Original Research Article

Impacts of Artificial Intelligence on Asset Management

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ABSTRACT

Artificial intelligence (AI) is rapidly transforming the asset management industry by enhancing investment strategy formulation, portfolio construction, and risk management. This study investigates the performance impacts of AI integration in asset management using a ten-year panel (2015–2024) of institutional fund holdings derived from SEC Form 13F filings via Whalewisdom. Funds were classified as traditional or quantitative based on turnover and holdings concentration, serving as proxies for AI adoption. Literature review findings reveal that leading institutions such as JPMorgan and BlackRock leverage AI for alternative data analysis, risk oversight, and hybrid human–machine decision-making. Results show that quantitative funds consistently exhibited higher volatility and greater market sensitivity (beta), while both fund types saw declining downside-adjusted performance (Sortino ratio). Notably, Sortino ratios converged over time, suggesting narrowing differences in downside-risk efficiency. Alpha was persistently negative for quantitative funds, indicating limited excess returns beyond market exposure. Overall performance differences were negligible except during the onset of COVID-19, when quantitative funds briefly outperformed. These findings highlight AI's dual role as both a source of adaptability and a driver of higher systemic risk, underscoring the importance of governance and transparency in its deployment.

Keywords: Artificial Intelligence; Asset Management; Large Language Models; Machine Learning; Finance

INTRODUCTION

Artificial intelligence (AI) has moved from the periphery of business innovation to the center of strategic decision-making across industries. From optimizing supply chains in global logistics to enabling hyper-personalized marketing campaigns (1), AI technologies are reshaping how organizations operate, compete, and deliver value. Nowhere is this transformation more evident than in the financial sector, where data-driven decision-making has always been a core function. Advances in machine learning, natural language processing, and big data analytics have introduced powerful tools capable of detecting subtle market patterns, processing vast unstructured datasets, and generating investment insights at speeds far beyond human capacity (2, 3).

Within asset management, the integration of AI is altering traditional portfolio construction and risk management frameworks. Firms such as BlackRock have leveraged systems like the Aladdin platform to combine

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fundamental analysis with predictive risk modeling (4), while hedge funds employ algorithmic trading strategies that react to market signals in milliseconds (1, 2). AI also enables the incorporation of alternative data sources such as satellite imagery and social media sentiment into investment decision-making (2), allowing managers to identify opportunities and risks earlier than conventional models permit. Against this backdrop, this study asks two central research questions: 1) What are the impacts of artificial intelligence on asset management performance and risk? and 2) What ethical and regulatory implications emerge as AI becomes more deeply embedded in financial decision-making? Yet current academic and industry research on AI in asset management often focuses on case studies, qualitative interviews, or high-level performance summaries, leaving a gap in systematic classification. It remains challenging to quantify the degree to which AI is integrated into a given fund's strategy and to empirically assess whether these differences translate into distinct performance or volatility profiles. Without a clear framework for categorization, comparisons between traditional, hybrid, and AI-driven funds risk being anecdotal or inconsistent.

This study addresses that gap by developing a classification methodology based on publicly available holdings and turnover data from Form 13F filings. By applying consistent quantitative thresholds, it becomes possible to distinguish between traditional, hybrid, and quantitatively oriented funds in a way that supports empirical testing. The aim is to provide a replicable, data-driven approach to categorizing funds and to explore how these classifications correspond to differences in investment behavior and market outcomes. At the same time, the study considers the ethical challenges of opacity, accountability, and systemic risk that AI introduces into financial markets. Together, these contributions offer researchers, practitioners, and regulators a clearer basis for evaluating the real-world impact of AI adoption, enabling more informed investment strategies and policy discussions.

LITERATURE REVIEW

The Impact of Artificial Intelligence on Asset Management

Artificial intelligence (AI) has emerged as a critical force in driving innovation within asset management, reshaping how investment strategies are formulated, and portfolios are managed. Technologies such as machine learning (ML), natural language processing (NLP), and big data analytics have empowered financial institutions to derive actionable insights from vast and complex datasets. These advancements support a more dynamic, forward-looking, and personalized approach to investing, in contrast to the more static, historically focused methods of older funds. More recently, large language models (LLMs) such as ChatGPT have introduced new ways to process and interpret unstructured financial texts, from corporate filings to earnings call transcripts. Their ability to extract insights from qualitative disclosures expands the scope of data that can inform investment decisions, highlighting how AI's role in asset management is moving beyond numbers into language and context.

This paper is related to two strands of literature. The first examines how AI tools and techniques are transforming the asset management industry. Within this body of work, several studies provide insight into the ways AI is actively being adopted across institutions and investment processes.

Kolanovic and Krishnamachari provide a comprehensive analysis of how institutional investors are incorporating big data and alternative overlay (AO) strategies (2). The study highlights a shift toward the use of unconventional data sources such as credit card transactions, satellite imagery, internet activity, and social media, which are processed through ML systems to detect patterns and predict price movements. These tools allow firms, particularly hedge funds and proprietary trading shops, to gain an edge by accessing insights earlier and responding faster than competitors. However, while their work demonstrates the breadth of alternative datasets, it does not evaluate whether such adoption systematically translates into distinct risk–return profiles across funds, leaving open the question of measurable performance impacts. Complementing this view, Novick et al. illustrate how AI is embedded into portfolio construction and risk oversight through its Aladdin platform [4]. While JPMorgan emphasizes alpha generation via alternative datasets, BlackRock focuses on how AI enhances the infrastructure for risk management, compliance, and scenario testing across its portfolio. Through its integration of AI into simulation and stress-testing tools, Aladdin exemplifies how AI is being used not only to optimize returns but also to strengthen resilience and regulatory alignment in multi-asset portfolios. While JPMorgan and BlackRock showcase different institutional applications of AI, both point to a broader industry trend toward the automation and augmentation of investment decision making. Cao, Jiang, Wang, & Yang build on this trend by empirically testing the value of integrating human and machine inputs in a hybrid decision making model (3). Their findings reveal that combining human analyst forecasts with AI-generated probabilities improves forecasting accuracy, outperforming both stand-alone human and machine predictions in a majority of cases. This study helps bridge the gap between the institutional implementations discussed by JPMorgan and BlackRock and the theoretical underpinnings of how human-AI collaboration can be structured. Finally, the Bank for International Settlements situates these developments in a global context, documenting widespread adoption of AI across the financial sector (1). The report highlights the increasing complexity of AI systems and the competitive advantage conferred by proprietary models and robust data infrastructures. However, it also introduces an important caveat. As AI tools become more sophisticated, issues of interpretability and transparency become more pressing, especially when regulators and end users cannot easily understand the basis of AI-driven decisions. This adds a layer of nuance to the optimistic narratives of AI integration, reminding us that technological progress must be balanced with governance and accountability. Taken together, the existing literature provides valuable insights into institutional practices and technical challenges, but it rarely offers a systematic, data-driven classification of funds by AI adoption level. This study contributes by bridging that gap, using observable portfolio turnover and holdings data to empirically assess how AI integration corresponds with fund performance and risk.

The second strand of the literature discusses the gains and losses in performance from funds adopting AI or machine learning techniques. This literature evaluates the extent to which AI delivers measurable improvements in fund performance, while also documenting the risks and limitations of these approaches. Despite the increasing integration of AI into asset management, performance results from AI-driven funds remain inconsistent. While some AI-based funds have posted impressive returns, others have underperformed, raising questions about the reliability and context-specific effectiveness of these models.

Lopez de Prado outlines several common pitfalls encountered by AI-powered investment strategies (5). One of the most problematic is overfitting, where a model shows strong performance on historical data but fails to adapt to new market conditions. This occurs when the model captures noise rather than genuine patterns, leading to weak performance outside the training sample. Another key challenge is the lack of transparency in AI models, often referred to as the "black box" issue. This is where it becomes difficult for portfolio managers and risk officers to interpret or challenge the model's predictions.This critique highlights methodological risks but does not address whether such pitfalls manifest in aggregate performance metrics across funds, a gap this paper seeks to explore through Sortino ratios and volatility measures. Cao, Jiang, Wang, & Yang revisit these challenges in the context of hybrid investment models (3). They argue that even high-performing machine learning tools require human oversight, particularly during periods of market disruption when historical data loses predictive value. Human professionals are often better equipped to recognize regime shifts or macroeconomic shocks, while machines excel at digesting and analyzing large datasets rapidly and systematically. This division of labor suggests that AI is most effective when used to augment, rather than replace, human judgment.

More recently, research has begun to explore how large language models (LLMs), such as ChatGPT, can assist in investment analysis. Kim, Muhn, & Nikolaev examine how ChatGPT processes detailed and technical corporate disclosures (6). The study finds that the model improves efficiency in identifying key financial information, especially for retail investors who may lack financial expertise. However, they also note that ChatGPT can introduce fabricated details or misinterpret complex financial nuances, which can compromise the value and reliability of investment decisions. However, these findings are based on disclosure analysis at the firm level; they stop short of connecting AI's text-processing capabilities to portfolio construction or risk-adjusted returns in practice.

Ethical and Regulatory Implications of AI in Asset Management

As AI becomes more common in investment workflows, the discussion of ethical and regulatory implications of AI points to three main themes: 1) accountability and governance, 2) transparency, fairness, and consumer protection, and 3) market integrity, operational resilience, and systemic risk.

Accountability and Governance

Global rules emphasize the need for clear oversight of AI systems and strong governance through the entire

AI lifecycle. The European Union's AI Act creates a risk-based system that places strict obligations on high-risk uses of AI, like requirements for risk management, data governance, technical documentation, logging, human oversight, and ongoing monitoring (7). Noncompliance with the system can result in heavy penalties. For financial firms, this means AI governance has to move beyond policies and into practices that can be audited.

In the United States, the NIST AI Risk Management Framework (AI RMF 1.0) and its 2024 Generative AI Profile translate principles of trustworthy AI—like validity, reliability, security, accountability, explainability, and fairness—into operational practices across AI design, development, and use (8, 9). For buy-side teams such as asset managers, hedge funds, private equity firms, institutional investors, exchange traded funds (ETFs) and mutual funds, these resources serve as a blueprint for how they manage model risk, keep records, and monitor performance.

The CFA Institute complements these approaches with an ethics framework designed specifically for investment management. It highlights duties such as loyalty, prudence, and care, and it provides checkpoints across the AI workflow to ensure ethical use (10).

<u>Transparency, Fairness, and Consumer Protection</u>

U.S. regulators are applying existing consumer protection laws directly to AI. The Consumer Financial Protection Bureau (CFPB) has clarified that lenders must give borrowers specific reasons for loan denials, even if those decisions come from complex AI models (11). This raises the need for explainable AI tools, documentation, and transparency, especially in credit-related asset management.

The CFPB has also warned that AI chatbots and generative tools may mislead consumers or prevent them from reaching human representatives (12). It has stressed the importance of human-in-the-loop review and proper recordkeeping. At the securities level, the Securities and Exchange Commission (SEC) has proposed rules on predictive data analytics (PDA) (13). These rules would require broker-dealers and advisers to address conflicts of interest if AI systems prioritize firm profits over client outcomes. This would push firms to map out their AI use cases, check for conflicts, and apply safeguards or drop the tool. Internationally, Singapore's Monetary Authority of Singapore (MAS) has introduced the FEAT principles, fairness, ethics, accountability, and transparency, and the Veritas initiative, which provide tools and metrics for financial firms to evaluate their AI systems (14). These serve as practical templates for global firms aiming to apply consistent standards across markets.

<u>Market Integrity, Operational Resilience, and Systemic Risk</u>

Global securities regulators are also looking at AI's impact on market integrity. The International Organization of Securities Commissions (IOSCO) has mapped AI use cases to risks like market abuse surveillance, suitability of recommendations, and reliance on third-party providers (15, 16). Recent reports have become more detailed, with suggested guidance on testing, audit trails, and model drift. Regulators in the U.K., including the Bank of England and the Financial Conduct Authority (FCA), have raised flags around risks like explainability, oversight, and reliance on outside providers like cloud services (17). They currently prefer technology-neutral rules but still expect firms to assign responsibility to senior managers. Lastly, broader individual rights-based frameworks also matter. In the U.S., the Blueprint for an AI Bill of Rights lays out principles such as data privacy, protection against algorithmic discrimination, notice and explanation of AI decisions, and access to human alternatives (18). Even though it is not a law, it sets a baseline that could influence firm policies.

METHODS AND MATERIALS

To assess the impact of AI on asset management performance, this study utilizes institutional fund holdings data obtained from Whalewisdom, a platform that aggregates quarterly Form 13F filings submitted to the U.S. Securities and Exchange Commission (SEC). These filings offer detailed disclosures of the equity holdings of institutional investment managers, making them a reliable source for fund-level performance analysis and statistics over time.

The dataset includes all U.S.-based asset managers that submitted 13F filings between the first quarter of 2015 and the fourth quarter of 2024, yielding a balanced ten-year panel of quarterly observations. For each fund, the following characteristics were collected: assets under management (AUM), equity holdings, 3-year Sortino ratio, 3-year standard deviation, turnover percentage, 5-year beta, 3-year alpha, and quarter-over-quarter performance. These variables were selected to capture a comprehensive view of fund performance, risk-adjusted returns, and portfolio stability.

Funds were categorized into three groups based on their degree of AI integration, using holdings and turnover data from the year 2015. To ensure comparability, the analysis only considers funds with more than 10 equity positions. Within this sample, the funds with the lowest turnover, approximately the bottom 40%, were classified as traditional, reflecting buy-and-hold strategies typical of conventional asset managers who prioritize long-term fundamental analysis and portfolio stability. The turnover cutoff for this group was set at 15.83 percent, meaning any fund with quarter-over-quarter turnover below this level was included. Funds with the highest turnover, approximately the top 40%, were classified as quantitative, consistent with AI-driven or algorithmic trading strategies characterized by frequent rebalancing. The cutoff for this group was set at 21.65 percent, with any fund above this threshold classified as quantitative. Funds with turnover between 15.83 percent and 21.65 percent, roughly the middle 20% of the sample, were excluded from classification to provide a buffer for intermediate strategies, recognizing that fund behavior exists along a spectrum and some funds may not clearly fit into either category. These thresholds were defined based on the distribution of turnover in the dataset, allowing for identification of the more clearly traditional and quantitative funds while minimizing misclassification. By organizing funds in this way, the study enables a comparative analysis of performance metrics between traditional and AI-driven strategies while reducing the risk of including ambiguous funds.

Turnover is not a perfect measure of AI adoption, but it offers a practical way to capture broad differences in trading style. Not all high turnover strategies involve AI since some may reflect discretionary approaches such as sector rotation or event driven trading. Likewise, funds using AI may not always show elevated turnover if their models are designed for longer holding periods. In this study turnover serves as a useful behavioral signal of portfolio management style but it should be understood as an approximation rather than a definitive indicator of AI integration.

RESULTS

This section evaluates how the integration of AI in asset management influenced fund performance over the ten-year sample period. To capture a comprehensive picture, the analysis compares quantitative and traditional funds across multiple dimensions of risk and return, including volatility (standard deviations), downside-adjusted returns (Sortino ratio), overall performance, market sensitivity (beta), and manager-specific skill (alpha). These metrics, supplemented by graphical evidence, highlight both the distinctions and points of convergence between AI-driven strategies and traditional investment approaches.

The analysis of standard deviations over the ten-year period from 2015 to 2024 revealed a persistent and widening gap between quantitative funds and traditional funds.

As shown in Figure 1, quantitative funds exhibited consistently higher levels of volatility, as measured by their standard deviations, across the entire sample period. Moreover, the difference in volatility between the two fund categories increased steadily over time. This divergence suggests that AI-driven and algorithmic strategies employed by quantitative funds may lead to more concentrated positions, higher turnover, and faster reaction to short-term market signals. While such strategies can enable rapid exploitation of market inefficiencies, they also expose portfolios to greater fluctuations when market conditions shift unexpectedly. In contrast, traditional funds, with their broader diversification and lower turnover, tend to maintain more stable return patterns, which naturally dampens volatility.

The Sortino ratio trends painted a different but equally notable picture in the figure below.

As shown in Figure 2, both quantitative and traditional funds experienced a decline in their Sortino ratios over the ten-year horizon, indicating that risk-adjusted performance deteriorated across the board. This decline likely reflects a combination of macroeconomic volatility, shifting market structures, and heightened competition for alpha during the study period. However, traditional funds consistently maintained higher Sortino ratios compared to quantitative funds, suggesting that their lower downside volatility has historically translated into stronger downside-adjusted returns.

Interestingly, the gap between the Sortino ratios of the two fund types has been narrowing over time, despite the absolute values decreasing for both. This convergence may indicate that the relative advantage of traditional funds in mitigating downside risk is eroding. Several factors could explain this trend: 1) quantitative funds improving their risk management frameworks, 2) traditional funds adopting more systematic or data-driven elements into their processes, or 3) structural

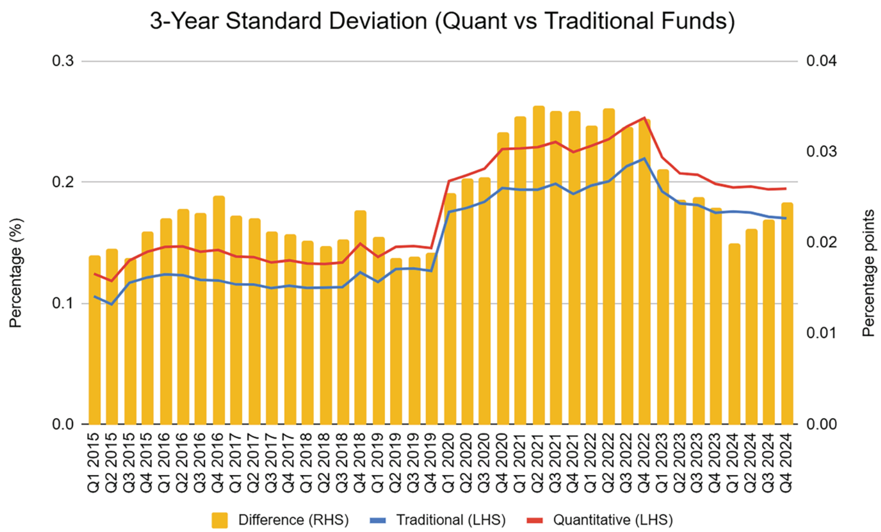

Figure 1. Three-year rolling standard deviation of monthly excess returns (relative to the S&P 500) for quantitative and traditional equity funds, 2015–2024. Volatility was computed as the standard deviation of monthly excess returns within each rolling 36-month window, expressed in decimal form (e.g., 0.15 corresponds to 15% annualized volatility). Funds were classified into categories based on turnover rates derived from portfolio holdings: traditional funds were defined as those with quarter-over-quarter turnover below 15.83 percent, reflecting buy-and-hold strategies, while quantitative funds were defined as those with turnover above 21.65 percent, consistent with AI-driven or algorithmic trading characterized by higher turnover. To ensure comparability, only funds with at least 10 equity positions were included.

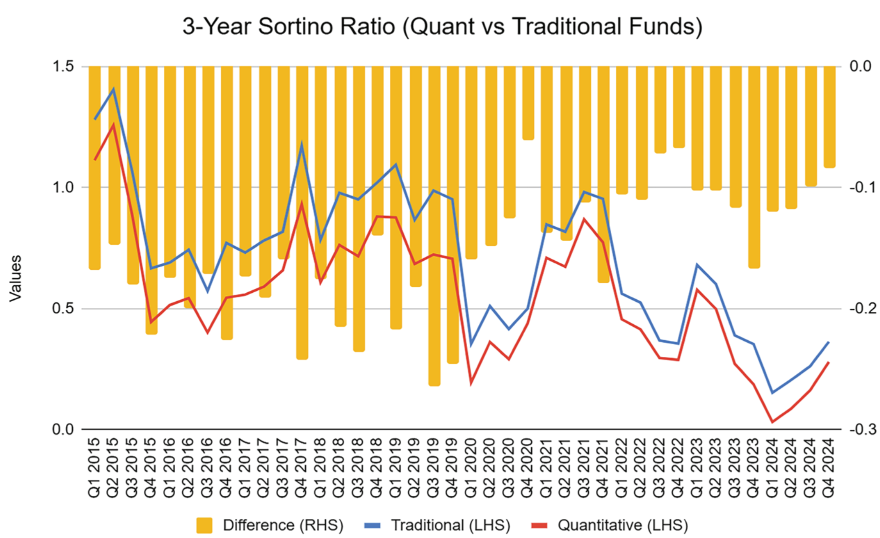

Figure 2. Three-year rolling Sortino ratio for quantitative and traditional equity funds, 2015–2024. The Sortino ratio measures risk-adjusted performance by dividing a fund's average monthly excess return (relative to the S&P 500) by its downside deviation, thereby penalizing only negative volatility. Ratios were calculated over rolling 36-month windows to smooth short-term fluctuations. Funds were categorized using portfolio turnover data: traditional funds were defined as those with quarter-over-quarter turnover below 15.83 percent, reflecting long-term, buy-and-hold strategies, while quantitative funds were defined as those with turnover above 21.65 percent, consistent with AI-driven, higher-turnover trading approaches. Only funds with at least 10 equity holdings were included to ensure comparability.

market changes that affect both strategies in a similar manner. The narrowing gap underscores that while fundamental differences remain between traditional and AI-driven approaches, certain performance characteristics may be converging as both styles adapt to evolving market conditions.

Beyond volatility and downside-adjusted returns, it is also important to examine each fund type's exposure to overall market risk. Figure 3 presents the five-year beta for quantitative and traditional funds.

Quantitative funds consistently exhibited higher beta values than traditional funds, reflecting greater sensitivity to broad market movements, as shown in Figure 3. This pattern suggests that AI-driven strategies, with their frequent rebalancing and data-driven signals, tend to amplify exposure to systematic risk. Traditional funds, in contrast, maintained lower and more stable betas, consistent with their long-term, fundamentals-based approach. The gap peaked during 2019–2021, coinciding with pandemic-driven volatility, when quantitative funds' betas rose well above one. In recent years, however, the spread has narrowed, with quantitative funds converging somewhat toward the steadier profile of traditional funds. Overall, these results highlight a trade-off: AI-driven funds capture more upside in strong markets but are more vulnerable to broad downturns, while traditional funds trade higher stability for lower market responsiveness. While beta captures how funds respond to overall market swings, alpha provides a measure of value added beyond market exposure. Figure 4 reports the three-year alpha for quantitative and traditional funds, offering insight into whether either group consistently generated excess returns.

The alpha results reveal a persistent underperformance for quantitative funds relative to traditional funds, as shown in Figure 4. Across most of the sample period, quantitative funds posted negative alpha values, suggesting that their returns were largely explained by market exposure rather than manager skill or unique strategy. Traditional funds also exhibited slightly negative alphas overall, but their values were consistently closer to zero and, at times, positive. The gap was especially wide from 2016 to 2022, when quantitative funds recorded their most negative alphas, coinciding with periods of heightened volatility where

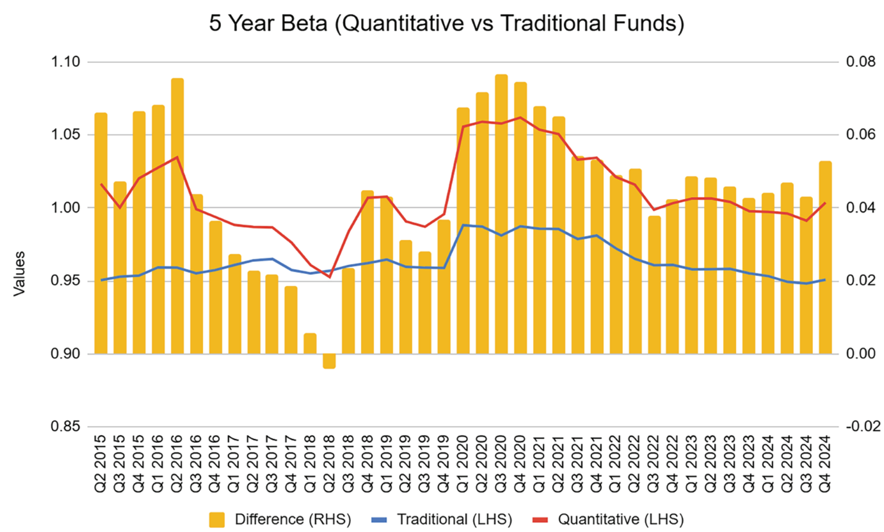

Figure 3. Five-year rolling beta for quantitative and traditional equity funds, 2015–2024. Beta measures a fund's sensitivity to overall market movements and is calculated as the slope coefficient from a regression of fund returns on S&P 500 returns. Values above 1 indicate greater systematic risk exposure, while values below 1 suggest lower sensitivity to market fluctuations. Betas were estimated over rolling 60-month windows to capture longer-term relationships and reduce short-term noise. Funds were categorized using portfolio turnover data: traditional funds were defined as those with quarter-over-quarter turnover below 15.83 percent, reflecting long-term, buy-and-hold strategies, while quantitative funds were defined as those with turnover above 21.65 percent, consistent with AI-driven, higher-turnover trading approaches. Only funds with at least 10 equity holdings were included to ensure comparability.

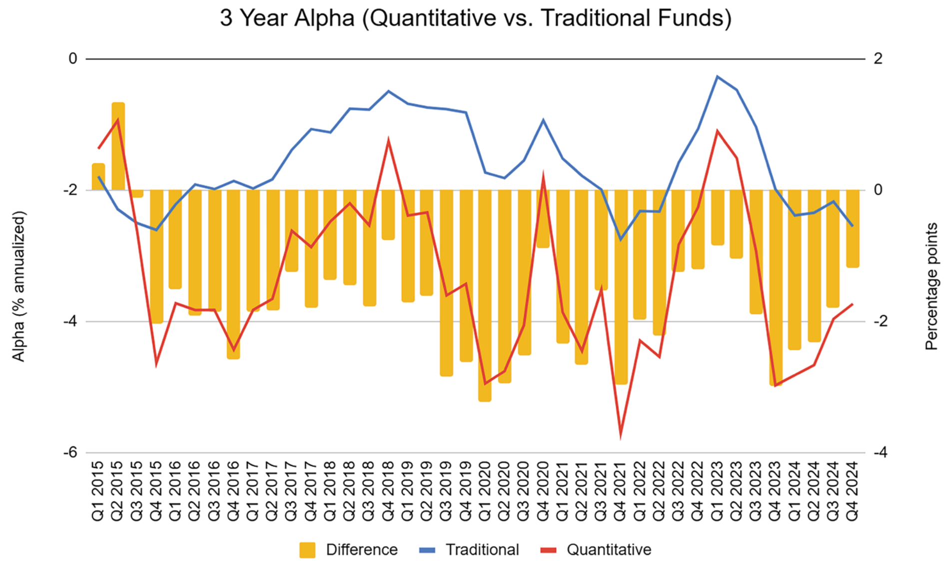

Figure 4. Three-year rolling alpha for quantitative and traditional equity funds, 2015–2024. Alpha measures a fund's excess return relative to the S&P 500 after adjusting for market risk, capturing the manager's ability to generate value beyond broad market exposure. It was calculated using rolling 36-month regressions of fund returns on market returns, with the intercept term representing alpha. Positive values indicate outperformance relative to the benchmark, while negative values indicate underperformance. Funds were categorized using portfolio turnover data: traditional funds were defined as those with quarter-over-quarter turnover below 15.83 percent, reflecting long-term, buy-and-hold strategies, while quantitative funds were defined as those with turnover above 21.65 percent, consistent with AI-driven, higher-turnover trading approaches. Only funds with at least 10 equity holdings were included to ensure comparability.

algorithmic models may have struggled to adapt. More recently, however, the difference narrowed somewhat, reflecting either improvements in AI-driven frameworks or diminishing advantages among traditional managers. It is also important to examine how realized fund performance evolved over time. Figure 5 reports annualized quarter-over-quarter performance for quantitative and traditional funds, highlighting both absolute returns and the relative gap between the two strategies.

For most of the sample period, the performance difference between quantitative and traditional funds was negligible, with both groups closely tracking one another, as shown in Figure 5. The main exception occurred during the onset of the COVID-19 pandemic in 2020, when quantitative funds significantly outperformed their traditional counterparts. This temporary advantage highlights the ability of AI-driven strategies to react quickly in rapidly shifting markets, though outside of this episode, their performance remained broadly in line with traditional approaches.

DISCUSSION

The empirical findings of this study reveal important patterns regarding the integration of artificial intelligence into asset management strategies. First, the volatility results show that quantitative funds, which are assumed to employ greater AI adoption, consistently displayed higher standard deviations compared to traditional funds. This widening gap over the ten-year sample underscores a fundamental feature of AI-driven trading: algorithmic rebalancing and rapid adaptation to short-term signals enhance responsiveness but also amplify exposure to fluctuations. This aligns with López de Prado's caution that machine-learning models often overfit historical data and struggle under new market regimes, leading to instability. For investors and regulators, this persistent volatility emphasizes the trade-off between speed and adaptability on one hand, and stability and predictability on the other.

Second, the Sortino ratio analysis illustrates a deterioration in downside-adjusted performance for

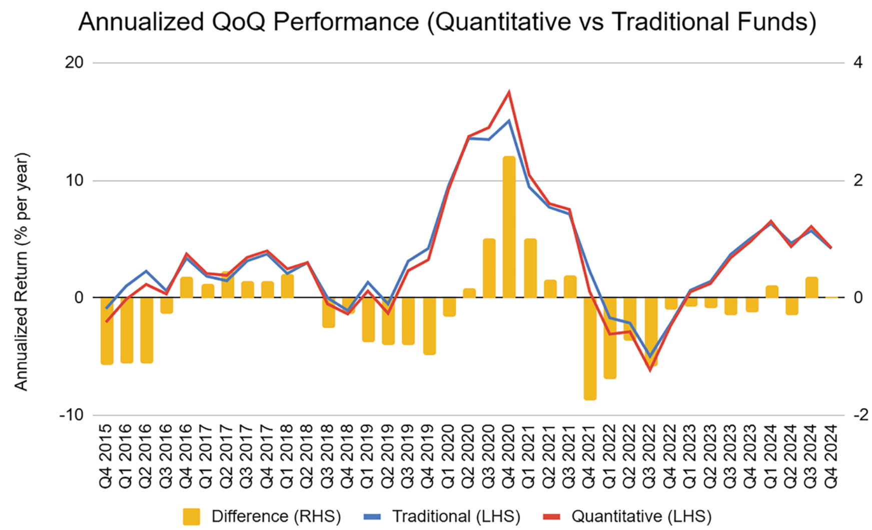

Figure 5. Annualized quarter-over-quarter performance for quantitative and traditional equity funds, 2016–2024. Performance is measured as the compounded quarterly return of each fund, annualized to facilitate comparability across time. Values were calculated over rolling quarterly intervals, with the blue and red lines showing the average performance of traditional and quantitative funds, respectively, and the yellow bars indicating the difference between the two groups. Funds were categorized using portfolio turnover data: traditional funds were defined as those with quarter-over-quarter turnover below 15.83 percent, reflecting long-term, buy-and-hold strategies, while quantitative funds were defined as those with turnover above 21.65 percent, consistent with AI-driven, higher-turnover trading approaches. Only funds with at least 10 equity holdings were included to ensure comparability.

both traditional and quantitative funds. However, the narrowing difference between them suggests that their risk management capacities are converging. Possible explanations include quantitative funds strengthening their controls and scenario testing frameworks, or traditional funds selectively incorporating systematic, data-driven methods into their operations. This convergence resonates with Cao, Jiang, Wang, and Yang's evidence on the benefits of hybrid human–machine collaboration, where blending machine precision with human judgment reduces vulnerabilities.

Third, the beta results demonstrate that quantitative funds were more sensitive to overall market conditions, particularly during 2019–2021, when pandemic-driven volatility pushed their betas well above one. Traditional funds, in contrast, maintained lower and steadier betas. These findings highlight a structural difference: quantitative funds tend to amplify systematic risk exposure, while traditional funds emphasize diversification and long-term positioning. This mirrors regulators' concerns, such as those raised by IOSCO and the Bank of England, about systemic fragility if many AI-driven strategies converge on similar signals during stress events.

Fourth, alpha analysis showed that quantitative funds consistently underperformed relative to traditional funds, with negative alphas throughout most of the sample period. This suggests that AI-driven approaches did not generate sustainable excess returns beyond their heightened market exposure, challenging the assumption that superior data-processing capabilities automatically translate into higher skill. While traditional funds also posted slightly negative alphas overall, their closer-to-zero values indicate a marginally stronger ability to deliver outcomes not entirely explained by market movements. These results echo Lopez de Prado's warning that AI's complexity does not guarantee better performance and may, in fact, introduce fragility.

Finally, realized performance patterns revealed that differences between traditional and quantitative funds were negligible for most of the period, except during the COVID-19 market shock in 2020, when quantitative funds significantly outperformed. This episode underscores one of AI's distinct advantages: the ability to adapt rapidly in crises and capitalize on abrupt regime shifts. Yet the fact that this edge was short-lived suggests that AI's performance benefits are episodic rather than persistent, dependent on contexts where rapid adaptation confers a clear advantage.

Taken together, the results provide a nuanced view of AI's role in asset management. Quantitative strategies bring responsiveness and occasional crisis-time advantages but at the cost of higher volatility, greater sensitivity to systemic risk, and limited persistent alpha. Traditional strategies offer stability and better downside-adjusted returns historically, but their edge appears to be narrowing as both fund types evolve. These dynamics reinforce the importance of governance, disclosure, and regulatory oversight. If investors cannot easily distinguish between AI-driven and traditional funds in terms of downside protection or alpha, transparent disclosures become essential to maintain trust and informed decision-making. Moreover, the evidence suggests that AI's impacts extend beyond individual fund outcomes to systemic considerations, warranting continued attention from regulators tasked with safeguarding financial stability.

CONCLUSION

This study applied a replicable classification method to distinguish traditional and AI-oriented funds using Form 13F holdings and turnover data, producing a decade-long comparative analysis of volatility, downside-adjusted returns, market sensitivity, alpha, and realized performance. Across these dimensions, several clear patterns emerged. Quantitative funds consistently exhibited higher volatility and higher beta, reflecting their reliance on rapid, data-driven rebalancing that amplifies both opportunity and risk. At the same time, their Sortino ratios, though lower than those of traditional funds, converged over time, suggesting that risk management practices may be improving or that traditional managers are integrating systematic methods. Persistent negative alphas for quantitative funds indicate limited success in generating excess returns, challenging the idea that AI-driven strategies reliably add skill-based value. Performance results showed broad similarity between the two groups except during the onset of COVID-19, when quantitative funds' adaptability produced short-term outperformance.

These findings highlight AI's dual role in asset management. On one hand, AI enables responsiveness and adaptability in dynamic markets, as demonstrated during crisis periods. On the other hand, it introduces higher volatility, systemic sensitivity, and a lack of persistent alpha, making it a double-edged tool. For fund managers, the challenge is to calibrate AI's speed and flexibility with safeguards that preserve stability and investor confidence. For policymakers, the results stress the importance of governance, transparency, and disclosure frameworks that ensure investors understand the risks and limitations of AI adoption. For researchers, the classification method provides a foundation for expanding empirical studies into additional asset classes, performance metrics, and direct measures of AI integration.

Overall, the study shows that while AI is reshaping asset management, it does not eliminate fundamental trade-offs between risk, return, and stability. Instead, it shifts how those trade-offs are expressed. As AI continues to mature, the industry's future will likely depend less on whether funds are "traditional" or "quantitative" and more on how effectively human and machine capabilities are integrated to balance performance, resilience, and trust.

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CONFLICT OF INTERESTS

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