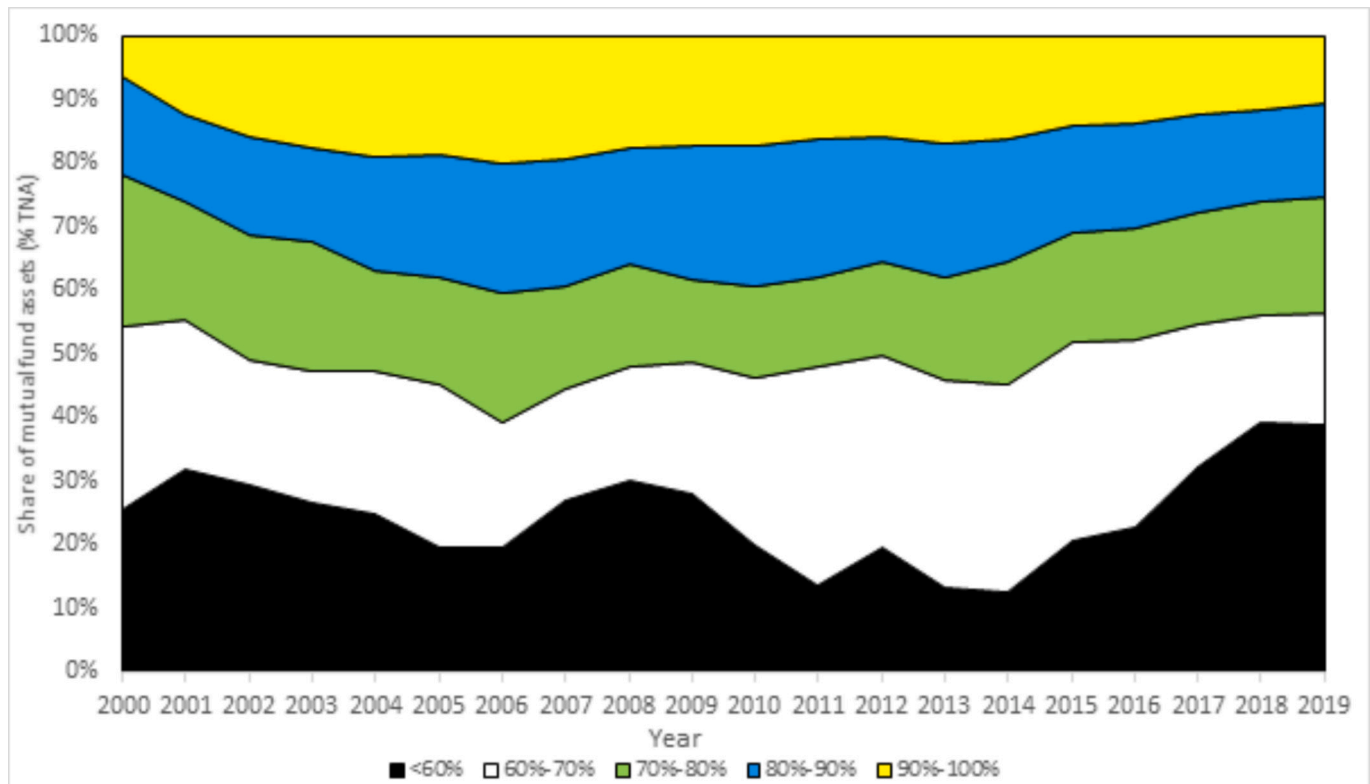


Fig. 5. Assets by active share group for non-quants by year.

This figure shows the fraction of mutual fund assets (% TNA) by AS group for non-quants for the 2000–2019 period. The AS groups are distinguished as follows: below 60 % (Closet indexers); between 60 % and 70 %; between 70 % and 80 %; between 80 % and 90 %; and between 90 % and 100 %. The sample is restricted to US open-end and actively managed domestic equity funds drawn from the *Lipper Hindsight* database for which holdings are available in *Factset*. See Appendix B for variable definitions.

counterparts.

4. The impact of active management on the performance of quants and non-quants

The seminal study by [Cremers and Petajisto \(2009\)](#) finds that AS predicts future fund performance. The authors show that funds with high AS notably outperform their benchmarks whereas those with low AS underperform. Other studies further confirm the positive relationship between AS and the performance of actively managed funds. [Petajisto \(2013\)](#) show that the effect extends across fund market-capitalization styles. [Cremers and Pareek \(2016\)](#), and [Cremers \(2017\)](#) find that the outperformance is stronger for funds employing patient investment strategies. [Cremers, Fulkerson, and Riley \(2021\)](#) note greater outperformance among funds that accurately depict their riskiness through a benchmark provided in the prospectus. [Cline and Gilstrap \(2021\)](#) show that only funds with high AS and high management skill outperform their benchmarks.

To examine the association between AS and performance for quants and non-quants, we first compute the subsequent year's four-factor alpha by AS quintile, separately for each type of fund. We use the monthly returns and monthly factors to compute the alpha for the portfolios in each quintile, as shown in Eq. (3). Panels A and B of [Table 6](#) report the annualized net and gross alphas, respectively, after portfolio construction via AS for both types of funds. The last column shows the alpha of a portfolio formed by going long quintile 5 and short quintile 1 portfolios (5–1). At the bottom of the table, for each AS quintile, we calculate the differences in alphas between quants and non-quants, i.e., the alpha of a portfolio formed by taking a long position in quants and a short position in non-quants.

Aligned with [Cremers and Petajisto \(2009\)](#), we observe that AS

enhances the performance of non-quants. Specifically, non-quants in the highest AS quintile outperform those in the lowest by a statistically and economically significant 0.62 % (net alpha) or 0.96 % (gross alpha).²⁸ In contrast, the relationship between AS and performance for quants is notably different. Our results indicate that AS diminishes rather than improves their performance. Quants in the highest AS quintiles underperform those in the lowest AS quintiles, with statistically and economically significant differences in net and gross alpha of –1.19 % and –0.71 %, respectively. Next, we compare the four-factor alphas of quants and non-quants across AS quintiles. While quants outperform non-quants in the bottom two quintiles, the differences are not statistically significant. However, in the top two quintiles, quants significantly underperform their counterparts, both before and after expenses. In quintile 4, the performance gaps are –0.64 % (net alpha) and –0.69 % (gross alpha). In quintile 5, the gaps widen further to –1.22 % (net alpha) and –1.27 % (gross alpha).

In Panels C and D of [Table 6](#), we proceed as in Panels A and B, respectively, but employ *TE* as a measure of active management. Consistent with [Cremers and Petajisto \(2009\)](#), we observe that higher *TE* reduces performance for both quants and non-quants. However, the economic impact of *TE* is more pronounced for quants, with net alpha reductions of –1.52 % compared to –0.95 % for non-quants, and gross alpha reductions of –1.06 % compared to –0.58 %. Despite these patterns, we do not find statistically significant differences in alphas between quants and non-quants across *TE* quintiles.

In Panels E and F of [Table 6](#), we present the four-factor alphas for the portfolios comprising the five active management categories outlined in

²⁸ Unlike [Cremers and Petajisto \(2009\)](#), we do not find evidence that funds with the highest AS significantly outperform their benchmarks after fees.

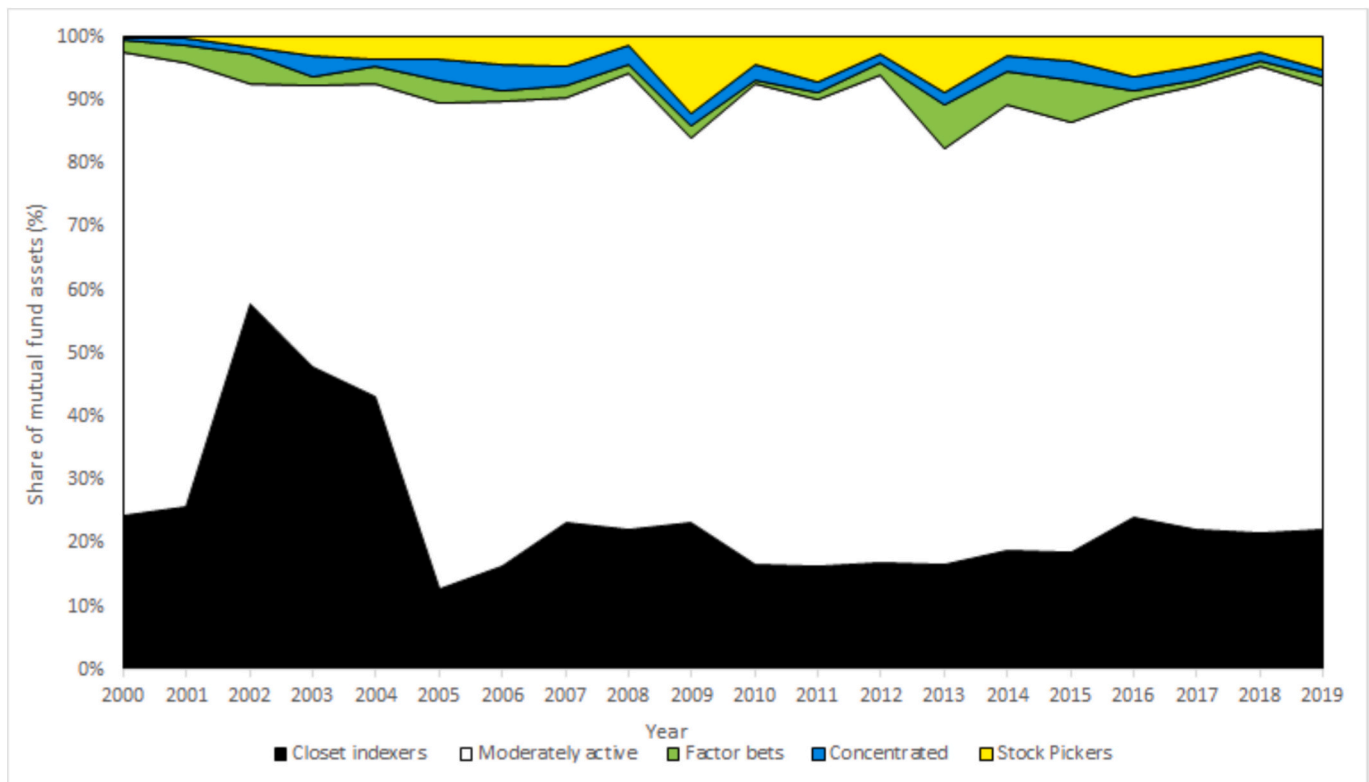


Fig. 6. Assets by fund active management category for quants by year.

This figure shows the fraction of mutual fund assets (% TNA) by fund category for quants for the 2000–2019 period. We use a 5×5 grid of *AS* and *TE* quintiles to identify five active management categories of funds, separately for quants and non-quants in our sample (see Table 2): (5) diversified stock pickers; (4) concentrated stock pickers; (3) factor bets; (2) moderately active funds; and (1) closet indexers. The sample is restricted to US open-end and actively managed domestic equity funds drawn from the *Lipper Hindsight* database for which holdings are available in *Factset*. Appendix B for variable definitions.

Table 2. The results indicate that none of the investment strategies generates value for investors, as the net alpha is negative across all categories for both types of funds. However, within the category of stock pickers, quants appear to underperform their counterparts both before and after fees. The adverse effect of stock selection in quants is further highlighted when comparing the performance of stock pickers with closet indexers. Quant stock pickers underperform closet indexers by 1.37 % and 0.87 % annually after and before fees, respectively. Conversely, for non-quants, the trend appears to reverse, with stock pickers outperforming closet indexers by 0.86 % and 1.15 %, net or gross of fees, respectively. These results hold both statistical and economic significance.

Furthermore, we observe that factor bets performed poorly for all investors, consistent with the findings in Cremers and Petajisto (2009) and Petajisto (2013). Factor bets emerge as the worst-performing category for both quants and non-quants, with no discernible differences observed in the alpha generated by the two types of funds. Additionally, quants tend to outperform non-quants in moderately and closet index strategies; however, these performance differences do not reach statistical significance.

It is possible that our measures of active management proxy for other fund characteristics that, in turn, predict fund performance. This effect might be different for quants and non-quants due to the observed differences among many of the characteristics of these funds (refer to Section 2.4). To address this, we run a panel regression, where fund performance is regressed on *AS* and *TE* alongside different explanatory variables, as follows:

$$Performance_{it} = \alpha + \beta_1 Active\ Share_{it} + \beta_2 Tracking\ error_{it} + \gamma X_{it-1} + \varepsilon_{it}; \quad (5)$$

where, performance is assessed using annual net or gross four-factor alpha, and *AS* and *TE* serve as proxies for active management, computed as described in Eqs. (1) and (2), respectively. X_{it-1} is a set of lagged control variables used by Cremers and Petajisto (2009), Petajisto (2013), and Cline and Gilstrap (2021). These variables include *TSC*, fund size and fund size squared, family size, the number of stocks in a fund's portfolio, four-factor alpha, flow and flow volatility, age, and fund manager tenure. We include style fixed effects and time fixed effects in our tests and compute robust standard errors clustered by fund and time.²⁹

Table 7, Panels A and B, present the results of running Eq. (5) for net and gross alpha, respectively. In both panels, Column (1) shows the results of a pooled regression, relating performance to control variables of all funds in our sample. Columns (2) and (3) report the results when we allow for different sensitivities to fund-specific characteristics between the two types of funds. Column (4) reports the differences in coefficients between quants and non-quants, along with the results of a *t*-test examining the statistical significance of the differences.

In Columns (3), we see that *AS* appears to be a statistically significant predictor of future performance for non-quants. In contrast, in Column (2), *AS* is negatively associated with the performance of quants. Economically, these results indicate that a 10 % increase in *AS* is associated with a 20 basis points decrease (or 24 basis points increase) in the next year's net alpha of quants (non-quants). Considering that the average four-factor alpha is −1.24 % for quants and −1.26 % for

²⁹ We follow Hoberg, Kumar, and Prabhala (2018) and compute fund style based on SMB and HML loadings. 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.

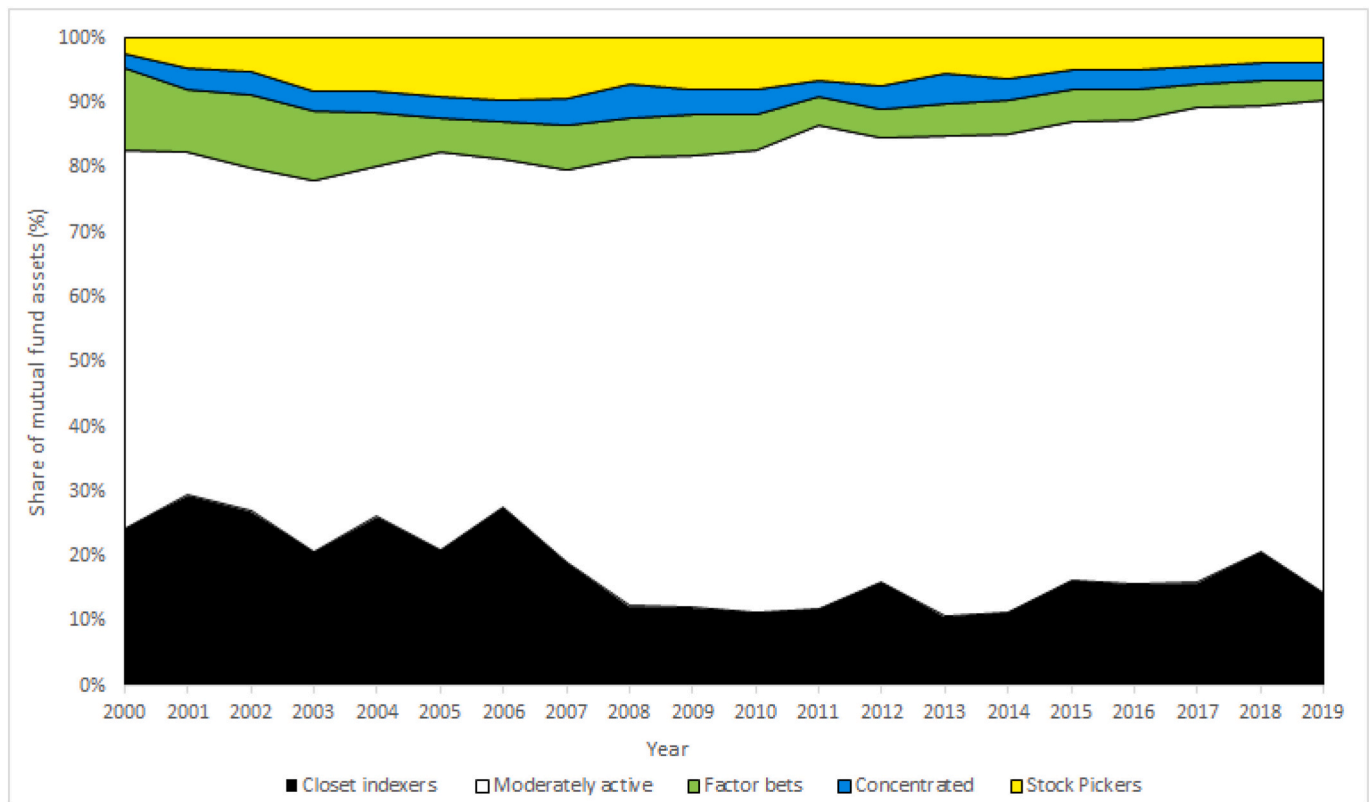


Fig. 7. Assets by fund active management category for non-quant funds by year.

This figure shows the fraction of mutual fund assets (% TNA) by fund category for non-quant funds for the 2000–2019 period. We use a 5×5 grid of *AS* and *TE* quintiles to identify five active management categories of funds, separately for quant and non-quant funds in our sample (see Table 2): (5) diversified stock pickers; (4) concentrated stock pickers; (3) factor bets; (2) moderately active funds; and (1) closet indexers. The sample is restricted to US open-end and actively managed domestic equity funds drawn from the *Lipper Hindsight* database for which holdings are available in *Factset*. Appendix B for variable definitions.

non-quant funds, our findings suggest economic relevance. Additionally, we find evidence indicating that *TE* is negatively associated with performance, with no statistically significant differences in its effects on the performance of the two types of funds.³⁰ Regarding other control variables, the results indicate performance persistence for non-quant funds and reversals for quant funds, consistent with the findings in Miguel and Chen (2021). However, aside from past performance, we do not find statistically significant differences in how other fund characteristics relate to the performance of these funds.

Next, we replace *AS* and *TE* in Eq. (5) with dummy variables for funds in different active management categories. The results are presented in Panels C and D of Table 7 for net and gross four-factor alpha, respectively. For brevity, we focus on the results for net performance only.

For quant funds, we observe that diversified and concentrated stock pickers underperform closet indexers by 1.46 % and 1.11 % per year, respectively. In contrast, non-quant funds' diversified stock pickers and

concentrated stock pickers exhibit higher net performance compared to closet indexers, with differences of 0.98 % and 0.77 % per year, respectively. Additionally, the average annual net four-factor alpha of quant diversified (concentrated) stock pickers is 1.64 % (1.08 %) lower than that of non-quant funds.³¹ Factor bets emerge as the poorest performing group for both fund types, consistent with the findings from Panels E and F of Table 6. In the case of moderately active funds and closet indexers, we observe that quant funds tend to exhibit better performance than non-quant funds; however, the differences in alpha do not reach statistical significance.

Overall, our regression-based tests are consistent with our earlier observations and validate our hypotheses. The results suggest that quant funds lack stock-picking ability and underperform non-quant funds in this area. Similarly, both quant and non-quant funds appear to be equally ineffective in factor betting, with factor bets consistently identified as the worst-performing category for quant funds. While quant funds appear to perform slightly better than non-quant funds in low *AS* strategies, these differences are not statistically significant. Finally, we observe that quant funds consistently underperform their benchmarks across all investment strategies.

³⁰ While *AS* and *TE* capture different aspects of the activeness of a portfolio – stock selection and factor timing, respectively – the use of *TE* error conflates benchmark deviations as an action by the fund manager with the impact of those deviations on subsequent performance (Cremers et al., 2016). In untabulated results, we check the robustness of our results by running additional specifications in which we include one proxy for active management at the time (i.e., only *AS* or only *TE*) in our regressions. We find that our results do not change.

³¹ The difference in performance between quant and non-quant stock pickers, in Column (4) of Panel C in Table 7, is computed using the total performance within this category of funds: $-0.0164 = [-0.0146 + (-0.0051)] - [0.0098 + (-0.0131)]$. The same reasoning applies to calculate the differences in performance between quant and non-quant funds for concentrated, factor bets, and moderately active management categories.

Table 4
Summary statistics for factor loadings, R^2 , and other mutual fund characteristics for quants and non-quants.

	Quants						Non-quants						Difference in means	
	Mean	Median	Standard deviation	Percentile 10	Percentile 90	Observations	Mean	Median	Standard deviation	Percentile 10	Percentile 90	Observations	(1)–(7)	(p-value)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Four-factor model loadings and R^2														
MKT	1.00	1.00	0.14	0.80	1.18	2345	0.95	0.96	0.18	0.86	1.15	29,705	0.05***	(0.00)
SMB	0.25	0.13	0.40	−0.22	0.85	2345	0.23	0.12	0.41	−0.21	0.90	29,705	0.02**	(0.04)
HML	0.06	0.05	0.31	−0.48	0.41	2345	−0.01	−0.01	0.37	−0.31	0.44	29,705	0.08***	(0.00)
MOM	0.06	0.05	0.15	−0.15	0.22	2345	0.03	0.02	0.16	−0.10	0.24	29,705	0.03***	(0.00)
R^2	0.92	0.94	0.10	0.77	0.97	2345	0.88	0.91	0.11	0.82	0.98	29,705	0.04***	(0.00)
Fund characteristics														
Raw return (%)	8.15	10.33	18.29	−12.30	32.04	2345	8.24	10.18	20.35	−12.86	32.22	29,705	−0.09	(0.41)
Four-factor alpha (%)	−1.24	−1.05	6.08	−7.71	5.14	2345	−1.26	−1.11	7.52	−9.09	6.13	29,705	0.02	(0.76)
TSC (%)	1.30	1.19	0.57	0.69	2.14	2345	1.45	1.31	0.62	0.79	2.32	29,705	−0.16***	(0.00)
TER (%)	1.15	1.10	0.40	0.67	1.64	2345	1.26	1.20	0.45	0.76	1.82	29,695	−0.11***	(0.00)
AF (%)	1.29	1.23	0.56	0.72	1.95	2345	1.38	1.31	0.60	0.83	2.11	29,684	−0.09***	(0.00)
TNA (\$ million)	836	227	1906	27	2074	2345	1674	304	6242	23	3456	29,705	−839***	(0.00)
TNA family (\$ million)	51,673	11,031	201,224	506	81,297	2345	77,148	11,178	209,237	131	168,886	29,705	−25,475***	(0.00)
Age (years)	13.98	12.25	9.27	5.42	23.42	2345	16.99	13.42	13.34	5.50	31.75	29,705	−3.01***	(0.00)
Flow (%)	9.03	−7.39	72.63	−33.96	48.96	2345	5.34	−7.50	69.06	−32.25	37.49	29,705	3.69**	(0.00)
Flow volatility (%)	14.57	7.17	23.58	2.14	31.85	2345	12.98	6.01	24.15	1.75	26.31	29,705	1.58***	(0.00)
Number of stocks	161.16	102.52	212.49	40.00	314.00	2345	125.24	77.00	226.52	35.00	216.63	29,705	35.92***	(0.00)
Manager tenure (years)	7.20	6.00	3.92	3.00	12.00	2345	8.49	7.08	4.88	4.00	14.00	29,705	−1.29***	(0.00)

This table presents details on factor loadings and R^2 from the four-factor alpha estimation and on other mutual fund characteristics for quants, in Columns (1)–(6), and for non-quants, in Columns (7)–(12). Columns (13)–(14) present differences in means between quants and non-quants and the results of a t -test, examining whether these differences are statistically significant, 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 for which holdings are available in *Factset*. The sample period is 2000–2019. See Appendix B for variable definitions.

Table 5
Explaining active management for quants and non-quants.

	AS				TE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Quantitative	−0.0412*** (−3.29)	−0.0410*** (−3.97)	−0.0406*** (−4.02)	−0.0401*** (−3.98)	−0.0104*** (−5.09)	−0.0102*** (−5.17)	−0.0099*** (−5.01)	−0.0097*** (−4.96)
TE		2.1055*** (29.72)	1.9329*** (27.94)	1.8345*** (27.55)				
AS						0.1024*** (35.93)	0.0950*** (33.86)	0.0952*** (33.88)
TSC			2.2991*** (5.26)	1.7515*** (4.14)			0.6015*** (7.43)	0.6145*** (7.35)
TNA (log)			0.0028 (0.55)	0.0096* (1.90)			−0.0069*** (−5.11)	−0.0064*** (−5.05)
(TNA (log)) ²			−0.0012*** (−2.60)	−0.0009** (−2.05)			0.0005*** (4.53)	0.0005*** (4.50)
Family size (log)				−0.0088*** (−7.51)				0.0002 (0.63)
Number of stocks/100				−0.0356*** (−3.43)				−0.0000 (−0.19)
Four-factor alpha				0.0977*** (9.04)				−0.0155*** (−3.88)
Flow				0.0011 (1.20)				0.0015*** (5.35)
Flow volatility				1.7515*** (4.14)				0.0094*** (6.27)
Age/100				−0.0902*** (−4.78)				−0.0019 (−0.60)
Manager tenure/100				0.1423*** (2.68)				0.0260** (2.57)
Adjusted R-squared	0.025	0.225	0.250	0.299	0.328	0.487	0.501	0.506
Number of observations	32,050	32,050	32,050	32,050	32,050	32,050	32,050	32,050

This table presents panel regressions to study differences in active management for quants and non-quants, according to Eq. (4), where active management is proxied by AS, in Columns (1)–(4), or by TE, in Columns (5)–(8). AS is the percentage of a fund's portfolio holdings that differ from its benchmark index holdings, calculated as in Eq. (1). TE represents the annualized volatility of the difference between a portfolio return and its benchmark index return, calculated as in Eq. (2). In Columns (1) and (5), we regress AS or TE, respectively, on a quantitative dummy variable (*Quantitative_{it}*) that takes the value of one if a fund *i* is classified by *Lipper Hindsight* as a quant and zero otherwise. In Columns (2) and (6) we add TE or AS, respectively, to the regression. In Columns (3) and (7), we also control for different fund characteristics, including TSC, fund size, and fund size squared. Finally, in Columns (4) and (8), we add to our model Family size (log), the number of stocks in a fund's portfolio, performance, measured as four-factor alpha, flow, flow volatility, fund age, and fund manager tenure. Regressions include time fixed effects. Robust *t*-statistics clustered by fund and year are reported in parentheses. *, ** and *** indicate significance at the 10 %, 5 % and 1 % level, respectively. See Appendix B for variable definitions.

5. Fund flows and active management

The primary interaction between investors and fund management occurs through the purchase and sale of funds, which determines net flows. Accordingly, the literature emphasizes the importance of considering incentives when examining the performance and AS of mutual funds. [Del Guercio and Reuter \(2014\)](#) argue that fund families allocate resources to generate alpha only when they expect such efforts to result in increased investor flows. Consistently, [Cremers et al. \(2016\)](#) show that fund managers increase AS in response to the competitive threat of other funds because they anticipate that this strategy will attract higher investor flows. Building on this, we examine whether the relationship between AS and investor flows differs between quants and non-quants and whether this difference might help explain why AS is lower for quants. To do so, we estimate a panel regression in which fund flows are modeled as a function of AS, performance, TE, and other explanatory variables, as follows:

$$\begin{aligned}
 \text{Flow}_{i,t} = & \alpha + \beta_1 \text{Active Share}_{i,t} + \beta_2 \text{Performance rank}_{i,t} \\
 & + \beta_3 \text{Performance rank} \times \text{Active Share}_{i,t} + \text{Tracking error}_{i,t} \quad (6) \\
 & + \gamma X_{i,t-1} + \varepsilon_{i,t};
 \end{aligned}$$

In Eq. (6), flow represents fund's yearly net flows, while AS and TE

are calculated as outlined in Eqs. (1) and (2), respectively. Performance is measured using the past 12 months' net four-factor alpha computed, as indicated in Eq. (3).³² Following [Cremers et al. \(2016\)](#), we employ fund performance rank, assigning a value of zero to funds in the bottom 20 % of performance, one to funds in the middle 60 %, and two to funds in the top 20 %. Since the relation between flows and AS is likely influenced by a fund's past performance, we include an interaction term between AS and the return quintile ranking of the fund. Control variables include TSC, fund size, family size, flow, flow volatility, and fund age (e.g. [Sirri & Tufano, 1998](#)). Additionally, we also control for the number of stocks in a fund's portfolio and fund manager tenure. We incorporate style and time fixed effects in our tests and compute robust standard errors clustered by fund and time. The regression is run separately for all funds, quants, and non-quants, following the same approach as in [Table 7](#).

The results in [Table 8](#), Column 3, indicate that non-quants with higher AS are associated with greater investor flows, with this relationship being more pronounced among funds ranked higher in performance. This finding is both statistically and economically significant: for a fund in the bottom quintile of performance, a one-standard deviation increase in AS is associated with a 2.04 % rise in flows (0.1230×16.45 %), while for funds in the top quintile, this figure increases to 7.01 % [$(0.1230 + 2 \times 0.1512) \times 16.45$ %]. In contrast, the results in Column

³² Untabulated results show that the findings remain consistent when we measure performance using raw returns or benchmark-adjusted returns.

Table 6
Fund performance and active management.

Panel A: Net four-factor alpha by AS quintile.						
	AS quintile					
Funds	1	2	3	4	5	5-1
Quants	-0.69* (-1.69)	-0.85** (-1.96)	-1.19*** (-2.71)	-1.57*** (-3.53)	-1.88*** (-4.12)	-1.19*** (-2.58)
Non-quants	-1.28*** (-4.07)	-1.41*** (-4.39)	-1.30*** (-4.17)	-0.93*** (-2.99)	-0.66** (-2.08)	0.62* (1.94)
Quants minus Non-quants	0.59 (1.55)	0.56 (1.52)	0.11 (0.32)	-0.64* (1.73)	-1.22*** (3.32)	
Panel B: Gross four-factor alpha by AS quintile.						
	AS quintile					
Funds	1	2	3	4	5	5-1
Quants	0.17 (0.42)	0.15 (0.37)	-0.14 (-0.30)	-0.36 (-0.82)	-0.54 (-1.17)	-0.71* (-1.70)
Non-quants	-0.23 (-0.77)	-0.24 (-0.81)	-0.10 (-0.33)	0.33 (1.07)	0.73** (2.30)	0.96*** (2.84)
Quants minus Non-quants	0.40 (1.07)	0.39 (1.08)	-0.04 (-0.14)	-0.69* (1.88)	-1.27*** (3.41)	
Panel C: Net four-factor alpha by TE quintile						
	TE quintile					
Funds	1	2	3	4	5	5-1
Quants	-0.67 (-1.59)	-0.75* (-1.75)	-1.12** (-2.57)	-1.40*** (-3.19)	-2.19*** (-4.85)	-1.52*** (-3.21)
Non-quants	-0.89*** (-2.92)	-0.92*** (-2.95)	-1.27*** (-4.13)	-1.36*** (-4.42)	-1.84** (-5.86)	-0.95*** (-2.81)
Quants minus Non-quants	0.22 (0.66)	0.17 (0.51)	0.15 (0.39)	-0.04 (-0.12)	-0.35 (-0.95)	
Panel D: Gross four-factor alpha by TE quintile.						
	TE quintile					
Funds	1	2	3	4	5	5-1
Quants	0.21 (0.50)	0.19 (0.44)	-0.02 (-0.05)	-0.24 (-0.55)	-0.85* (-1.88)	-1.06** (-2.30)
Non-quants	0.15 (0.49)	0.18 (0.58)	-0.04 (-0.13)	-0.12 (-0.39)	-0.43 (-1.37)	-0.58* (-1.75)
Quants minus Non-quants	0.06 (0.18)	0.01 (0.03)	0.02 (0.05)	-0.12 (-0.36)	-0.42 (-1.14)	
Panel E: Net four-factor alpha by active management category.						
Category	Label	Funds		Quants minus Non-quants		
		Quants	Non-quants			
5	Stock Pickers	-1.81** (-2.39)	-0.36 (-0.60)	-1.45** (-2.49)		
4	Concentrated	-1.46* (-1.89)	-0.84 (-1.59)	-0.65 (-1.22)		
3	Factor bets	-2.08*** (-2.84)	-2.32*** (-3.28)	0.23 (0.42)		
2	Moderately active	-0.53 (-1.04)	-1.29*** (-3.14)	0.76 (1.55)		
1	Closet indexers	-0.44 (-1.01)	-1.22*** (-2.97)	0.78 (1.37)		
(5-1)	Difference	-1.37** (-2.52)	0.86** (2.12)			
Panel F: Gross four-factor alpha by active management category.						
Category	Label	Funds		Quants minus Non-quants		
		Quants	Non-quants			
5	Stock pickers	-0.48 (-0.79)	0.97* (1.81)	-1.46** (-2.51)		
4	Concentrated	-0.04 (-0.06)	0.63 (1.12)	-0.67 (-1.26)		
3	Factor bets	-0.81 (-1.08)	-0.93 (-1.42)	0.12 (0.19)		
2	Moderately active	0.53 (0.99)	-0.13 (-0.36)	0.66 (1.34)		
1	Closet indexers	0.39 (0.76)	-0.17 (-0.41)	0.56 (0.98)		

(continued on next page)

Table 6 (continued)

Panel F: Gross four-factor alpha by active management category.				
Category	Label	Funds		Quants minus Non-quants
		Quants	Non-quants	
(5–1)	Difference	–0.87* (–1.67)	1.15*** (2.78)	

This table presents the annualized equal-weighted four-factor alpha (in percent) across AS quintiles, in Panels A and B, across TE quintiles, in Panels C and D, and across the five categories of active management identified in Table 2 – Closet indexers, Moderately active, Factor bets, Concentrated, and Stock pickers –, in Panels E and F, for quants and non-quants. In Panels A, C, and E we compute net four-factor alpha, while in Panels B, D, and F we calculate gross four-factor alpha. In Panels A–B and C–D, we first sort quants and non-quants into quintiles based on prior year AS or TE, respectively: 1 refers to the performance of the first-quintile portfolio (low AS or low TE), and 5 refers to the performance of the fifth-quintile portfolio (high AS or high TE). Next, we use monthly returns and monthly factors to compute the four-factor alpha, separately for quants and non-quants, for the portfolios in each AS or TE quintile, as indicated in Eq. (3). The last column reports 5–1, which 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 quintile, we compute differences in alphas between quants and non-quants, i.e., the alpha of a portfolio formed by going long quants and short non-quants. In Panels E and F, we use monthly returns and monthly factors to compute the four-factor alpha, separately for quants and non-quants, for each of the portfolios that form the five categories of active management. At the bottom of the table, for quants and non-quants, we present the four-factor alpha for all funds, and 5–1, which is the difference in four-factor alpha between Stock pickers and Closet indexers. The last column presents differences in four-factor alpha between quants and non-quants for each type of active management group. t-statistics (presented in parentheses) are based on White's standard errors. *, ** and *** indicate significance at the 10 %, 5 % and 1 % level, respectively. See Appendix B for variable definitions.

Table 7

Fund performance and active management – panel regressions.

Panel A – The impact of AS and TE on net four-factor alpha.				
	All funds	Quants	Non-quants	Quants minus Non-quants (p-value)
	(1)	(2)	(3)	(4)
AS	0.0185*** (4.03)	–0.0199** (–1.97)	0.0235*** (4.86)	–0.0434*** (0.00)
TE	–0.2337*** (–10.50)	–0.2535*** (–3.44)	–0.2308*** (–10.05)	–0.0227 (0.34)
TSC	–0.4655*** (–6.22)	–0.4273* (–1.86)	–0.4594*** (–5.85)	0.0321 (0.90)
TNA (log)	–0.0019* (–1.77)	–0.0055 (–1.09)	–0.0016 (–1.39)	–0.0039 (0.45)
(TNA (log)) ²	0.0000 (0.27)	0.0001 (0.27)	0.0000 (0.01)	0.0001 (0.79)
Family size (log)	0.0014*** (6.63)	0.0017** (2.28)	0.0014*** (6.33)	0.0003 (0.69)
Number of stocks/100	0.0006*** (3.97)	0.0005 (1.47)	0.0006*** (3.56)	–0.0001 (0.94)
Four-factor alpha	0.0282*** (3.04)	–0.0277** (–2.08)	0.0306*** (3.58)	–0.0583*** (0.00)
Flow	–0.0009* (–1.68)	0.0004 (0.33)	–0.0010* (–1.75)	0.0014 (0.31)
Flow volatility	0.0050** (2.33)	0.0099 (1.51)	0.0048** (2.15)	0.0051 (0.46)
Age/100	0.0066** (2.30)	0.0089 (0.72)	0.0063** (2.13)	0.0026 (0.72)
Manager tenure/100	0.0131 (1.49)	–0.0181 (–0.49)	0.0124 (1.36)	–0.0305 (0.42)
Adjusted R-squared	0.165			0.168
Number of observations	32,050			32,050
Panel B – The impact of AS and TE on gross four-factor alpha.				
	All funds	Quants	Non-quants	Quants minus Non-quants (p-value)
	(1)	(2)	(3)	(4)
AS	0.0179*** (3.91)	–0.0180* (–1.78)	0.0214*** (4.46)	–0.0394*** (0.00)
TE	–0.2080*** (–9.33)	–0.2362*** (–3.21)	–0.2047*** (–8.90)	–0.0320 (0.68)
Adjusted R-squared	0.155			0.158
Number of observations	32,050			32,050
Panel C – Net four-factor alpha by active management category.				
	All funds	Quants	Non-quants	Quants minus Non-quants (p-value)
	(1)	(2)	(3)	(4)
Stock pickers	0.0089*** (3.73)	–0.0146** (–2.50)	0.0098*** (4.06)	–0.0164*** (0.00)
Concentrated	0.0070** (2.38)	–0.0111** (–2.00)	0.0077** (2.49)	–0.0108* (0.10)

(continued on next page)

Table 7 (continued)

Panel C – Net four-factor alpha by active management category.				
	All funds	Quants	Non-quants	Quants minus Non-quants (p-value)
	(1)	(2)	(3)	(4)
Factor bets	−0.0108*** (−5.20)	−0.0160** (−2.47)	−0.0097*** (−4.47)	0.0017 (0.31)
Moderately active	0.0011* (1.68)	−0.0006 (−0.18)	0.0011* (1.70)	0.0063 (0.19)
Closet indexers	−0.0129** (−2.04)	−0.0051 (−0.29)	−0.0131** (−2.07)	0.0080 (0.15)
Adjusted R-squared	0.156			0.159
Number of observations	32,050			32,050
Panel D – Gross four-factor alpha by active management category.				
	All funds	Quants	Non-quants	Quants minus Non-quants (p-value)
	(1)	(2)	(3)	(4)
Stock pickers	0.0116*** (6.12)	−0.0101* (−1.81)	0.0125*** (6.07)	−0.0167*** (0.00)
Concentrated	0.0105*** (4.02)	−0.0058 (−1.03)	0.0113*** (4.97)	−0.0112* (0.09)
Factor bets	−0.0081*** (−3.91)	−0.0125** (−1.97)	−0.0069*** (−3.19)	0.0003 (0.56)
Moderately active	0.0020** (2.06)	0.0013 (0.36)	0.0021** (2.08)	0.0051 (0.21)
Closet indexers	−0.0025 (−0.41)	0.0033 (0.19)	−0.0026 (−0.43)	0.0059 (0.19)
Adjusted R-squared	0.149			0.152
Number of observations	32,050			32,050

This table presents panel regressions to study differences in the impact of active management on the performance of quants and non-quants, with performance measured using net four-factor alpha computed as indicated in Eq. (3), in Panels A and C, and gross four-factor alpha, in Panels B and D. In Panels A and B, we regress fund four-factor alpha on prior-year AS, calculated as in Eq. (1), and prior-year TE, calculated as in Eq. (2), together with lagged control variables as indicated in Eq. (5). In Panels C and D, we do likewise, except that we replace AS and TE with dummy variables for funds in the different categories of active management identified in Table 2. The coefficients of Closet indexers reflect the total performance for funds in this category, while the coefficients on Moderately active, Factor bets, Concentrated, and Stock pickers categories represent the difference in performance between funds in that particular category and Closet indexers. The set of lagged control variables (omitted in Panels B, C, and D) include TSC, fund size, and fund size squared, family size, the number of stocks in a fund's portfolio, performance, measured as four-factor alpha, flow, flow volatility, fund age, and fund manager tenure. In Column (1) we present the results of a pooled regression that contains all funds in our sample taken together, i.e., quants and non-quants. In Column (2) 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 quant. In Column (3) 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 quant. Column (4) presents the difference in coefficients between quants and non-quants – in Panels C and D, the difference in performance for Moderately active, Factor bets, Concentrated, and Stock pickers active management categories is computed using the total performance within each active management category –, and the results of a *t*-test examining whether these differences are statistically significant. Regressions also include fund style and time fixed effects. Robust *t*-statistics clustered by fund and year are reported in parentheses. *, ** and *** indicate significance at the 10 %, 5 % and 1 % level, respectively. See Appendix B for variable definitions.

(2) suggest a negative but statistically insignificant relation between AS and flows for quants. When the effect of AS is excluded, there is no observable difference in the flow-performance sensitivity between quants and non-quants. This is further supported by the results in Column (4), which indicate no statistically significant differences in the performance rank coefficients across the two fund types. These findings are consistent with the conclusions of Miguel and Chen (2021).

Overall, our results suggest that the lower AS in quants relative to non-quants, may stem from a lack of investor-driven incentives. This aligns with the idea that investors perceive quants as fundamentally different, employing systematic strategies rather than the discretionary management typical of non-quants. As such, investors may view AS as less relevant or even detrimental for quants, where high AS could signal a deviation from their expected systematic approach, undermining confidence in the fund's methodology. This perception is further supported by the absence of statistically significant differences in

flow-performance sensitivity between quants and non-quants.

6. Fund fees and active management for quants and non-quants

In this section, we examine differences in fees between quants and non-quants using both the TER and the AF as measures of fund fees.³³ In Table 4, our summary statistics show that, on average, quants charge 11 bps less in TER and 9 bps less in AF compared to non-quants. This finding is consistent with previous research (Abis, 2022; Miguel and Chen, 2021), which suggests that quants generally charge lower fees compared to funds managed by humans.

Given that fees vary based on the level of active management, we proceed to examine fees for quants and non-quants across the categories of active management identified in Table 2. Table 9, Panels A and B, presents the results with fees proxied by TER or AF, respectively, in a format resembling that in Panels E and F of Table 6 for performance.

³³ Introduced by Cremers and Curtis (2016), AF assesses the cost of active stock picking by adjusting the TER for the level of AS and the cost of investing in the benchmark. Comprehensive definitions for both variables are outlined in Appendix 2. Additionally, in robustness tests, we introduce a third fee measure in our analysis – TSC. We find identical results when we measure fees using TSC (see Table IA7).

Table 8
Fund flows and active management.

	All funds	Quants	Non-quants	Quants minus Non-quants (p-value)
	(1)	(2)	(3)	(4)
Active share	0.1078*** (2.59)	−0.0239 (−0.45)	0.1239*** (2.73)	−0.1478*** (0.00)
Performance rank	0.0296* (1.91)	0.0267 (0.96)	0.0301* (1.93)	−0.0034 (0.76)
Performance rank x Active share	0.1308*** (3.18)	−0.0344 (−0.57)	0.1512*** (3.50)	−0.1856*** (0.00)
Tracking error	0.2776** (2.25)	0.2787 (1.04)	0.2771** (2.16)	0.0016 (0.56)
TSC	−1.3248** (−2.23)	−2.4408* (−1.94)	−1.2145** (−2.01)	−1.2255* (0.07)
TNA (log)	−0.0246*** (−6.95)	−0.0565*** (−3.42)	−0.0222*** (−6.11)	−0.0343** (0.04)
TNA Family (log)	0.0196*** (8.18)	0.0365*** (3.31)	0.0179*** (7.25)	0.0186 (0.10)
Number of stocks/100	0.0092*** (7.68)	0.0134 (1.35)	0.0093*** (7.94)	0.0041 (0.68)
Flow	0.1039*** (8.74)	0.0735* (1.67)	0.1060*** (8.67)	−0.0325 (0.48)
Flow volatility	1.0973*** (16.11)	1.1982*** (4.46)	1.0914*** (15.51)	0.1068 (0.70)
Age/100	−0.0608*** (−9.63)	−0.0847*** (−2.64)	−0.0593*** (−9.24)	−0.0254 (0.44)
Manager Tenure/100	−0.1532** (−2.09)	−0.0882 (0.48)	−0.1595** (−2.16)	0.0710 (0.29)
Adjusted R-squared	0.178			0.181
Number of observations	32,050			32,050

This table presents panel regressions to examine the differences in the impact of AS on the flow–performance sensitivity of quants and non-quants, as indicated in Eq. (6). We regress a fund's yearly net flows, defined as new external money growth as percentage of TNA, on prior-year AS, calculated as in Eq. (1), fund performance rank, and prior-year AS interacted with fund performance rank. Performance rank is measured using the past 12 months' net four-factor alpha, computed as indicated in Eq. (3). It is coded as zero for funds in the bottom 20 % of performance, one for funds in the middle 60 %, and two for funds in the top 20 %. We also include prior-year TE, calculated as in Eq. (2), together with lagged control variables, including TSC, fund size, and fund size squared, family size, the number of stocks in a fund's portfolio, flow, flow volatility, fund age, and fund manager tenure. In Column (1) we present the results of a pooled regression that contains all funds in our sample taken together, i.e., quants and non-quants. In Column (2) 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 quant. In Column (3) 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 quant. Column (4) presents the difference in coefficients between quants and non-quants, and the results of a *t*-test examining whether these differences are statistically significant. Regressions also include fund style and time fixed effects. Robust *t*-statistics clustered by fund and year are reported in parentheses. *, ** and *** indicate significance at the 10 %, 5 % and 1 % level, respectively. See Appendix B for variable definitions.

From Table 9, statistically significant differences between quants and non-quants emerge only in the categories of active management characterized by low or moderate levels of AS. The economic relevance of these differences is notably pronounced for closet indexers reaching up to 17 bps and 0.21 bps for TER and AF, respectively. By contrast, in the categories of diversified and concentrated stock pickers, no statistically significant differences in fees are observed. The results in Table 9 also document a considerably larger difference in fees between stock pickers

Table 9
Fund fees and active management.

Panel A – TER by active management category.					
Category	Label	Funds		Quants minus Non-quants	
		Quants (1)	Non-quants (2)	Difference (3)	(p-value)
5	Stock pickers	1.30	1.34	−0.04	(0.13)
4	Concentrated	1.40	1.45	−0.05	(0.11)
3	Factor bets	1.26	1.37	−0.11***	(0.00)
2	Moderately active	1.05	1.18	−0.13***	(0.00)
1	Closet indexers	0.86	1.03	−0.17***	(0.00)
(5–1)	Difference (p-value)	0.44*** (0.00)	0.31*** (0.00)		
Panel B – AF by active management category					
Category	Label	Funds		Quants minus Non-quants	
		Quants (1)	Non-quants (2)	Difference (3)	(p-value)
5	Stock pickers	1.35	1.37	−0.02	(0.19)
4	Concentrated	1.44	1.50	−0.06	(0.16)
3	Factor bets	1.48	1.57	−0.09*	(0.05)
2	Moderately active	1.21	1.32	−0.11***	(0.00)
1	Closet indexers	1.28	1.48	−0.21***	(0.00)
(5–1)	Difference (p-value)	0.08 (0.13)	−0.11*** (0.00)		

This table presents the average annual fee (in percent) for quants (Column 1) and non-quants (Column 2) across the five categories of active management identified in Table 2 – Closet indexers, Moderately active, Factor bets, Concentrated, and Stock pickers. Fees are measured as TER and AF, presented in Panels A and B, respectively. At the bottom of the table, for both quants and non-quants, we present (5–1), representing the difference in fees between Stock pickers and Closet indexers along with the results of a *t*-test examining the statistical significance of this difference. Column 3 presents the differences in fees between quants and non-quants for each type of active management group and the results of a *t*-test testing whether these differences are statistically significant. *, ** and *** indicate significance at the 10 %, 5 % and 1 % level, respectively. See Appendix B for variable definitions.

(and other investment categories) and closet indexers among quants compared to non-quants.

To address the impact of fund characteristics on the fees of both quants and non-quants, we also employ a regression approach. Specifically, we start by regressing fees on a dummy variable, *Quantitative*, which takes the value of one if the fund is classified as a quant and zero otherwise. Additionally, we incorporate several explanatory variables into the regression model:

$$Fees_{i,t} = \alpha + \beta_1 Quantitative_{i,t} + \gamma X_{i,t-1} + \varepsilon_{i,t}. \quad (7)$$

Fees are proxied using TER or AF. $X_{i,t-1}$ represents a set of lagged control variables employed in the literature (Cremers and Petajisto, 2009 and Gil-Bazo and Ruiz-Verdú, 2009). These variables include AS and TE, fund size and fund size squared, family size, the number of stocks in a fund's portfolio, performance, flow, age, and manager tenure. We incorporate fund style and time fixed effects, and standard errors are clustered by fund and time.

The results in Panel A of Table 10 are in line with those observed in Table 4. We find that quants levy an annual fee that is 10 bps and 9 bps lower than that imposed by non-quants, as indicated in Columns (4) and (8) for TER and AF, respectively.

Next, we replace our proxies for active management in Eq. (7) with dummy variables for funds in the different categories of active management and run the regression separately for all funds, quants, and

Table 10

Fund fees and active management – panel regressions.

Panel A – TER and AF for quants and non-quants								
	TER				AF			
Quantitative	−0.0009*** (−11.72)	−0.0008*** (−10.23)	−0.0011*** (−14.98)	−0.0010*** (−14.41)	−0.0007*** (−6.17)	−0.0006*** (−5.38)	−0.0010*** (−8.76)	−0.0009*** (−7.42)
AS		0.0044*** (25.74)	0.0030*** (18.94)	0.0024*** (15.23)				
TE		0.0254*** (28.28)	0.0203*** (25.68)	0.0202*** (26.04)		0.0238*** (19.43)	0.0142*** (13.04)	0.0113*** (10.38)
TNA (log)			−0.0010*** (−16.16)	−0.0007*** (−12.29)			−0.0010*** (−10.88)	−0.0009*** (−9.39)
(TNA (log)) ²			0.0000*** (3.36)	0.0000 (1.31)			−0.0000 (−0.60)	−0.0000 (−0.97)
Performance			−0.0021*** (−7.22)	−0.0020*** (−6.71)			−0.0034*** (−7.00)	−0.0033*** (−6.70)
Family size (log)				−0.0002*** (−18.10)				−0.0001*** (−7.02)
Number of stocks/100				−0.0002*** (−28.87)				−0.0002*** (−12.74)
Flow				−0.0000 (−1.43)				−0.0001 (−1.52)
Age/100				−0.0005*** (−3.25)				−0.0007*** (−2.85)
Manager tenure/100				0.0014*** (3.36)				0.0027*** (4.09)
Adjusted R-squared	0.145	0.233	0.350	0.359	0.076	0.094	0.200	0.209
Number of observations	32,050	32,050	32,050	32,050	32,050	32,050	32,050	32,050
Panel B – TER by active management category								
	All funds		Quants		Non-quants		Quants minus Non-quants (p-value)	
	(1)		(2)		(3)		(4)	
Stock pickers	0.0023*** (28.33)		0.0035*** (10.58)		0.0019*** (22.76)		−0.0007 (0.15)	
Concentrated	0.0027*** (30.38)		0.0043*** (11.75)		0.0026*** (27.72)		−0.0006 (0.16)	
Factor bets	0.0022*** (26.09)		0.0030*** (10.01)		0.0021*** (23.79)		−0.0014* (0.08)	
Moderately active	0.0008*** (13.62)		0.0012*** (5.68)		0.0007*** (12.58)		−0.0018** (0.02)	
Closet indexers	0.0113*** (51.75)		0.0092*** (9.97)		0.0115*** (51.21)		−0.0023*** (0.00)	
Adjusted R-squared	0.346						0.349	
Number of observations	32,050						32,050	
Panel C – AF by active management category.								
	All funds		Quants		Non-quants		Quants minus Non-quants (p-value)	
	(1)		(2)		(3)		(4)	
Stock pickers	−0.0012*** (−8.73)		0.0010* (1.72)		−0.0014*** (−10.11)		−0.0001 (0.29)	
Concentrated	0.0002 (1.35)		0.0016*** (2.92)		0.0000 (0.05)		−0.0009 (0.13)	
Factor bets	0.0011*** (7.32)		0.0020*** (4.74)		0.0009*** (5.75)		−0.0014* (0.09)	
Moderately active	−0.0021*** (−18.05)		−0.0014*** (−3.14)		−0.0022*** (−19.23)		−0.0017** (0.03)	
Closet indexers	0.0158*** (46.83)		0.0138*** (10.76)		0.0163*** (50.08)		−0.0025*** (0.00)	
Adjusted R-squared	0.239						0.242	
Number of observations	32,050						32,050	

This table presents panel regressions to study differences in fund fees for quants and non-quants, according to Eq. (7), where fees are measured as *TER*, in Panel A, Columns (1)–(4), and Panel B, and as *AF*, in Panel A, Columns (5)–(8), and Panel C. In Panel A, we regress fees on a quantitative dummy variable (*Quantitative_{it}*) that takes the value of one if a fund *i* is classified by *Lipper Hindsight* as a quant and zero otherwise. In Columns (2) and (6) we add *TE* or *AS*, respectively, to the regression. In Columns (3) and (7), we also control for different fund characteristics, including, fund size, fund size squared, and performance, measured as four-factor alpha. Finally, in Columns (4) and (8), we add to our model Family size (log), the number of stocks in a fund's portfolio, flow, fund age, and fund manager tenure. In Panels B and C we study differences in fund fees across the five categories of active management identified in Table 2 – Closet indexers, Moderately active, Factor bets, Concentrated, and Stock pickers – for quants and non-quants. In both Panels B and C, we regress fund fees in dummy variables for funds in the different categories of active management. The coefficients of Closet indexers reflect the total fee for funds in this category, while the coefficients on Moderately active, Factor bets, Concentrated, and Stock pickers categories represent the difference in fees between funds in that particular category and Closet indexers. The lagged control variables in the regressions are the same as in Columns (4) of Panel A. Column (1) presents the results of a pooled regression that contains all funds in our sample taken together, i.e., quants and non-quants. In Column (2) 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 quant. In Column (3) 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 quant. Column (4) presents the difference in coefficients between quants and non-quants – the difference in fees for the different active management categories is computed using the total fee within each active management category –, and the results of a *t*-test

examining whether these differences are statistically significant. Regressions also include time and fund style fixed effects. Robust *t*-statistics clustered by fund and year are reported in parentheses. *, ** and *** indicate significance at the 10 %, 5 % and 1 % level, respectively. See Appendix B for variable definitions.

non-quants, following the same approach as in Table 7 for performance. Table 10, Panels B and C, present the results for *TER* and *AF*, respectively. The results in Table 10 corroborate those in Table 9, indicating economically and statistically significant differences in the fees charged by quants and non-quants but only for funds in low *AS* groups. Notably, for closet indexers, quants charge 23 *bps* less in *TER* and 25 *bps* in *AF*. Conversely in categories with high *AS*, namely stock pickers and concentrated, the fees charged by quants are not statistically different to those of their counterparts. Additionally, there is evidence that, relative to closet indexers, the *AF* of high *AS* funds increases for quants, while it decreases for non-quants. This finding aligns with the trend of increasing fees and relatively lower *AS* observed for quants as we move from categories of low *AS* to high *AS* levels.³⁴

In summary, our findings suggest that the lower fees documented in existing literature for quants stem from low *AS* strategies characterized by limited discretionary decisions and high scalability. Conversely, for strategies requiring greater complexity and resources, we observe no significant differences in fees between the two types of funds.

7. Robustness tests

We ensure the robustness and generality of our results by conducting a comprehensive set of supplementary tests. The analysis and tables for these tests are presented in the Internet Appendix.

To address concerns regarding the imbalance in the sample of quants and non-quants, we employ a propensity score matching method. This approach aims to improve the comparability of the two groups by accounting for observed differences in their characteristics, thereby providing a more robust basis for interpreting the observed associations. Table IA2 shows that this methodology yields consistent results. We re-estimate our main tests by accounting for different market capitalization groups and for differences in the benchmarks of quants and non-quants (see Table IA3). Following the approach of Cline and Gilstrap (2021), in Table IA4, we examine how *AS* relates to performance across various levels of management skill. In Table IA 5, we conduct additional analysis controlling for a fund's trading activity to assess the impact of fund turnover on our results. As an alternative measure of active management, we use the Amihud and Goyenko (2013) *R-squared* measure (see Table IA6). Table IA7 shows the results when we examine differences in fees between quants and non-quants using *TSC*. We find identical results. Lastly, we explore different methods of clustering standard errors in untabulated results. In all instances, our findings are robust to these adjustments.

8. Conclusion

In this paper, we use the classification provided by the *Lipper Hind-sight* database to study the *AS* of nominally active quants. Our results suggest a prevalence of closet indexing among quants, with a substantially larger fraction of assets allocated to closet indexers compared to what we observe for non-quants.

We proceed to investigate the impact of *AS* on the performance of

both types of funds. We find that *AS* is associated with future performance for non-quants, but it diminishes the performance of quants. Quants with stock selection tend to underperform closet indexers. Following the methodology in Cremers and Petajisto (2009) and Petajisto (2013), we use *TE* alongside *AS*, to classify funds based on their degree of active management. Our results confirm the passive behavior of quants relative to non-quants. We also find that, regardless of the type and degree of active management observed, quants exhibit lower levels of active management and engage in more closet indexing than their counterparts. In further tests, we observe a lack of discernible stock-picking ability among quants and show that they match the equally poor performance of non-quants in factor betting strategies.

We also find evidence suggesting that, after accounting for fees, quants do not outperform their benchmarks, as the net alpha is negative across all investment strategies.

In additional analyses, we examine the response of flows to *AS* and find that flows for quants are less sensitive to *AS* than those for non-quants, suggesting that the lower *AS* observed in quantitative strategies may stem from a lack of investor-driven incentives.

Finally, we conduct a comprehensive analysis of the fees of quants. Our results suggest that quants charge lower fees than non-quants but this difference is observed only in investment strategies with low levels of *AS*. For high *AS* strategies, we observe no significant differences in the fees of these two types of funds.

Overall, our results suggest limitations of quants in implementing strategies that generate value for investors, particularly those relying on significant discretionary judgment while also facing scalability constraints. While ongoing innovations in artificial intelligence and data processing may have already mitigated some of these constraints and will likely continue to do so, we believe that our findings offer a valuable framework for understanding these challenges and evaluating the implications of future advancements in the field.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Quants classification and sample selection

This section explains in detail the classification of quants and our final sample selection.

³⁴ In robustness tests, we introduce a third fee measure in our analysis – *TSC*. We find identical results when we measure fees using *TSC* (see Table IA7).

A.1. Classification of quants

To identify quants, we utilize the classification provided by *Lipper Hindsight*. This classification follows the funds' Principal Investment Strategy reported in their prospectus disclosures. *Lipper* flags funds which are purely quantitative-oriented: “funds that use a rule-based mathematical model in order to initiate buy and sell decisions”, i.e., those funds that rely exclusively on quantitative models to buy and sell stocks. For example, the *Leuthold Undervalued & Unloved Fund (UGLYX)* states 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.” While many funds employ quantitative screening to narrow down the investment universe, investment decisions in these cases are ultimately made at the portfolio manager's discretion. This means that humans are involved in selecting trades. *Kopernik International I (KGIIX)* is an example of such a fund. Its 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.” *Lipper* classifies this fund as non-quant.

To the best of our knowledge, *Lipper Hindsight* is the only database that provides this classification. Other studies, including [Zhao \(2006\)](#), [Abis \(2022\)](#) and [Beggs et al. \(2023\)](#), perform textual analysis of mutual fund prospectuses to identify quants. [Zhao's \(2006\)](#) classification aligns with *Lipper Hindsight's* by considering quants to be those funds relying solely on computer models to select securities (*purely quantitative-oriented funds or quant jocks*). [Abis \(2022\)](#) and [Beggs et al. \(2023\)](#), however, allow for the possibility of classifying some hybrid or mixed funds as quants. “Over identification resulting from the use of the word ‘quantitative’ may cause funds that use simple value screens to be identified as quants” [Beggs, Brogaard, and Hill-Kleespie \(2023, p. 8\)](#).

Interestingly, both studies have similar sample periods but display a significant difference in the number of funds identified as quants, suggesting limitations in using textual analysis for classification. At the end of 2015, [Abis \(2022\)](#) identifies 465 quants, while [Beggs et al. \(2023\)](#) identify 168.

A.2. Final sample selection

The *Lipper Hindsight* database lists a total of 32,058 US equity mutual funds at the end of 2019, including 1592 quants. After excluding closed-end funds, index-tracking funds, exchanged-traded funds and funds of funds, we are left with a total of 27,653 funds, including 1397 quants. Non-primary funds are then eliminated, resulting in a final sample of 8749 funds, including 408 quants.

We impose additional filters to construct the 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 alpha observations for each fund; (3) we exclude those funds for which holdings are not available in *LionShares*; (4) we require mutual funds to have data on all our control variables. The resulting final sample consists of 3330 unique funds with a TNA of \$4206 million at the end of 2019. Of these, 204 are quants with a TNA of \$168 million and 3126 are non-quants with a TNA of \$4038 million (see [Table 1](#)).

Appendix B. Variable definitions

Variable	Definition
Raw return	Fund net return in US dollars (percentage per quarter or year) (<i>Lipper</i>).
Four-factor alpha	Net four-factor alpha (percentage per quarter or year) estimated as indicated in Eq. (3).
AS	Percentage of a fund's portfolio holdings that differ from its benchmark index holdings calculated as in Eq. (1).
TE	Standard deviation (annualized) estimated with three years of past monthly benchmark-adjusted return as in Eq. (2).
TER	Total annual expenses as a fraction of TNA (<i>Lipper</i>).
AF	Measure of the cost of active stock picking. <i>AF</i> adjusts the <i>TER</i> for the level of <i>AS</i> and the cost of investing in the benchmark. Following the methodology in Cremers and Curtis (2016) , we calculate the Active fee of fund <i>i</i> in year <i>t</i> as: $\text{Active fee}_{i,t} = \frac{\text{TER}_{i,t} - (1 - \text{AS}_{i,t}) \times \text{Index fund fee}_{i,t}}{\text{AS}_{i,t}}$ Where: $\text{TER}_{i,t}$ is the total expense ratio of fund <i>i</i> in year <i>t</i> ; $\text{AS}_{i,t}$ denotes the Active Share of fund <i>i</i> in year <i>t</i> , and $\text{Index fund fee}_{i,t}$ is the expense ratio charged by index funds that closely track the fund's <i>i</i> benchmark index.
TSC	Fund's annual total expense ratio plus one-fifth of front-end load (<i>Lipper</i>).
Quantitative	Dummy variable that takes the value of one if the fund is classified by <i>Lipper Hindsight</i> as a quantitative fund – a fund relying solely on computer models to select securities– and zero otherwise.
TNA	Total net assets in millions of US dollars (<i>Lipper</i>).
Family size	Family total net assets in millions of US dollars of other equity funds in the same management company excluding the own fund TNA (<i>Lipper</i>).
Number of stocks	Number of stocks held by a fund (<i>Factset</i>).
Flow	Percentage growth in TNA in each year, net of internal growth (assuming reinvestment of dividends and distributions). Fund flow for fund <i>i</i> at period <i>t</i> is calculated as: $\text{Flow}_{i,t} = \frac{\text{TNA}_{i,t} - \text{TNA}_{i,t-1}(1 + R_{i,t-1})}{\text{TNA}_{i,t-1}}$ where $\text{TNA}_{i,t}$ is the total net asset value in US dollars of fund <i>i</i> at the end of quarter <i>t</i> , and $R_{i,t}$ is fund <i>i</i> 's raw return in quarter <i>t</i> . Net annual fund flow is the sum of net quarterly fund flows.
Flow volatility	Annualized standard deviation of fund flows, computed using monthly flows over the past 12 months.
Age	Number of years since the fund launch date (<i>Lipper</i>).
MKT	Loadings on the market factor from four-factor alpha estimations.
SMB	Loadings on the small minus big size factor from four-factor alpha estimations.
HML	Loadings on the high minus low factor from four-factor alpha regressions.

(continued on next page)

(continued)

Variable	Definition
MOM	Loadings on the momentum factor from four-factor alpha estimations.
R2	R2 from four-factor alpha estimations.

Appendix C. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.irfa.2025.104173>.

Data availability

No

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