Active Machine Learning Based Trading and Mutual Fund Performance*

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ABSTRACT

We propose a novel Active Machine Learning Based Trading (AMLT) measure to comprehensive study the utilization of ML technology by U.S. equity mutual funds to enhance investments and performance. AMLT, a signed active-share measure, captures how mutual funds actively align their portfolio decisions with forward-looking ML-based trading signals, generated from a three-layered Deep Neural Network (DNN) model leveraging extensive quantitative and textual information (i.e., a total of 235 predictors). Our evidence reveals a significant rising trend in the adoption of the AMLT strategy by mutual funds over the past two decades, with top-decile AMLT funds outperforming bottom-decile funds by 2.4% to 3.0% per year on a risk-adjusted basis. We find that the superior performance is driven by better stock selection skills, lower expenses, and efficient trading cost management (i.e., lower portfolio turnover and higher return gap), despite the inherently high turnover of ML-based strategies. Using our flexible methodology, we show that linear quasi-ML models and models with reduced information sets (i.e., solely quantitative or textual inputs) generate at most half the performance of the full AMLT, highlighting ML's ability to process diverse information and capture complex interactions as a key driver of superior fund performance. Additionally, fund managers' skill in combining ML technology with human expertise is another vital contributor to the sustained superior performance observed over long horizon, across different market conditions, and investment styles. Finally, we identify self-designated AI funds and perform comprehensive analysis of AI talent of mutual fund employees to validate our methodology.

Keywords: Mutual Funds, Mutual Fund Performance, Managerial Skill, Machine Learning, Artificial Intelligence, Active Share.
JEL Codes: C55; G11; G14; G23.

1 Introduction

The advancement of artificial intelligence (AI) technology over the past two decades, coupled with the rise of big data, has transformed the landscape of knowledge production (Abis and Veldkamp, 2024). In particular, machine learning (ML), with its remarkable ability to process vast amounts of information at high speed and extract valuable signals, has revolutionized information production. These developments have significant implications for the asset management industry, which depends on rapid and precise information processing to gain competitive edge and generate performance. Therefore, understanding the impact of ML technology on professional asset managers' trading practices and performance outcomes is of critical importance.

It is unclear, ex ante, whether professional investors, such as mutual funds, can effectively leverage this revolutionary technology and utilize ML-generated signals to enhance performance. On the one hand, machine learning models that process vast amounts of information have been shown to produce trading signals with exceptional investment returns, significantly outperforming traditional regression-based strategies.[1] On the other hand, adopting ML technology is highly complex and requires substantial human and physical capital. The greater challenge lies in the difficulty of profitably executing an ML-based trading strategy, which depends on predominantly short-lived trading signals, hard-to-arbitrage stocks, high trading costs, and constrained market conditions (Avramov et al. (2023); Jensen et al. (2024)). Successfully implementing such a strategy demands a high level of investor sophistication and advanced trading expertise.

In this paper, we take on the tasks to comprehensively investigate the adoption of ML-based trading strategy by U.S. active equity mutual funds over the past two decades. We ask the following questions. First, do mutual funds utilize ML-based trading strategy in their

[1]The ability of machine learning models to generate profitable investment opportunities has been extensively documented, see among others Gu et al. (2020); Kelly et al. (2019); Freyberger et al. (2020); Kozak et al. (2020); Lettau and Pelger (2020); Bianchi et al. (2021); Cong et al. (2022); Choi et al. (2024); Feng et al. (2024); Chen et al. (2024); and Han et al. (2024).

investment practices? Second, can ML-based trading help mutual funds to achieve superior portfolio performance? Third, what are the mechanisms that drive performance of funds that adopt the ML-based trading strategy?

To identify the utilization of ML technology in mutual fund investment practices, we propose an Active Machine Learning Based Trading (AMLT) measure. AMLT is a signed active-share measure that captures how a fund actively aligns its portfolio weight deviations from its passive benchmark each quarter with the forward-looking ML-based trading signals for the next period. Specifically, the ML-based trading signals are generated by following the ML return-prediction procedures outlined in Gu et al. (2020) using a Deep Neural Network (DNN) and a near universe of public information inputs, including both extensive quantitative and textual information (i.e. a total of 235 individual predictors).[2] Importantly, since the ML-based trading signal is strictly out-of-sample, mutual funds could trade on it in real time. To capture active trading decisions, we follow the procedure of Cremers and Petajisto (2009) to compute the deviations of fund portfolio weights from its benchmark weights utilizing twenty-one widely used benchmark indexes. The fund-level signed active share measure is then computed by multiplying the active trade deviations by ML trading signal indicators and aggregating the products over all positions. Thus, AMLT comprehensively evaluates a fund's active trading decisions towards its entire portfolio to assess the alignment of its investments with an ML-based trading strategy.

The AMLT measure offers several key advantages in addressing the research questions outlined in this paper. First, it provides a sharp identification of ML adoption specifically in enhancing investment strategy and fund performance. AI adoptions that are unrelated to enhancing portfolio trading and performance, such as customer relations and marketing, are not picked up by the AMLT measure. Second, our methodology enables us to dive deeper into the mechanisms behind performance. AMLT metric allows for easy adaptations

[2]Expanding on the extensive numerical dataset from Green et al. (2017), we incorporate three comprehensive textual corpora widely studied in the literature (financial filings, news, and earnings call transcripts), resulting in a final set of 235 unique predictors.

to measure trading strategies based on different ML models and various categories of information, providing valuable insights into how both ML technology and information inputs contribute to investment outcomes. Third, our holdings-based methodology can be applied to the entire U.S. mutual funds universe at the fund level, enabling a systematic and targeted analysis of the impact of ML adoption on mutual fund trading and performance, while some other identification methods (e.g., based on self-reported information or labor market data) may be subject to data limitations. Nevertheless, we provide validations of our measure by performing a series of analyses, including examining self-designated AI funds identified via online searches, constructing employee AI talent of fund companies following Babina et al. (2024), and investigating trading strategies based on trading signals from individual anomaly categories.

First, using a comprehensive sample of actively managed U.S. equity funds over the period from 2002 to 2022, we find evidence of mutual funds adopting ML-based trading strategies, with substantial variation in adoption both cross-sectionally and over time. The sample median of AMLT is around zero, while the standard deviation is about 65% with a decile spread of 223%. Moreover, by focusing on AMLT_tilt, a component of AMLT that captures correct portfolio tilts based on ML signals, we observe that funds in the top AMLT decile correctly align with ML signals by 23.3% in terms of active portfolio tilts from their benchmark, while funds in the bottom AMLT decile misalign by 36.5%. Second, we observe a significant increase in the adoption of the AMLT strategy by mutual funds over time. For example, the AMLT measure at the 80^{th} percentile begins at 20% in the early 2000s and gradually accelerates, reaching almost 45% by 2022. This trend is further confirmed by an AI adoption measure we constructed based on labor market information. We find the share of employee with core AI talent of mutual fund advisory companies began at around 0.99% in the early 2000s and reach about 1.93% in 2022. Finally, the upward trend prevails in almost all style groups.

Examining determinants of AMLT strategy, we find a series of interesting results. First,

better-performing funds, as indicated by strong past returns and low fund risk, achieve higher AMLT and they charge lower expenses. Second, our evidence shows that high AMLT funds are capable of effectively managing trading costs, while aligning their portfolio with ML signals. Despite the extremely high turnover associated with the ML strategy (i.e., 113% monthly decile portfolio turnover spread in Gu et al. (2020)), we find funds with high AMLT exhibit low turnovers. Moreover, small funds are good at following the AMLT strategy, consistent with that funds with small total assets are in a better position to manage trading impact in forming ML-based portfolios (Jensen et al., 2024). Time-series wise, we find AMLT is higher in high VIX periods, consistent with the evidence that ML signals generate stronger profits amid elevated market volatility. Additionally, AMLT is also higher in non-recession periods, suggesting that funds are good at stock selections during market expansions (Kacperczyk et al., 2012).

Our second set of evidence focuses on performance outcomes of AMLT. We find that funds employing the AMLT strategy achieve superior abnormal returns. Specifically, funds in the top AMLT decile generate a significant abnormal performance of 1.1% to 1.4% annually across various risk adjustment models, outperforming those in the bottom AMLT decile by 2.4% to 3.0% per year. These findings are robust across various trading signal transformations and are particularly strong for transformations that emphasize long positions. Further, performance decomposition shows that superior performance of AMLT funds stems from better stock selection skills, lower expenses, and higher return gap, indicating superior interim trading benefits and lower trading costs.

Importantly, we find strong persistence in both the AMLT measure and future fund performance, suggesting Active ML-based trading is a deliberate and consistent strategy that funds employ to achieve sustainable performance. Additionally, the transition matrix analysis reveals that, beyond delivering superior performance, high AMLT funds also exhibit higher survival rates compared to low AMLT funds.

Our third set of evidence illustrates the underlying mechanisms behind AMLT perfor-

mance. We find that great information processing capacity of ML technology and human investment skills are the two main drivers of the superior performance of AMLT funds. First, consistent with the strength of machine learning models at processing vast amounts of information, we find that high AMLT funds holding companies with a greater volume of information inputs achieve even stronger performance. Second, the ability of ML technology in accommodating complex interactions among diverse information sets contributes to AMLT performance. We find AMLT based on Elastic Net (ENet), a quasi-ML model, that does not accommodate complex interactions in predictions generates fund performance that is only 49% of that of the full AMLT funds. Moreover, employing ML-based strategies that rely solely on quantitative information and solely on textual information generate one half and one third of the performance of the full-scale AMLT strategy, respectively. Together, our evidence shows that the number, diversity of information inputs, and interactions among different types of inputs play crucial roles in driving superior performance from the ML-based strategy.

Another key driver of outperformance is the ability of mutual fund managers to combine their investment and trading expertise with ML-based signals to successfully implement the AMLT strategy. We find, AMLT-adopting funds tilt their portfolios toward larger stocks, more liquid stocks, and stocks with greater information inputs to fully leverage the strengths of ML technology. Moreover, implementing ML-based trading strategies in practice presents significant challenges because such strategies rely on short-lived trading signals, high turnovers, hard-to-arbitrage stocks, and constrained market conditions. In sharp contrast to these challenges, we find that high AMLT funds are able to generate persistent long-term performance and perform well in all market conditions (i.e., based on the level of VIX, investor sentiments, and illiquidity) and across all investment styles. Impressively, these funds also manage trading costs well, as evidenced by their lower portfolio turnover and higher return gap. Our results therefore echoes the insights of Cao et al. (2024) in that superior mutual fund performance from AMLT is the result of a powerful combination of

human investment expertise and advanced ML technology.

Our last set of analyses provide further validation to our results. First, we identify a small sample of self-designated AI funds through fund names and extensive online searches. We find significantly higher AMLT associated with self-designated AI funds, illustrating the capability of AMLT measure in picking up AI-adopting funds. Next, using employee profile data from Lightcast, we construct the share of mutual fund employees with core AI skills, with core AI skills being defined as AI, ML, Natural language processing, and Computer Vision following Babina et al. (2024). We find that this AI talent measure based on labor market information is highly correlated with our trade-alignment based AMLT. When putting both measures together, AMLT remains the only significant predictor of future fund performance. These findings provide additional support to our holding-based methodology and illustrate the strength of AMLT in capturing AI adoption specifically aimed at enhancing trading strategies and fund performance. In contrast, the AI talent measure may capture AI adoption for broader business operations unrelated to investments and may be coarse due to data coverage limitations. Lastly, we demonstrate that AMLT performance is unlikely driven by other strategies. For example, none of the strategies based on trading signals of the six anomaly categories (Hou et al., 2020) exhibit significant performance. This is consistent with the in-sample nature of anomaly profits that tend to disappear in recent years, and the concentration of such profits on the short side, which makes them difficult for mutual funds to capture (McLean and Pontiff (2016); Avramov et al. (2023)).

We contribute to the broader mutual fund performance literature by examining the timely and critical question of how mutual funds implement the cutting-edge ML technology in their investment practice to enhance fund performance. Through a comprehensive analysis of U.S. active equity mutual funds over the past two decades, we document a clear upward trend in the adoption of ML technology in trading and demonstrate the significant value added by this practice. For our research purposes, we develop a novel signed active-share measure, AMLT, that quantifies the extent to which funds actively align their portfolio investment de-

cisions with ML-generated trading signals. Our method is unique in that it is grounded in a thorough examination of funds' investment actions and avoids capturing AI adoptions unrelated to portfolio investments. Methodologically, our paper is closely related to the mutual fund performance literature that employs holdings-based measures to assess fund performance (Daniel et al. (1997), Kacperczyk et al. (2007), Kacperczyk et al. (2008); Huang et al. (2011)) and in particular, the growing literature examining the activeness of portfolio management (e.g., Cremers and Petajisto (2009); Cremers et al. (2013); Petajisto (2013); Stambaugh (2014); and Jiang and Zheng (2018)). By combining active weight deviations with the powerful ML trading signals, the AMLT measure not only helps enhance performance evaluation but also provides a metric for understanding the underlying investment strategy driving the value added.

Second, our paper also contributes to the literature that examines information utilization and fund performance. Although some mutual fund managers can add value by following private information (Cohen et al., 2008), reliance on public information, such as analyst recommendations or news coverage are associated with poor fund performance (Kacperczyk and Seru (2007); Fang et al. (2014)). However, the substantial advancement of AI technology over the past two decades has significantly transformed the landscape of information production (Abis and Veldkamp, 2024). By focusing on ML-based strategies capable of efficiently processing vast amounts of public information and extracting valuable trading signals, our study provides new insights into how advanced AI technology can help funds gain informational edge and drive superior performance. With the flexibility of our methodology, we further illustrate that the volume of information inputs (i.e., total number), the diversity of information (e.g., qualitative and textual data), and the interplay among various information inputs (i.e., complexed interactions) all contribute to the ML-driven information edge and the superior outperformance of the AMLT strategy.

Third, our paper contributes to a fast growing literature that examines the utilization of machine learning models in various areas in finance, e.g., predicting asset prices (Gu et al.

(2020); Lettau and Pelger (2020); Bianchi et al. (2021); Chen et al. (2024); and Han et al. (2024)), robo-advising (D'Acunto et al., 2019), earnings forecast (Van Binsbergen et al., 2023), analyst's recommendation (Cao et al., 2024), fund performance evaluations (Li and Rossi (2020); Kaniel et al. (2023), and DeMiguel et al. (2023)), lending decisions (Liu (2022); Fuster et al. (2022)), innovation evaluation (Zheng, 2024), and estimating bank risk (Hanley and Hoberg, 2019). Our paper contributes to this literature by focusing on the application of ML trading signals in real investment practices of mutual funds. While ML models have shown substantial theoretical investment profits, existing literature highlights the significant challenges of implementing ML-based trading strategies in practice due to the concentrations in hard-to-arbitrage stocks, fleeting signals and high trading costs (Avramov et al. (2023); Jensen et al. (2024)). Our study advances this literature by demonstrating that mutual fund managers possess the skills to successfully integrate machine learning signals into their portfolio investments, generating superior and persistent fund performance. Our evidence aligns with the insights of Cao et al. (2024).

Our paper adds to the understanding of how the rise of new technologies, including both AI and new data, is reshaping the asset management industry. Bonelli and Foucault (2023) explore how the emergence of alternative data affects mutual fund investment practices. Several recent papers measure the hiring of AI talent and data scientists at the asset management company level and examine how labor market practices influence business operations (Chen et al., 2025) or investment outcomes (Zhang (2024); Cen et al. (2024)) of asset managers. Our paper differs from these studies in that we study how mutual funds adopt ML-generated trading signals specifically aimed to enhance investment strategies and performance. To this end, our method is unique and is rooted in examining active trading decisions of mutual funds. In a related paper, Sheng et al. (2024) shows that the utilization of ChatGPT to process conference call information helps hedge funds generate performance. While ChatGPT is an emerging technology since 2022 that can be easily adopted by a wide range of investors, our study focuses on a comprehensive study of how sophisticated investors

utilize the far more complex ML technology in trading practice, a topic that demands special attention because professional money managers have both the capability and the need to establish an information advantage through implementation of cutting edge technology as it becomes available. We highlight the rising trend of mutual funds adopting ML-powered trading strategy over the past two decades and show that such a strategy enables mutual funds to add value through the remarkable information processing capability with exhaustive data inputs.

The rest of the paper is organized as follows. In Section 2, we discuss data and sample constructions. Section 3 introduces the AMLT measure, presents the ML models, and the ML-based trading signals. The baseline results of AMLT and fund performance are presented in Section 4. Section 5 dives into the ML-driven information advantage and AMLT performance. Section 6 provides additional analysis on AI funds, Quant funds and AI employee talent, and Section 7 concludes.

2 Data and Sample Construction

In this section, we briefly discuss the evolution of AI and ML technologies and their growing adoption by the asset management industry to enhance investment decision-making, followed by a discussion of our data and sample construction.

2.1 The Evolution of AI and ML technologies and the adoption in Asset Management

Artificial intelligence (AI) broadly refers to computational systems designed to replicate human cognitive functions such as pattern recognition, decision-making, and problem-solving (Russell and Norvig, 2016). Within AI, machine learning (ML) is a subset that focuses on algorithms that learn from data and improve predictive performance without explicit programming (Mitchell, 1997).

ML methods can be categorized based on their complexity and ability to model relationships in data. Regularized linear models, such as ridge Regression, LASSO regression, and elastic net, provide robust predictive modeling by penalizing large coefficients and selecting relevant features. Beyond linear methods, decision trees, and ensemble models like random forests allow for nonlinearities. Further advancements, such as Gradient boosting techniques refine predictive accuracy by iteratively improving weak models. At a more advanced level, neural networks and deep learning methods enable the capture of highly complex, nonlinear relationships.

Early adoption of ML in asset management can be traced back to the 1990s, as computational advancements enabled firms to develop more sophisticated trading and risk management strategies. One of the earliest and most successful adopters was Renaissance Technologies, which established its flagship Medallion Fund in 1988. The firm uses computer-based models, such as pattern recognition, analyzing as much data as can be gathered to identify market patterns. In the mid-1990s, Goldman Sachs launched the Global Alpha Fund, a quantitative hedge fund that employed computer-driven models to evaluate risks and identify investment opportunities across various asset classes. These early implementations of ML and AI laid the groundwork for the widespread adoption of advanced computational techniques in asset management, significantly influencing modern investment strategies.

A major breakthrough occurred in the early 2000s with the increasing adoption of neural networks in financial modeling. Originally conceptualized by McCulloch and Pitts (1943), neural networks gained practical relevance following the development of the backpropagation algorithm (Rumelhart et al., 1986), which enabled efficient training of multi-layer networks. LeBaron (1999) demonstrated the viability of neural networks in forecasting asset returns, further solidifying their importance in quantitative finance. With the increasing availability of financial data and improvements in computational power, neural networks emerged as a feasible and scalable solution for asset managers in the early 2000s.

The 2010s marked a paradigm shift in AI adoption within asset management, driven

by the explosion of big data and advancements in deep learning. Asset management firms increasingly turned to natural language processing for sentiment analysis, reinforcement learning for dynamic portfolio optimization, and deep neural networks for anomaly detection. Leading asset management firms including both hedge funds and mutual funds, such as BlackRock, Two Sigma, AQR, Vanguard Group, State Street Global Advisors, and Cerebellum Capital, leveraged these AI-driven models to extract predictive signals from diverse data sources, including macroeconomic reports, alternative datasets, and textual sentiment analysis.[3] The integration of deep learning in asset management has enabled more sophisticated investment strategies, reinforcing the industry's reliance on AI.

Despite indications of AI adoption in asset management from news, online articles, and fund websites, the extent to which the industry integrates ML into trading strategies remains largely unknown, as asset managers may not have incentives to disclose their underlying trading strategies to public or competitors. This is especially true for mutual funds, who already operate under greater scrutiny and face stricter disclosure requirements.

Recognizing this challenge, in this study, we propose a unique trade-alignment-based measure, Active Machine Learning Based Trading (AMLT), based solely on fund portfolio holdings, to systematically study the adoption of ML by the mutual fund industry in enhancing trading and performance. As AI continues to reshape the investment landscape, a systematic assessment of ML adoption in mutual fund trading is crucial for assessing the overall impact of AI on asset management and financial markets.

[3]https://hedgefundalpha.com/ai-hedge-fund-returns;
https://www.wired.com/2016/01/the-rise-of-the-artificially-intelligent-hedge-fund;
https://www.statestreet.com/alpha/insights/artificial-intelligence;
https://ir.vcm.com/news/news-details/2016/Victory-Capital-Announces-Investment-in-Cerebellum-Capital;
https://www.bloomberg.com/news/articles/2024-02-06/vanguard-quietly-embraces-ai-in-13-billion-of-quant-stock-funds
https://loanworks.ai/artificial-intelligence-in-financial-services-a-historical-review

2.2 Data Sources

Mutual fund data

For our research purposes, we focus on U.S. actively managed equity mutual funds over the period 2002 to 2022 based on the CRSP Survivorship Bias Free Mutual Fund database. The CRSP database includes mutual fund characteristics such as fund returns, total net assets (TNA), fees, flows, and investment objectives. We exclude balanced, bond, international, money market and index funds, as well as funds that on average hold less than 80% of their assets in common stock if the investment objective is missing. To avoid the incubation bias identified by Evans (2010), we also exclude funds that in the previous month manage less than $10 million, funds with missing fund names in the CRSP database, and funds for which the observation year is in the same year or in an earlier year than the reported fund start. Mutual fund share classes are aggregated at the fund level. We aggregate fund returns, expense ratios, and turnover ratios by asset-weighting the corresponding characteristics of the individual share classes. The TNA of a fund is aggregated by summing the TNAs of the individual share classes, and fund age is set to the age of the oldest share class.

We merge the CRSP mutual fund database with the Thomson-Reuters Mutual Fund Holdings database and the CRSP Stock Database using the MFLINKS file based on Wermers (2000) and available through Wharton Research Data Services (WRDS). The Thomson-Reuters data provides mutual funds' equity holdings on specific disclosure dates, which allow us to study mutual fund investment and trading decisions.

Table 1 presents summary statistics for the equity mutual funds in our sample. Panel A presents the summary statistics for fund characteristics at the quarterly level. Funds in our sample have an average expense ratio of 1.022% and exhibit a turnover ratio of about 60.1%. The average fund manages $2,469 million and is around 16 years old. The average fund family total net asset value is about $63,286 million. For risk-related variables, the average total risk is 4.845, while the market beta has a mean of 1.033 with a standard deviation of

0.221, indicating that most funds exhibit market exposure close to one. The idiosyncratic volatility has an average of 1.160, while the active share measure, which captures the extent of deviation from benchmark holdings, has a mean of 0.706, suggesting active management across funds. Panel B provides summary statistics for monthly fund returns. The average monthly net fund return is 0.669%, with a standard deviation of 5.076%. The risk-adjusted returns, computed using the CAPM, Fama-French three-factor model, and Carhart four-factor model, all exhibit negative mean values, suggesting that, on average, mutual funds do not outperform passive benchmarks on a risk-adjusted basis. The average return gap is -0.077%.

Firm-level predictors

Next, we discuss the data that underlies our ML-based trading signals. We define our firm universe as all publicly traded companies listed on the NYSE, AMEX, or NASDAQ that have common stock outstanding, a reported month-end market value in CRSP, and a non-missing book-to-market ratio from Compustat. Monthly stock returns are sourced from CRSP, incorporating delisting returns following the methodology of Shumway and Warther (1999). Similar to Gu et al. (2020), we do not apply any filters to the firm universe. Our sample spans from 1987 to 2022, covering 18,803 unique stocks, with an average of 4,708 stocks per month. We compute individual stock excess returns using the Treasury-bill rate as a proxy for the risk-free rate. To construct our predictive variables, we incorporate a comprehensive set of information inputs, including both extensive quantitative and qualitative (textual) predictors, drawing on insights from previous literature on both asset pricing, textual and sentiment analysis in Finance.

For the quantitative set, we follow Gu et al. (2020), incorporating 94 stock-level characteristics as in Green et al. (2017).[4] Among these, 61 are updated annually, 13 quarterly, and 20 monthly. Additionally, we include 74 industry dummies based on the first two digits of

[4]Appendix Table in Green et al. (2017) lists all variables, their definition and source.

the Standard Industrial Classification (SIC) codes.

In addition to the extensive quantitative information, we significantly expand the information set by incorporating three comprehensive textual corpora widely used in the literature on textual and sentiment analysis. Specifically, for the qualitative (textual) information, we construct firm-level predictors from three distinct textual corpora. These include financial filings (10-K, 10-Q, and 8-K reports) from SEC Analytics (27 predictors) starting from 1997, earnings call transcripts from Wall Street Horizons (19 predictors) starting from 2004, and firm-specific news articles from RavenPack News Analytics (10 predictors) starting from 2000, which covers more than 40,000 news media sources globally. Those textual predictors include fundamental attributes such as file size and word counts, as well as sentiment variables derived from dictionaries proposed by Loughran and McDonald (2011) and Garcia et al. (2023).

Beyond firm-specific characteristics, we include eight macroeconomic predictors following Welch and Goyal (2008) and three stock-level institutional ownership variables: the number of 13F institutional investors holding the stock, the percentage of shares outstanding owned by 13F institutional investors, and the ownership concentration as measured by the Herfindahl-Hirschman Index. In total, our dataset comprises 235 individual predictors.

We align all characteristics in calendar time, imposing data availability constraints to ensure realistic implementation. We assume annual accounting data is available in month t if the firm's 10-K was published in month t or if the fiscal year-end occurred at least six months prior. Annual data remains available for up to 12 months after its initial release. Similarly, we assume quarterly accounting data is available in month t if the firm's 10-Q was published in month t, if the report date (RDQ) in Compustat corresponds to month t, or if four months have passed since the fiscal quarter-end. Quarterly data remains available for up to four months after publication. Monthly data, such as past stock returns and IBES forecasts, are assumed to be available instantaneously.

Employee profiles and AI skills

Finally, to enhance our study with additional analyses and validations, we use labor market information from Lightcast (formerly BurningGlass), who provides both extensive employee profile and job posting data. For over two decades, Lightcast has systematically collected job postings from more than 160,000 online sources and aggregated publicly available individual resumes and professional profiles from linked-in and other online platforms. Lightcast profile data covers 140 million employees spanning the period from 2000 to 2024. It provides detailed information on employer names, employee job titles, skills, occupation categories, educational background, and employment history, enabling us to perform a systematic investigation of the AI talent of mutual fund employees.

3 Machine Learning Model and Mutual Fund Trading Strategy

To investigate the adoption of ML technology by mutual funds specifically to enhance investment strategy and fund performance, we propose an Active Machine Learning Based Trading (AMLT) measure. We define our measure and provide some discussions of our methodology in this subsection.

3.1 Active Machine Learning Based Trading measure

Construction of AMLT measure

AMLT is constructed as an signed active-share measure in the spirit of Cremers and Petajisto (2009) and Jiang and Zheng (2018), capturing the alignment of a fund's active portfolio weight deviations from its benchmark with the ML-based trading signals.

Formally, we define $AMLT_{f,t}$ for mutual f at quarter t as:

$$AMLT_{f,t} = \sum_{i=1}^{n} \left(w_{i,t}^{f} - w_{i,t}^{B} \right) \times ML\ Signal_{i,t+1|t} \tag{1}$$

where $w_{i,t}^{f}$ denotes the portfolio weight of stock i in fund f at the end of quarter t, and $w_{i,t}^{B}$ denotes portfolio weight of stock i in fund f's benchmark portfolio at the end of quarter t. $ML\ Signal_{i,t+1|t}$ is a forward-looking ML-based trading signal for stock i in the subsequent quarter $t+1$ given information available at the end of quarter t.

Specifically, at each quarter t, we assume that funds utilize information available up to that quarter t to generate ML-based stock return predictions for the upcoming quarter $t+1$. Based on these predictions, funds make active adjustments of their portfolio weights relative to their benchmark portfolio during quarter t. Therefore, AMLT at quarter t measures how a mutual fund actively aligns its investments in quarter t with forward-looking ML-based trading signal for quarter $t+1$ based on information available at quarter t.

AMLT measure is constructed based on the products of two components: the active portfolio deviations and ML-based trading signals. First, to measure a fund's active portfolio weight deviations from its benchmark, we follow the literature and select the benchmark index from a set of twenty-one widely used indices from the S&P/Barra and Russell families.[5] Following Cremers and Petajisto (2009), for each fund each quarter, we compute the active share measures of the fund with respect to all twenty one indexes and then pick as the fund's benchmark the index that produces the lowest active share. This approach ensures that the selected benchmark best represents the fund's investment strategy and asset allocation.

Second, to construct ML-based trading signals, we apply a rank-based transformation to raw ML predictions to reduce noise. Each quarter, we sort stocks into deciles based on

[5]Specifically, we use nine indices from the S&P/Barra family, including the S&P 500, S&P 500/Barra Growth, S&P 500/Barra Value, S&P MidCap 400, S&P MidCap 400 Growth, S&P MidCap 400 Value, S&P SmallCap 600, S&P SmallCap 600 Growth, and S&P SmallCap 600 Value, and twelve indices from the Russell family, including the Russell 1000, Russell 2000, Russell 3000, and Russell Midcap, along with their respective value and growth subcomponents.

ML-generated predictions for the stocks for the subsequent quarter. Stocks are assigned a score ranging from -5 to +5, with those in the bottom decile (lowest predicted returns) receiving an ML signal of -5 and those in the top decile (highest predicted returns) receiving an ML signal of +5. The transformation ensures that the ML signal reflects the relative ranking of stocks rather than relying on potentially noisy return predictions, enhancing the interpretability and stability of the AMLT measure. Based on this signal transformation, we construct our baseline AMLT measure. In addition, given that mutual funds tend to follow long-only investment strategies due to regulation constraints on leverage and short-selling, we also apply an alternative asymmetric transformation that emphasizes the long side of the ML-based trading opportunities. Specifically, we assign a score ranging from +1 to +5 to stocks in the top 5 deciles based on the ML predictions and 0 for those in the bottom 5 deciles. We construct the AMLT_long measure accordingly.[6]

Overall, AMLT, as a signed active share measure weighted by ML trading signals, captures the degree by which a mutual fund aligns its investments with ML-based trading signals. Therefore, a high AMLT means that the fund is actively engaged in ML-based trading strategy.

Finally, we also construct a simple AMLT_tilt measure to better capture the magnitude of the correct alignments of a fund's active deviations with the ML predictions. Specifically, we multiply a fund's active deviation toward a stock by either +1 or -1, depending on whether the trade is considered aligned with the ML prediction or not (i.e. +1 (-1) for trades toward stocks ranked above (below) the cross-sectional median of ML predictions). AMLT_tilt therefore captures the percentage portfolio deviation of a fund that aligns (misaligns) with the ML signals.

[6]To ensure robustness, we also perform additional transformations to emphasize the most valuable signals. For example, we assign a number ranging from +1 to +3 (-1 to -3) for top (bottom) 3 deciles and 0 otherwise for alternative symmetric transformation, and a number ranging from +1 to +3 for only top 3 deciles and 0 otherwise for corresponding asymmetric transformations.

Discussion of AMLT measures

We aim to study ML adoption by mutual funds specifically in enhancing investment strategy, obtaining information edge and improving fund performance. The AMLT measure offers several key advantages in addressing these research questions.

First, it provides a sharp identification of ML utilization specifically in trading practices, rather than in other tasks. For example, fund companies may adopt AI technology to enhance other aspects of business operations such as customer relations, marketing and retail financial planning, and other general tasks such as IT and data management. AMLT measure will not pick up these AI adoptions unrelated to enhancing portfolio trading and performance.

Second, our methodology enables us to dive deeper into the mechanisms behind performance. AMLT metric allows for easy adaptations to measure trading strategies based on different ML models (e.g. Elastic Net utilizing a linear transformation of inputs) and various categories of information (e.g. quantitative versus textual inputs, sub-categories of anomalies and textual inputs), enabling us to gain valuable insights into how key features of ML technology and various information inputs contribute to investment outcomes.

Third, our holdings-based methodology can be applied to the entire U.S. mutual funds universe at the fund level, enabling a systematic and targeted analysis of the impact of ML adoption on mutual fund trading and performance, while other identification methods (e.g., based on fund names, prospectus, or labor market information) can be subject to data and coverage limitations.

To provide validations to our measure, we perform a series of analyses. First, in Section 6.1, we identify a small sample of self-designated AI funds and quant funds through fund names and extensive online searches. If the AMLT measure captures AI adoption in investments, we should expect higher AMLT associated with self-designated AI funds as compared to other funds in the same style. Further, traditional quant funds focus on trading strategies based on conventional statistical models and quantitative information inputs (such as stock prices, earnings and market trends). AI funds can be viewed as a subset of quant funds that

are more advanced in adopting cutting-edge AI technologies. Therefore, we should expect the average AMLT measure of quant funds to be higher than a typical mutual fund but lower than full-fledged AI funds, and AMLT of quant funds should come primarily from aligning trades with quantitative signals. Our evidence in Section 6.1 supports these conjectures.

Second, in Section 6.2, we construct AI adoption measure using labor market information. Using employee profile data from Lightcast, we compute the share of mutual fund employees with core AI skills following Babina et al. (2024). If AMLT captures AI adoption in mutual fund investments, we should expect funds with high AMLT to have high employee AI talent. In addition, if AMLT provides a sharper identification of AI adoption specifically in enhancing investment strategy and performance than labor-market-based AI adoption measure, we should expect AMLT to dominate labor-market-based measures of AI talent in predicting fund performance. Our evidence in this subsection supports both hypotheses.

Third, in Section 5.2, we compare AMLT with other hypothetical strategies based on individual information input, such as strategies based on trading signals of the six individual anomaly categories (Hou et al., 2020) and ten individual anomalies. In contrast to the out-of-sample nature of ML-based trading signals that comes from both long and short sides, anomaly profits tend to be in-sample, disappear over time and concentrate on the short side that are hard for mutual funds to capture (McLean and Pontiff (2016); Avramov et al. (2023); and Akbas et al. (2015)). Therefore, we do not expect mutual funds to add value by following individual anomalies and AMLT performance should not come from these individual trading signals. Our evidence lends support to this conjecture.

Lastly, if AMLT picks up other random signals that happen to be correlated with ML signals, we should not expect funds to exhibit persistent AMLT over time. Our evidence in Section 3.3 (i.e., the transition matrix and time-series plot of AMLT) supports the persistence of AMLT.

3.2 Machine Learning Model

One of the key components of the proposed AMLT measure, defined in Equation 1, is the ML-based trading signal. In this subsection, we establish our ML return prediction procedure and the profitability of the resulting ML trading signals.

Machine Learning Based Trading Signals

It is paramount that the ML-based trading signal is out-of-sample, not suffering from any forward looking bias, so that a hypothetical mutual fund could trade on it in real time. We follow the ML procedures outlined in Gu et al. (2020), describing a stock's expected return with a flexible prediction function:

$$E_t(r_{i,t+1}) = \hat{g}(z_{i,t}; \theta) \tag{2}$$

where $E_t(r_{i,t+1})$ represents the expected excess return $r_{i,t+1}$ for stock i during the subsequent quarter $t+1$, vector $z_{i,t}$ is the full set of predictors, and θ denotes the parameter set of the prediction model.

We select a traditional feed-forward neural network architecture as our prediction model $g(\cdot)$. This structure consists of an input layer comprising raw predictors, one or more hidden layers that capture interactions and apply nonlinear transformations, and an output layer that synthesizes information from the hidden layers to generate predictions.

We select a three-layer architecture (NN3) consisting of 32, 16, and 8 neurons in successive hidden layers. Across all layers, we employ the rectified linear unit (ReLU) activation function, a widely used choice that promotes sparsity and facilitates efficient gradient-based optimization. We adopt following transformation to the dependent variable and the predictors. We first winsorize excess returns to at -25% and 25% and subsequently standardize them cross-sectionally. Predictors are rank-transformed and scaled to range from 0 to 1.

We also employ an ensemble approach to training our neural networks, following the

methodologies of Hansen and Salamon (1990) and Dietterich (2000). Specifically, we initialize the neural network estimation with multiple random seeds and aggregate predictions by averaging forecasts across ten trained networks. This technique mitigates prediction variance by reducing sensitivity to the stochastic nature of the optimization process, which can lead to variations in forecasts depending on the initialization.

To optimize model performance, we tune hyperparameters through grid search, utilizing a 10-year training window and a 4-year validation window. Our out-of-sample predictions commence in 2002. Given the substantial computational cost of machine learning models, we do not re-estimate the network each month. Instead, we re-tune hyperparameters annually, rolling the training and validation windows forward by one year while maintaining a consistent sample length. However, we re-estimate the model using the selected hyperparameters for every monthly prediction. This approach balances computational efficiency with adaptability, ensuring that the model remains responsive to evolving market conditions.

Taken together, at the end of each month t and using the estimated neural network $\hat{g}(\cdot)$, we generate the expected return for each stock i during the subsequent quarter.

Portfolio Performance

Next, we validate the ML-based trading signal by documenting that a portfolio strategy based on it creates alpha. At the end of each quarter, we sort stocks into deciles based on the ML trading signal and compute the monthly portfolio returns over the subsequent three months. The portfolios are rebalanced quarterly, and stocks within each decile are assigned equal weights. Finally, we then construct a zero-net-investment portfolio that takes a long position in the stocks within the highest decile (decile 10) and a short position in those within the lowest decile (decile 1).

Table 2 presents the out-of-sample performance results for the ML portfolios. On average, each portfolio consists of 463 stocks. The bottom decile portfolios exhibit either negative monthly returns or returns that are not significantly different from zero, whereas

the top decile portfolios generate significantly positive average monthly returns. The top long portfolio (decile 10) achieves an average monthly raw return of 1.2% (equivalent to 15.0% annualized) with an average monthly volatility of 4.5% (annualized at 15.6%). Meanwhile, the long-short portfolio, which goes long in the top decile and short in the bottom decile, earns an average monthly raw return of 2.1% (25.3% annualized) with an average monthly volatility of 7.7% (26.7% annualized). The magnitudes are highly consistent with Gu et al. (2020)[7].

We estimate the risk-adjusted returns on the portfolios as intercept alphas from time-series regressions, using the capital asset pricing model (CAPM) with the market factor, Fama and French's (1993) three-factor model and Carhart's (1997) four-factor model, which augments the Fama-French factors with Jegadeesh and Titman's (1993) momentum factor and the five-factor model, which adds Pástor and Stambaugh's (2003) liquidity risk factor to the four-factor model. For instance, the Carhart four-factor alpha is the intercept from the following time-series regression:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{p,m}(R_{m,t} - R_{f,t}) + \beta_{p,SMB} SMB_t + \beta_{p,HML} HML_t + \beta_{p,UMD} UMD_t + \varepsilon_{p,t} \quad (3)$$

where $R_{p,t}$ is the return in month t for fund portfolio p, $R_{f,t}$ is the 1-month Treasury-bill rate in month t, $R_{m,t}$ is the value-weighted stock market return in month t, SMB_t is the difference in returns between small and large capitalization stocks in month t, HML_t is the return difference between high and low book-to-market stocks in month t, and UMD_t is the return difference between stocks with high and low past returns in month t.

Risk-adjusted performance measures further confirm the economic significance of the ML portfolios. For all models, risk-adjusted monthly returns are all positive and highly significant for both the top long portfolios and the long-short portfolio. For instance, the long-short portfolio delivers a monthly CAPM alpha of 2.6%, translating to an annualized

[7]See Gu et al. (2020) Table 7, performance of the machine learning portfolios for NN3.

alpha of 31.3%, underscoring the ability of ML-based signals to generate abnormal returns beyond traditional risk factors.

3.3 AMLT, Fund Characteristics and Time Trend

With the ML-based trading signals generated from the previous section, we compute AMLT measure following Equation 1 for our mutual fund sample. Table 1 presents the summary statistics. Overall, the median AMLT is around zero, while the standard deviation is about 65.0%, indicating a substantial variation in the adoption of ML-based trading strategies. Similarly, the median AMLT_long (AMLT_tilt) is around zero but with a standard deviation of 43.2% (18.3%).

Next, we examine how AMLT is related to various mutual fund characteristics and market conditions, the overall time trend, as well as the persistence of AMLT.

Fund Characteristics

In Panel A of Table 3, we sort mutual funds in our sample into decile portfolios according to AMLT each quarter and compute various fund characteristics of each portfolio. First, we observe that AMLT varies significantly in the cross-section. Funds in the top decile exhibit an average AMLT of 87.2%, while funds in the bottom decile show an average AMLT of -135.7%. Since AMLT is a signed AMLT measure weighted by ML trading signals, to better understand the magnitude of active deviations made by funds, in the second column, we present AMLT_tilt. We observe that funds in the top AMLT decile actively deviate from their benchmark by 23.3% of their portfolio weights to align with ML trading signals, while funds in bottom AMLT decile make the opposite move, misaligning with ML signals by 36.5%.

We next examine fund characteristics by AMLT portfolios. A few interesting results emerge. First, we observe that funds with better past performance exhibit higher AMLT. They also show lower fund risk, regardless of the risk measures used (i.e., total, market beta or

idiosyncratic fund risk). High AMLT funds also charge lower expenses. These results provide some early indication that AMLT adoption seems to be associated with strong investment abilities.

Next, surprisingly, we observe that high AMLT funds exhibit low portfolio turnover. ML-based trading strategies are shown to have extremely high turnover. As illustrated in Gu et al. (2020), the monthly portfolio turnover spread between top and bottom ML portfolio can reach 113%. In contrast, we find that funds in the top AMLT portfolio produce an average annual fund turnover of only 57.8%, 13.7% lower than funds in the bottom AMLT portfolio. In addition, we find small funds and funds from small fund families are better at following the AMLT strategy. This is consistent with Jensen et al. (2024) that asset managers with small total assets under management should be in a better position to manage trading impact in forming ML-based portfolios. These findings together suggest that high AMLT funds are capable of aligning their portfolio positions with ML signals while effectively managing trading costs. Finally, funds in the top AMLT portfolio actually exhibit lower active share than funds in the bottom AMLT portfolio, although both top and bottom AMLT funds are more active in portfolio management than other funds.

We provide additional regression analyses in Panel B of Table 3. Column 1 of Panel B confirms the above observations on AMLT and fund characteristics. Adding fund style scores in the regression in column 2 of Panel B, we observe that value funds and small-cap funds are associated with higher AMLT adoption, while AMLT strategy does not seem to be associated with the momentum style. Turning to various market conditions in the last column of Panel B, we find, consistent with the evidence that ML signals generate stronger profits during periods with elevated market volatility, AMLT is higher in high VIX periods. AMLT is also higher in non-recession periods, suggesting that funds may be good at active stock selections during market expansions (Kacperczyk et al., 2012).

Time trend

Figure 1 illustrates the time trends of the AMLT measure across the mutual fund universe using the median and 80th percentile of AMLT over the past two decades. The plot reveals a clear upward trajectory in the adoption of AMLT by the mutual fund industry. For example, the AMLT measure at the 80th percentile begins at about 20% in the early 2000s and gradually accelerates, reaching nearly 45% by 2024. Moreover, as revealed in Figure 2, the upward trend prevails in almost all style groups. Value funds emerge as early adopters, while growth funds tend to pick up the speed in ML adoption over time. These patterns highlight the growing prevalence of AMLT implementation across the mutual fund industry.

Persistency of AMLT

We next investigate the persistence of the AMLT strategy. If mutual funds exhibit high AMLT due to picking up random trading signals that are correlated with ML signals, we should not expect persistence of AMLT over time.

To investigate this, we compute the transition matrix in Table 4. In each quarter, we sort mutual funds into quintiles according to the AMLT measure. The first five columns in Panels A to C of Table 4 report the transition probabilities of each AMLT quintile over the next one quarter to one year after portfolio formation. Column six shows the proportion of funds that exit the sample (i.e., attrition rate), while the last column computes the difference between the probabilities of transitioning into the same quintile (i.e., probability in the diagonal cell) versus into other quintiles (i.e., the average probability of the off-diagonal cells). We find significant persistence of the AMLT measure. For example, Panel A shows that 61.1% of funds in quintile five remain in the top quintile after one quarter, significantly higher than the probability of transiting into any other quintiles. This transition probability stays at 51.3% and 43.4% after six months and one year as shown in Panels B and C, respectively. Interestingly, the last columns of Table 4 illustrate that funds in top AMLT quintile are more likely to survive, with attrition rates being 0.4% and 1.6% lower over the next quarter and

next year, respectively, as compared to funds in the bottom AMLT quintile.

Next, for a visual inspection, Figure 3 depicts the persistence of the AMLT measure eight quarters after portfolio formation of the AMLT portfolios. Specifically, each quarter, we sort mutual funds into deciles by AMLT and compute future AMLTs for each portfolio over the next two years. As evident from Figure 3, AMLT exhibits substantial persistence in that the relative ranks among the decile portfolios remain unchanged over the next eight quarters. The evidence, together, suggests that AMLT is a consistent investment strategy that some mutual funds follow.

4 AMLT and Mutual Fund Performance

In this section, we examine the relation between AMLT strategy and subsequent mutual fund performance. We start by investigating the basic relation using both a portfolio approach and multivariate regressions. We then dive deeper into understanding the source and sustainability of the fund performance.

4.1 Baseline Results

Portfolio-based Analysis

We first employ a portfolio-based approach to examine the relation between AMLT and subsequent fund performance. Each quarter, we sort mutual funds into decile portfolios according to their AMLT measure of the quarter. Then we compute equally weighted returns for each decile portfolio over the following three months and the portfolios are rebalanced quarterly. We use gross returns to capture investment skills. We estimate the risk-adjusted returns on the portfolios as intercept alphas from time-series regressions, as in Equation 3, using standard asset pricing models.

The results are reported in Table 5. Panel A is based on the AMLT measure that captures both the long and short sides of the ML trading signals, while Panel B is based on

the AMLT_long measure that emphasizes only the long side of the ML trading signals. We observe that that AMLT strategy is positively associated with subsequent fund performance. As shown in Panel A, in the quarter following the portfolio formation, funds in the top AMLT decile significantly outperform funds in the bottom AMLT decile on a risk-adjusted basis by 19.8 to 24.0 basis points per month based on various factor models, which are equivalent to 2.4% to 2.9% annually. Moreover, funds in the top AMLT decile show positive and significant abnormal performance ranging from 8.9 to 11.8 basis points, equivalent to 1.1% to 1.4% annually, which lends further support to the notion that these funds are able to gain superior performance through actively aligning with ML-based trading strategy.

Moving to Panel B, results based on AMLT_long that focuses on only the long side of the trading signals provide highly consistent and slightly stronger results. Funds in the top AMLT decile outperform funds in the bottom AMLT decile by 2.4% to 3.0% annually after risk adjustment. These results are consistent with the evidence that unlike individual anomalies with profit coming primarily from short positions, machine learning signals yield considerable profit in the long positions and mutual funds who are constrained to short are more likely to take advantage of long positions. In untabulated results, we examine AMLT measure based on various different ML signal transformations and we find highly consistent results.

Multivariate Regression

We next use multivariate regression approach to examine the relation between AMLT strategy and future mutual fund performance. This approach allows us to control for additional fund characteristics and fund styles that may affect performance. Specifically, we perform the following regression at a monthly frequency.

$$Perf_{f,t} = \beta_0 + \beta_1 AMLT_{f,t-1} + \boldsymbol{\beta}' \boldsymbol{X}_{f,t-1} + \gamma_t + \eta_s + \varepsilon_{f,t} \tag{4}$$

where the dependent variable $Perf_{f,t}$ is alpha in percent per month for each fund f in month

t, computed as the difference between fund return in the month and the expected return based on betas estimated based on a factor model (i.e., CAPM one factor, Fama-French three factor, or Carhart-Fama-French four factor models) using fund returns over the past 36 months (i.e., from month $t-36$ to month $t-1$) and the factor values in month t. The main independent variable is $AMLT$ computed at the most recent quarter end as of month $t-1$. $AMLT$ is updated quarterly for each fund. We include a vector of various controls ($X_{i,t-1}$) in the regressions, including lagged fund performance (Ret_{t-1}) measured as the average fund return over the previous 12 months, expense ratio ($Exp\ ratio_{t-1}$), fund size ($log(TNA)_{t-1}$) measured as logarithm of TNA, turnover ratio ($Turnover_{t-1}$) and fund age ($Fund\ age_{t-1}$). All controls are lagged for a year. The regressions include time (γ_t) and style fixed effects (η_s). We run the regression at monthly frequency. Standard errors are clustered at the fund level.

Table 6 reports the results. Consistent with the evidence from the portfolio approach, we observe a strong positive relation between AMLT strategy and fund performance in the following quarter. Using Carhart alpha reported in Column (4) as an example, the coefficient on AMLT is 0.055 and highly significant at 1% level. A decile portfolio spread in AMLT of 2.229 indicates that funds in the top decile outperform bottom funds by about 1.5% per year after controlling for fund characteristics and styles. In addition, we observe that low expense ratio, small fund size and low turnover are associated with high future fund performance, which is largely consistent with findings in the existing literature (Chen et al. (2004); Gil-Bazo and Ruiz-Verdu (2009); and Jiang and Zheng (2018)).

Taking together, our results reveal a robust and significant relation between AMLT strategy and future mutual fund returns, even after controlling fund styles and fund characteristics. These results suggest that mutual funds with effective adoption of AMLT in their investment practice are able to deliver superior portfolio performance. We next dive deeper to understand the source and sustainability of the performance.

Performance Decomposition

To understand the source of superior performance, we perform performance decomposition analysis.

We follow Sialm and Zhang (2020) to decompose fund returns into stock selection, style timing, style selection, expenses, and return gap (i.e., interim trading benefits and trading costs).

$$RH_{i,t} = CS_{i,t} + CT_{i,t} + AS_{i,t} - EXP_{i,t} + RG_{i,t} \tag{5}$$

The decomposition procedure starts by decomposing the net fund return into the gross holdings return, fund expenses, and the return gap following Kacperczyk et al. (2008). The gross holdings return (RH) is defined as the value-weighted return of the previously disclosed fund holdings, where the weights correspond to the relative value of each fund position at the end of the previous month. The return gap (RG) captures the impact of unobserved actions on fund returns, including the trading costs and the interim trading benefits. Funds with lower trading costs and higher interim trading benefits will exhibit better return gaps. Second, following Daniel et al. (1997), we further divide the RH into a characteristic selectivity measure (CS), a characteristic timing measure (CT), and an average style measure (AS). CS is a measure of stock selection ability and uses as a benchmark the return of a portfolio of stocks that is matched to each of the fund's stock holdings each quarter along the dimensions of size, dividend yield, and momentum. CT is a measure of style timing ability, which examines whether fund managers can generate additional performance by exploiting time-varying expected returns of the benchmark portfolios. Finally, AS captures the returns due to a fund's tendency to hold stocks with certain style characteristics.

Table 7 reports results from our baseline regression (Equation (4)) using the various performance components as dependent variables. Panel A (Panel B) reports results based on univariate and multivariate regressions, respectively. We find that performance of AMLT

strategy derives mainly from the ability to select securities and the average style of funds, while style timing ability is insignificant. Next, consistent with observations in Table 2, AMLT strategy is associated with low expense ratio, which may be consistent with the finding in previous literature that high performance funds that target sophisticated investors tend to charge low fees (Gil-Bazo and Ruiz-Verdu, 2009). Lastly, we observe a positive relation between AMLT and return gap. Despite being insignificant after including full controls, this finding illustrates that funds following AMLT strategy possess trading skills to efficiently manage trading costs and avoid eroding their performance while implementing ML strategy with high turnovers.

Overall, the superior performance of funds with investments strategy more aligned with AMLT can be explained primarily by their superior stock selection ability, their favorable style exposures, and the skill to efficiently manage trading costs.

4.2 Additional Analyses on Performance

Despite the considerable promise of ML-based trading signals, implementing such strategies in the real world can be challenging. In this subsection, we investigate whether mutual funds can achieve sustained performance by adopting AMLT strategy, focusing on performance over the long term, across different market conditions, and for various investment styles.

Long-term Performance

Since ML models tend to generate fleeting signals with high turnover and trading costs involved, sustainable investment profit may be hard to achieve. Therefore, an important question is whether mutual funds are capable of implementing the AMLT strategy to gain long-term performance.

To understand this, we investigate how AMLT is associated with future fund performance in the subsequent eight quarters using our baseline regression in Equation (4) with a full set of controls. In Table 8, we report 4 snapshots: performance in the subsequent quarter

(Quarter t), at the end of the first half-year (Quarter $t+1$), the first year (Quarter $t+4$) and the 2nd year (Quarter $t+8$). The results clearly indicate that AMLT leads to long-term persistent fund performance. This suggests that some mutual fund managers possess superior skills in integrating ML-based trading signals with their investment expertise to generate sustainable fund performance.

AMLT performance and Market Conditions

Another challenge of implementing ML-based strategy in practice is that the economic gains tend to be concentrated in volatile market conditions (Avramov et al., 2023). In Table 9, we investigate the performance outcome associated with the AMLT strategy in different market conditions.

We define high and low market conditions based on the median cutoffs of three well-known market indicators, i.e., investor sentiment from Baker and Wurgler (2007) (Sentiment), monthly VIX index of implied volatilities of S&P 500 index options (VIX), and market illiquidity (Market_illiquidity), defined as the equally-weighted average of stock-level Amihud (2002) illiquidity for all NYSE/AMEX stocks in a month (Avramov et al., 2016). We augment our baseline regression in Equation (4) by High, an indicator variable denoting above median market condition, and an interaction term, AMLT $\times$ High. Our results, as shown in Table 9, demonstrate that funds with high AMLT outperform in both high and low market conditions, as indicated by the significantly positive coefficients associated with AMLT. In addition, consistent with previous literature that ML strategy generates greater profit in high market conditions, we find significant positive coefficients on all three interactions terms.

AMLT Performance and Fund Styles

ML-based trading strategies also dominate in small and illiquid stocks (Avramov et al. (2023); Jensen et al. (2024)), posing an additional challenge for practical implementation for

mutual funds, especially since funds may need to follow style mandates and may not be able to invest in these stocks.

In Table 10, we investigate whether AMLT strategy can be implemented successfully by funds in different style groups. We divide our sample funds into four style groups based on the size and value scores of fund holdings following Daniel et al. (1997) and run our baseline regression for each subsample. Our results show that funds in all style groups are able to add value by utilizing AMLT strategy.

Overall, our evidence demonstrates that, despite challenges in ML-based trading, AMLT-adopting funds are able to generate persistent long-term performance and perform well in all market conditions and across all investment styles. In addition, these funds also manage trading costs well, as evidenced by their lower portfolio turnover and higher return gap. Our results therefore echoes the insights of Cao et al. (2024) in that superior mutual fund performance from AMLT is the result of a powerful combination of human investment expertise and advanced ML technology.

5 AMLT and Information Advantages

After establishing the main results, we further investigate how ML technology and information inputs help mutual fund gain information edge and achieve superior performance. Specifically, we examine the volume, diversity, and interactions of information inputs to better understand their role in delivering ML-based fund performance.

5.1 The Volume of Information and Information Advantage

First, we examine the role of information volume in driving AMLT performance. A key reason that ML technology revolutionizes information production is its strength in handling vast amounts of data at remarkable speed. Therefore, funds that adopt AMLT should tilt their portfolios toward stocks with more public information, where the use of ML technology

can yield greater information advantages.

To test this, we count the number of information inputs that each firm has out of the 235 inputs used in our AMLT model (N. Signals). To capture funds' active portfolio tilt toward information-rich stocks, we construct a fund-level active tilt measure (ATILT_N.Signals) toward N. Signals. First, similarly to Daniel et al. (1997), we categorize the universe of U.S. common stocks into deciles based on N. Signals and assign each stock a score from -5 to 5 according to the rankings. We then compute the fund-level ATILT measure by multiplying the active portfolio weight deviations (from the benchmark) by the scores and aggregating the products over all positions. The ATILT measures capture mutual funds active decision to invest in information-rich stocks relative to their style benchmarks.

Table 11 Panel A presents regression results linking ATILTs to fund AMLT. The findings show that, compared to style benchmarks, funds following a high AMLT strategy allocate more capital to firms with a greater number of available information inputs. Specifically, funds with a one standard deviation higher AMLT tilt toward stocks with high information inputs by 13.3%, suggesting that funds adopting AMLT make active portfolio decisions to leverage the strength of ML technology to gain an informational edge.

Next, to confirm that funds adopting AMLT indeed gain by tilting more toward information-rich stocks, we conduct performance analysis in Panel B of Table 11. We define a dummy variable, High_Info, which identifies funds with above medium holdings of information-rich stocks based on N. Signals. We then interact AMLT with High_Info. The results show that funds holding more information-rich stocks to leverage AI technology indeed perform better. For example, column (2) reveals that tilting toward stocks with a large number of information inputs enhances fund performance from the AMLT strategy by 44.7%.

5.2 Information Diversity and Interactions

In addition to processing vast amounts of information, another key strength of ML technology lies in its flexibility to optimize and fit unspecified functional forms, allowing for highly complex interactions among diverse information inputs – a critical factor in generating valuable signals. Next, we explore how this strength enables ML-adopting funds to create value.

Non-linear Interactions

We start by investigating the value added by ML technology in accommodating complex interactions among information sets. For this purpose, we consider a quasi-ML model, the Elastic Net (ENet) (Cao et al., 2024), which captures the essence of dimension reduction by ML models but relies solely on linear combinations of predictors. We estimate the ENet model to generate trading signals using the full set of information as in our base ML model. We then compute AMLT_ENet by following Equation 1, replacing ML signals with ENet trading signals.

We examine the performance of the full AMLT strategy versus the AMLT_ENet strategy in Panel A of Table 12. It is evident from Columns (1) and (2) of Panel A that the AMLT_ENet strategy, which uses the same amount of information but is based on technology that does not accommodate nonlinear predictive relationships, generates performance that is only 49.1% of that of the full AMLT. This exercise clearly demonstrates that a key feature of the full-fledged ML model – its ability to capture complex interactions – is vital for delivering strong AMLT performance.

Quantitative versus Textual Information

Next, we examine the value of ML technology's ability to combine diverse information inputs. With the rise of big data, investors are increasingly utilizing not only traditional financial indicators but also new unstructured textual data. We investigate the value added

from combining quantitative information with textual information in generating ML-based strategies. To do so, we classify the variables into two broad categories: quantitative signals and textual signals, then re-estimate our ML models using each type separately to generate trading signals and compute AMLT_quant and AMLT_textual measures accordingly.

Performance results are provided in Panel A of Table 12, where we regress Carhart alpha on the full AMLT, AMLT_quant, and AMLT_text separately. Results in columns (1), (3), and (4) show that, in addition to the full AMLT strategy, both AMLT_quant and AMLT_text strategies are associated with significant future fund performance. However, in terms of magnitude, AMLT_quant and AMLT_text are able to generate performance that is only about half and one-third, respectively, of the magnitude of the full AMLT strategy. The findings illustrate the substantial value added by combining diverse information in ML to generate trading signals. They also highlight the power of adding unstructured textual information into the traditional ML model based on quantitative data in boosting the profits of investment strategy, which has not been explored before in the literature.

Overall, the results so far demonstrate that the superior performance of AMLT is driven by the capacity of ML models to effectively integrate diverse information and accommodate complex interactions among information inputs.

Multiple versus Individual Information Input

We next classify our information inputs into six anomaly and three textual-based categories to further understand the value of ML-based strategies that combine multiple information inputs versus those relying on a single specific input. We classify quantitative information into six anomaly categories following Hou et al. (2020): Momentum, Value versus Growth, Investments, Profitability, Intangibles, and Trading Frictions, and textual-based information into three categories: News, Earnings Calls transcripts, and SEC financial filings. We estimate nine ML models separately using each of the nine information sets. We then feed each set of resulting trading signals into our AMLT calculations (to replace the ML signals) and

derive nine AMLT measures based on the subset of information (i.e., AMLT_sub).

We examine the performance of these strategies. To better understand both the long and short sides of these strategies, Figure 4 plots the Carhart alphas for the Long (top decile), Short (bottom decile), and Long-minus-Short portfolios based on these AMLT_sub strategies and the full AMLT strategy. Statistical significance is indicated by the color of the bars, with black representing significance and light color indicating insignificance, defined by the 5% threshold. First, it is evident from both Panel B (Long) and Panel C (Long-minus-Short) results that these AMLT_sub strategies fail to produce performance even close to that of the full AMLT, represented by the black bar on the right. In fact, most of the sub-categories produce negative performance.

Second, examining these AMLT_sub strategies more closely, we find that none of the six anomaly categories exhibit significant performance. For example, Momentum, a major anomaly category, shows insignificant and negative performance. This may reflect the fleeting nature of the signals, the fading of in-sample anomaly profits in recent years, and the concentration of the profits on the short side, making them difficult for mutual funds to capture.(McLean and Pontiff (2016); Avramov et al. (2023)). This is also consistent with the lack of evidence in the mutual fund literature on funds' ability to exploit individual anomalies. If anything, the literature documents the "dumb money" effect of mutual fund flows toward major individual anomalies (Akbas et al., 2015).[8] Next, tuning to textual information, we observe that trading based on individual textual inputs, such as news or SEC filings alone, leads to positive but statistically insignificant performance. [9]

Overall, our findings further illustrate the substantial value added by ML models in extracting information from a combination of multiple information categories, as opposed

[8]In untabulated results, we also investigate 10 individual anomaly strategies with the highest correlations with ML signals and construct 10 placebo AMLTs. We find that mutual funds are unable to achieve significant performance based on any of these single anomaly strategies.

[9]Earnings call input alone results in negative performance. Since earnings calls only became available in 2006, whereas other information are available for the full sample period, we do not include earnings calls in Figure 4 for comparability.

to relying on any individual information input. Moreover, these results also indicate that AMLT is a unique and independent strategy that funds follow.

6 AI Funds, Quant Funds and Mutual Fund AI Talent

We find strong evidence that mutual funds that align their investment strategy with ML trading signals are able to generate superior fund performance. Our holdings-based methodology has unique advantages in identifying AI utilization specifically in trading. But there are some potential questions, for example, does AMLT measure really capture AI-adopting funds? What is the relationship between AMLT and quantitative (or quant) funds?

In this section, we further establish our results by performing a series of additional analyses, including investigating self-designated AI funds and quant funds, as well as AI talent of fund advisor companies.

6.1 AMLT, Self-designated AI Funds and Quant Funds

We start by identifying self-designation AI funds using fund names reported in CRSP and via online searches. We are able to identify only five AI funds through fund names and additional 41 funds through extensive online searches of AI funds, related articles, fund websites, and etc. The very limited sample of AI funds identified after the extensive searches illustrates the obstacle of using this approach to study AI adoption. Second, we are able to identify 46 quant funds through fund names (i.e., names containing the term "quant" or "quantitative").

We next examine the relation between the AMLT measures and self-designated AI and quant funds. Some interesting results emerge in Table 13. First, self-designated AI funds exhibit significantly higher AMLT than other funds within the same style group for the same quarter. For example, the AMLT of AI funds are 0.679 higher than other funds, which is about one standard deviation of AMLT. Moreover, both AMLT_quant and AMLT_text are

higher, with AMLT_quant being stronger. These results illustrate the capability of AMLT measure in picking up AI-adopting funds.

We next turn to quant funds. Traditional quant funds focus on trading strategies based on conventional statistical models and quantitative information inputs (such as stock prices, earnings and market trends). AI funds can be viewed as a subset of quant funds that are fast in adopting cutting-edge AI technologies and utilizing all the information available, including the new textual ones. Consistent with this, we find that quant funds exhibit higher AMLT measure than an average fund in the same style, but the magnitude is much smaller than AI funds (i.e. only 1/5 that of AI funds). More interestingly, the higher AMLT associated with quant funds comes solely from AMLT_quant, consistent with that traditional quant funds do not focus on textual data.

Overall, despite the limited samples, these findings lend support to our methodology in capturing AI-adoption funds.

6.2 AMLT and AI talent of Fund Advisors

To provide further validation to our AMLT measure, we next examine AI talents of mutual fund employees. Implementing complex ML models in forming trading strategies requires special talent in AI technology. If AMLT captures AI adoption in mutual fund investments, we should expect funds with high AMLT to have high employee AI talent.

To investigate this, we conduct a systematic examination of employee AI talent of mutual funds using profile data from Lightcast. Lightcast provides both employee profile and job posting data. For our purposes, we focus on employee profile data. While job postings are useful for projecting companies' future demand for AI talent, employee profiles are better suited for measuring companies' current stock of AI talent. The latter is more relevant to our analysis, as we focus on mutual funds' existing capacity in adopting ML-based trading. Moreover, job posting data starts only from 2010, while profile data covers the entire period of our sample from 2000 to 2022, which complements our main analyses aiming for systematic

documentation of AI adoption in the mutual fund industry.

We start by matching mutual fund advisory companies reported in CRSP to companies covered in Lightcast profile data.[10] Through name mapping, we are able to identify 1,183 mutual fund advisory companies, accounting for 62.7% of all advisory companies in our sample. Over the whole sample, we identify more than 2.15 million unique employee profiles associated with these mutual fund advisory companies. Of those, we define an employee as having core AI skills if they have at least one of following skills: Machine Learning, Artificial Intelligence, Natural Language Processing, and Computer Vision.

Figure 5 depicts the yearly percentage of employee profiles with core AI skills. We observe a clear upward trajectory in AI adoption by the mutual fund industry over the past two decades, as reflected by core AI talent employed, which confirm the upward trend in ML adoption captured by the AMLT measure in Figure 1. This overall trend in AI adoption that we document for the mutual fund industry is highly consistent with the recent evidence reported by Babina et al. (2024) on general companies and by Chen et al. (2025) on investment advisors over the recent decade. Unlike studies based on job postings, we focus on the existing stock of AI talent using employee CVs, providing unique and complementary evidence to early studies. We show that the mutual fund industry started investing in AI talent already in the early 2000s with share of core AI talent began at around 1%. The share of core AI talent gradually increased and accelerated after 2015, reaching about 1.93% in 2022.

Next, we construct an AI talent measure at the fund advisory company quarter level: the share of employees with core AI skills (Share_core AI). Share_core AI is defined as the share of employees with core AI skills out of all employees with profiles associated with the company in quarter t [11] On average, based on existing employee profiles, mutual fund

[10]Since most employees report employer names at fund advisory company level instead of fund level, analysis based on the AI talent measure using labor market information can only be conducted at fund advisory company level.

[11]We also compute an alternative Share_related AI measure following Babina et al. (2024) in defining related AI skills and find highly consistent results.

advisory companies have about 1% of employees with core AI skills, with a standard deviation of 2.14%.

We next investigate the relation of the employee profile-based Share_core AI measures and our holdings-based AMLT measure. We regress AMLT on Share_core AI over the same quarter, controlling other fund characteristics and number of profiles in the fund company. The results in Panel A of Table 14 reveal a significant positive relation between AMLT and Share_core AI talent. The evidence that AI talent measures based on labor market information of fund companies are highly correlated with trade-alignment based AMLT provide additional support to our methodology of using AMLT to capture AI adoption in mutual funds.

In Panel B of Table 14, we re-estimate our baseline performance regression using both the AMLT and the Share_core AI measures. We observe in column (1) that Share_core AI is positively related to future fund performance with a weak statistical significance. When putting both measures together in column (2), AMLT remains a significant and strong predictor of future fund performance while Share_core AI becomes insignificant. The finding illustrates the strength of the AMLT measure in capturing AI adoption specifically aimed at enhancing trading strategies and portfolio performance. In contrast, the AI talent measure is weak in predicting fund performance, which is consistent with that such labor market based measure can capture AI adoption for broader business operations unrelated to investment strategies, and may be coarse due to data coverage limitations.

7 Conclusion

Our study provides a comprehensive analysis of how U.S. equity mutual funds integrate ML technology into their investment strategies over the past two decades. We propose a novel Active Machine Learning Based Trading (AMLT) as a signed active-share measure that captures how mutual funds actively align their portfolio weight deviations from its

passive benchmark with forward-looking ML-based trading signals, generated by employing a three-layered Deep Neural Network leveraging a near universe of public information inputs, including both extensive quantitative and textual information.

Our methodology makes novel contributions to both mutual fund performance evaluation and the identification of AI adoptions. First, by combining active weight deviations with the powerful ML trading signals, the AMLT measure helps enhance performance evaluation and also provides a metric for understanding the underlying investment strategy driving the value added. Second, in contrast to employee-based AI talent measures, AMLT provides a sharp identification of ML adoption specifically targeted at portfolio trading and performance, and is not confounded by AI adoption in other areas of the fund. Moreover, the flexibility of the measure (i.e., incorporating ML-signals based on alternative models or restricted set of predictors) allows us to identify the mechanism driving performance.

We document a significant rising trend of ML adoption in investment strategy by mutual funds over the past two decades, with top-decile AMLT funds outperforming bottom-decile funds by 2.4year on a risk-adjusted basis. We find that the superior performance is driven by better stock selection skills, lower expenses, and efficient trading cost management (i.e., lower portfolio turnover and higher return gap), despite the inherently high turnover of ML-based strategies.

We identify two main drivers of the superior performance of AMLT funds. First, the flexibility of our methodology allows us to quantify how much of the performance is due to model complexity and the scope of the information set. we show that linear quasi-ML models (i.e., Elastic Net) and reduced information sets (i.e., solely quantitative or textual inputs) generate at most half the performance, highlighting ML's ability to process diverse information and capture complex interactions as a key driver of superior fund performance. Second, our analysis underscores the critical role of fund managers in combining human expertise with ML technology in successfully implementing AMLT strategies. Despite challenges of ML-based trading identified by previous literature, we show that high AMLT funds

deliver persistent performance across different market conditions and investment styles and demonstrate impressive efficiency in managing trading costs.

To complement our study, we perform comprehensive analysis using employee profile data from Lightcast and construct the share of mutual fund employees with core AI skills. The AI talent measure based on labor market information confirms the rising trend in ML adoption we document earlier and is also highly correlated with our trade-alignment based AMLT. Moreover, when putting both measures together, AMLT remains the only significant predictor of future fund performance, validating AMLT as a sharp measure in identifying ML adoption in enhancing trading and performance.

This study contributes to the literature by offering new perspectives on the intersection of AI/machine learning, and active mutual fund portfolio management. We contribute to the mutual fund literature on performance evaluation methodolgy, fresh evidence on managerial skills, and new evidence of value added from public information processing based on cutting-edge ML technology. Moreover, we contribute to the growing literature on the utilization of ML models in various areas in finance by providing the much needed evidence of real-world application of ML-based trading signals in mutual fund investment practices.

Our results highlight how AI is reshaping traditional investment practices and that combining ML-based signal with human investment skill can enhance decision making and generate long-term value. As the asset management industry continues to evolve with advancements in AI and alternative data sources, understanding the complementary role of AI and human expertise will remain a critical area for future research.

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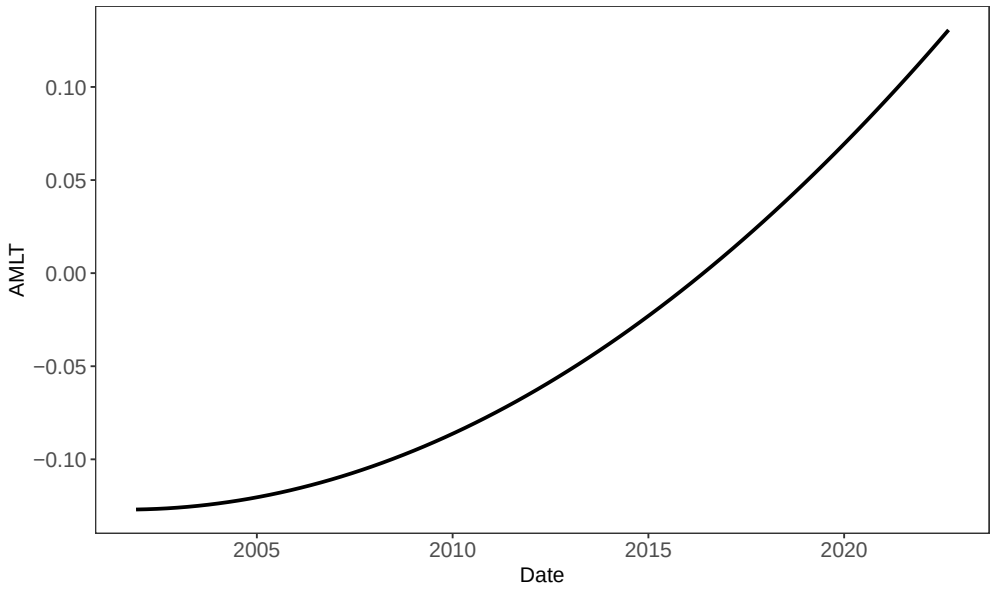
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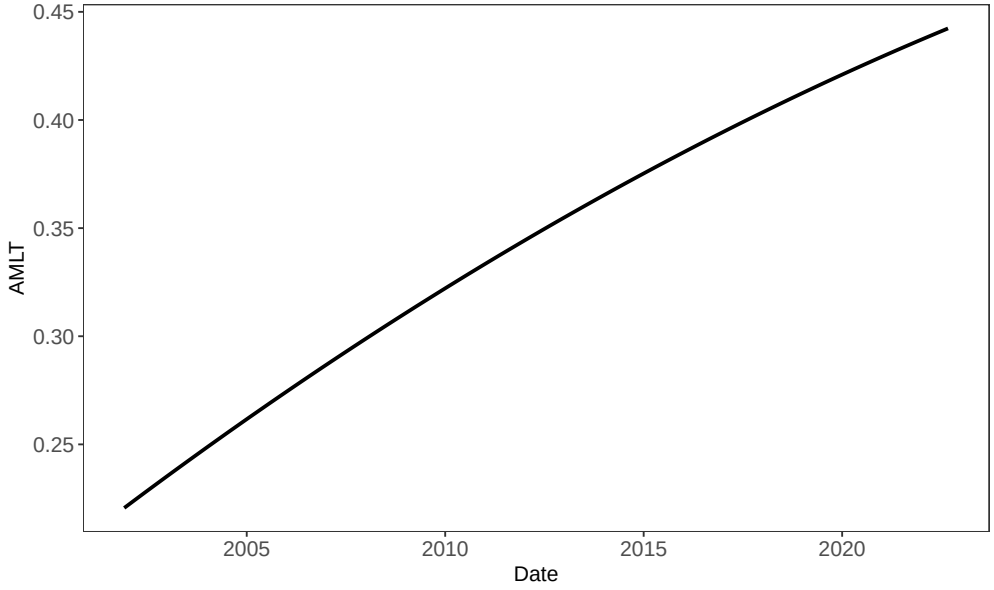
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(a) 50th percentile



(b) 80th percentile

Figure 1: **Time-series Variation in AMLT**

This figure depicts a fitted polynomial of the second-order to quarterly percentiles of AMLT between 2002 and 2022. Panel A (B) displays the 50th (80th) percentile.

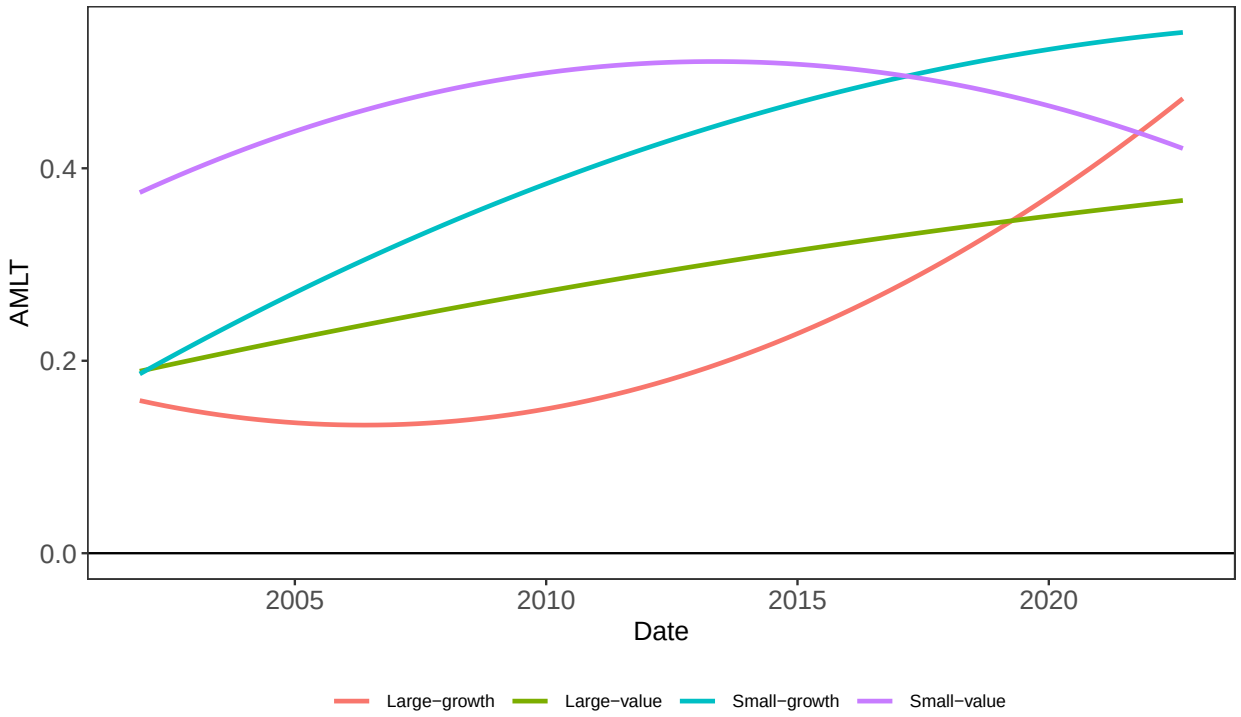


Figure 2: **Time-series Variation in AMLT per Style**

This figure depicts a fitted polynomial of the second-order to quarterly percentiles of AMLT per style between 2002 and 2022. Each quarter, funds are assigned to one out of four styles. Funds are first categorized into two groups based on a size score. Within each size group, funds are categorized into two groups based on a value score. A fund's size score and value score are determined based on the average quintile rankings of the firms in its portfolio, using NYSE quintile cutoffs as benchmarks for market capitalization (size) and book-to-market ratio (value).

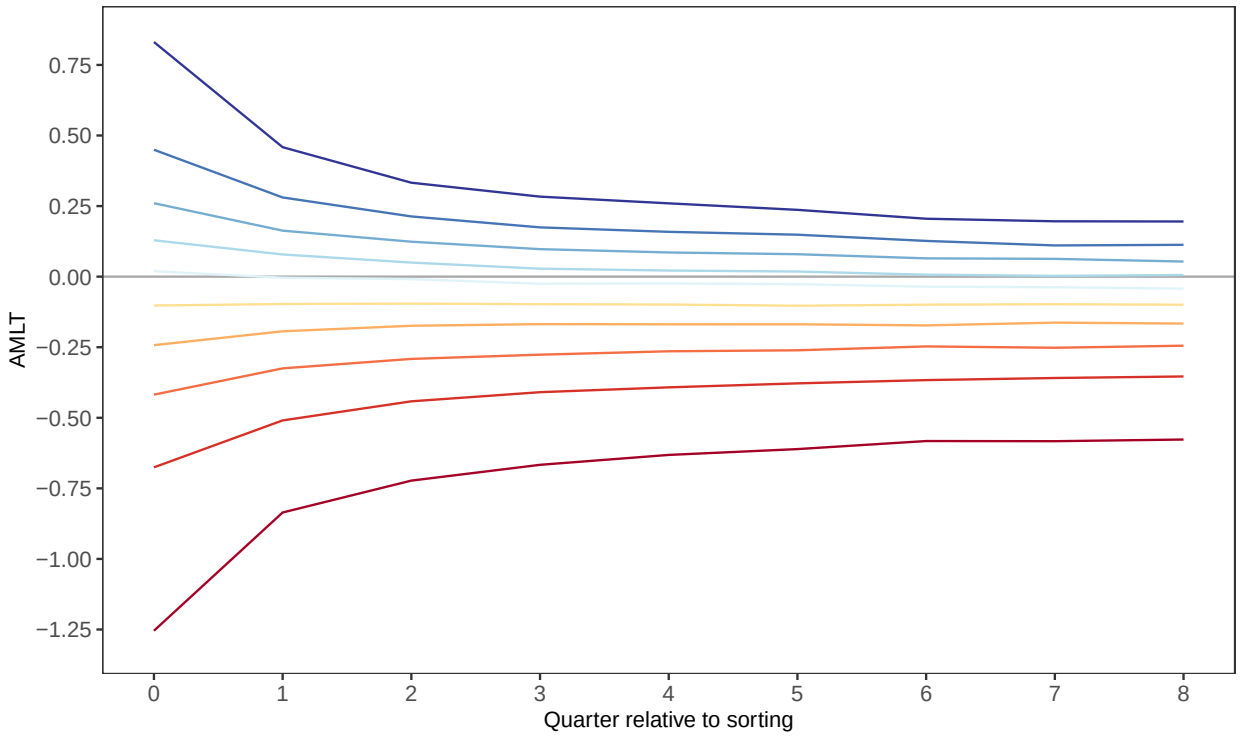
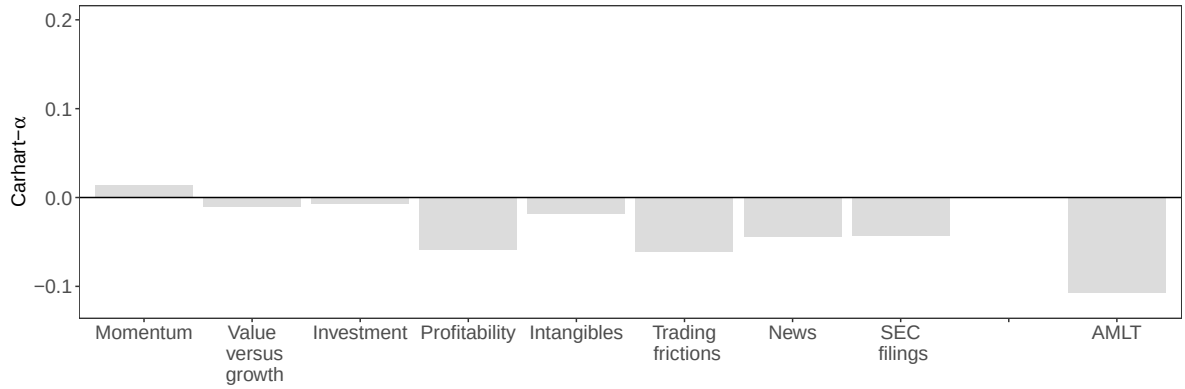
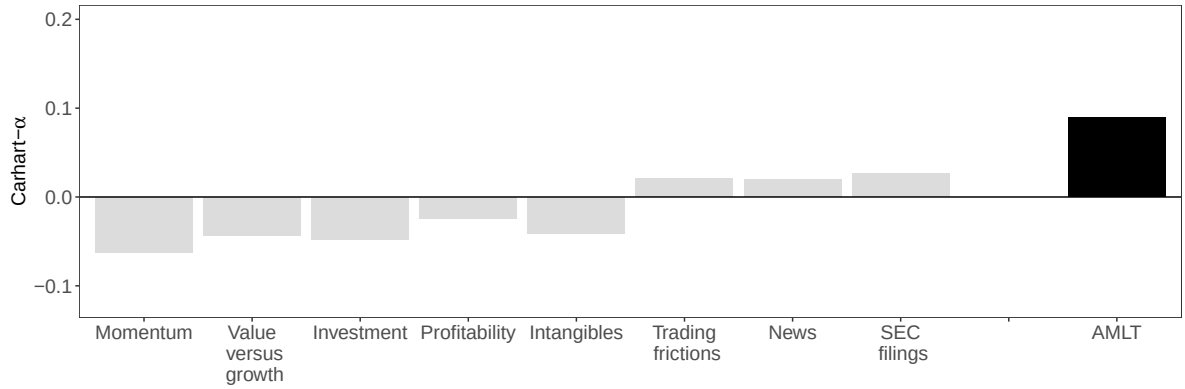


Figure 3: **Persistence of AMLT**

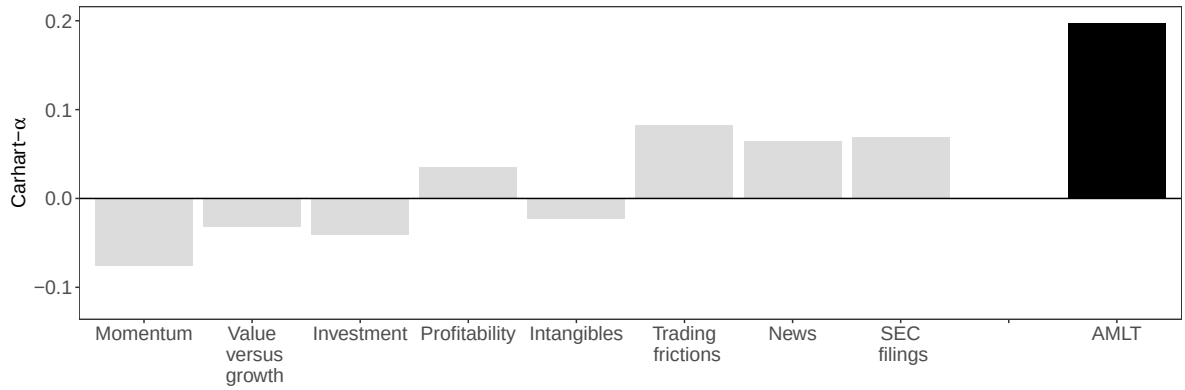
The figure depicts the average AMLT levels for the ten AMLT portfolios eight quarters after the portfolio formation.



(a) Short Portfolios



(b) Long Portfolios



(c) Long-minus-Short Portfolios

Figure 4: **Machine Learning Models with Individual Information Set**

This figure presents abnormal monthly returns of portfolios of mutual funds sorted by the most recent AMLT measure, limiting the information set of the machine learning model. We evaluate eight different sets of information inputs in the ML model. We display portfolio one ("Short Portfolio"), portfolio ten ("Long Portfolio"), and a zero-net-investment portfolio ("Long-minus-Short Portfolio"). We report intercepts from factor regressions based on the Carhart four factor model. The colour indicates whether the coefficients surpass the 5% significance threshold (black). All returns are expressed in % per month.

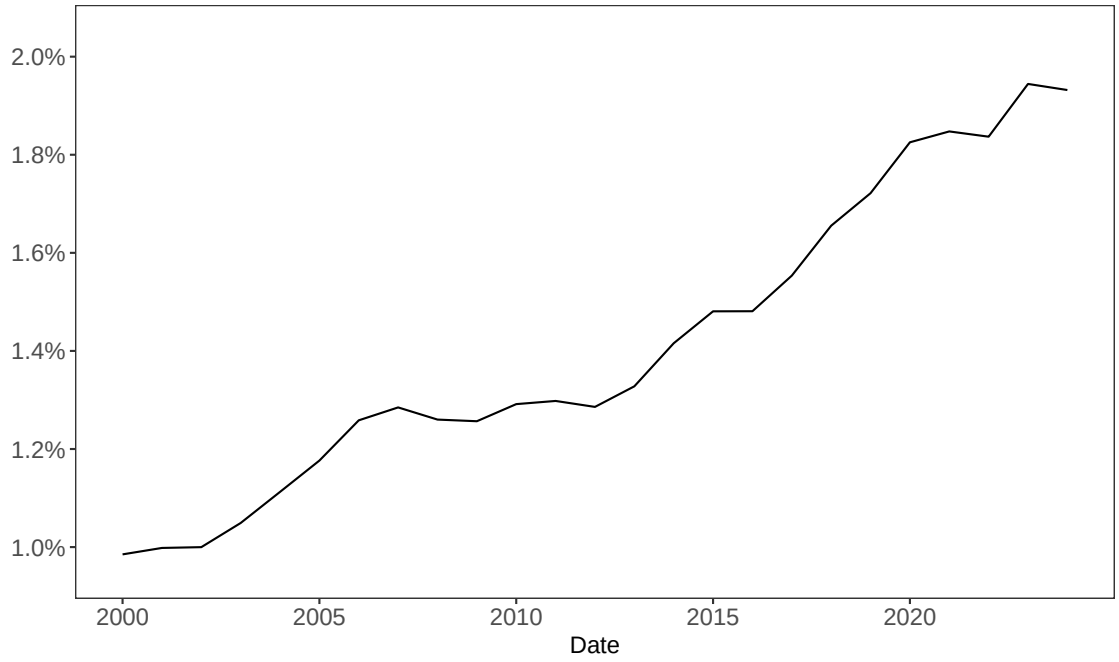


Figure 5: **Time-series Variation in Percentage of Employees with AI Talent**

This figures presents the percentage of employees with AI talent in the mutual fund advisory companies. An employee is defined as having AI talent, if they list one out of the four AI core skills in their profile: Artificial Intelligence, Machine Learning, Natural Language Processing, and Computer Vision.

Table 1: **Descriptive Statistics**

This table reports the descriptive statistics for our sample of mutual funds from January 2002 to December 2022. Panel A presents summary statistics for quarterly fund characteristics. Panel B presents summary statistics for monthly returns. Risk-adjusted returns are calculated according to the CAPM ("CAPM-α"), the Fama-French three-factor model ("FF-α"), and the Carhart four-factor model ("Carhart-α"). Characteristic selectivity ("CS"), characteristic timing ("CT"), average style ("AS") are calculated based on Daniel et al. (1997). Return gap ("RG") is based on Kacperczyk et al. (2008).

Panel A – Summary Statistics for Quarterly Fund Characteristics

Variable	Mean	Std. Dev.	q25	q50	q75
AMLT	-0.110	0.650	-0.408	-0.008	0.269
AMLT_long	-0.071	0.432	-0.280	-0.008	0.183
AMLT_tilt	-0.027	0.183	-0.110	-0.001	0.077
Exp ratio	1.022	0.455	0.763	1.028	1.283
Turnover	0.601	0.440	0.260	0.500	0.840
Fund age	15.697	13.527	7.000	12.000	20.000
TNA	2,469	13,022	92	339	1,325
TNA family	63,286	185,352	1,022	7,490	28,199
Past perf	0.718	1.602	-0.029	0.893	1.637
Total risk	4.845	1.728	3.547	4.663	5.873
β_{MKT}	1.033	0.221	0.927	1.015	1.139
Idio vol	1.160	0.835	0.737	1.010	1.388
Active share	0.706	0.232	0.617	0.758	0.875
Size score	4.147	0.959	3.505	4.618	4.894
Value score	2.860	0.413	2.570	2.877	3.144
Momentum score	3.092	0.430	2.797	3.085	3.364

Panel B – Summary Statistics for Monthly Returns

Variable	Mean	Std. Dev.	q25	q50	q75
Net return	0.669	5.076	-1.862	1.153	3.624
CAPM-α	-0.096	2.076	-1.051	-0.101	0.848
FF-α	-0.124	1.624	-0.869	-0.096	0.642
Carhart-α	-0.132	1.626	-0.868	-0.102	0.627
CS	0.022	1.402	-0.671	0.022	0.726
CT	-0.004	0.703	-0.331	0.001	0.322
AS	0.807	4.882	-1.656	1.356	3.592
RG	-0.077	0.989	-0.363	-0.059	0.221

Table 2: **Performance of the Machine Learning Portfolios**

This table reports the performance of ML-signal-sorted portfolios from January 2002 to December 2022. Each quarter, all stocks are sorted into deciles based on their predicted returns for the next quarter. We report equally weighted portfolio return per month, raw and risk-adjusted according to the CAPM ("CAPM-α"), the Fama-French three-factor model ("FF-α"), the Carhart four-factor model ("Carhart-α"), and Pastor-Stambaugh five-factor model ("PS-α"). We also report the standard deviation of average realized monthly returns ("SD"), Sharpe ratios ("SR"), the most extreme negative monthly return ("Max 1M Loss"), the equally weighted portfolio maximum drawdowns ("Max DD"), the average number of firms in each portfolio ("Nr firms"), and the average quarterly percentage change in holdings ("Turnover").

Portfolio	Raw	CAPM-α	FF-α	Carhart-α	PS-α	SD	SR	Max 1M loss	Max DD	Nr firms	Turnover
1	-0.859	-1.946***	-1.994***	-1.712***	-1.721***	10.052	-0.296	-26.958	96.849	463	75.044
	(0.779)	(0.479)	(0.403)	(0.349)	(0.351)						
2	0.476	-0.528*	-0.564**	-0.363*	-0.372*	8.123	0.203	-28.210	73.932	463	75.209
	(0.621)	(0.305)	(0.241)	(0.209)	(0.208)						
3	0.635	-0.267	-0.297*	-0.137	-0.144	6.959	0.316	-25.247	65.797	463	75.220
	(0.519)	(0.227)	(0.168)	(0.150)	(0.147)						
4	0.720	-0.121	-0.145	-0.037	-0.045	6.279	0.397	-25.629	64.189	463	75.251
	(0.452)	(0.188)	(0.124)	(0.112)	(0.106)						
5	0.812**	0.035	0.014	0.085	0.081	5.723	0.491	-24.817	61.615	463	75.265
	(0.405)	(0.156)	(0.108)	(0.104)	(0.101)						
6	0.923**	0.192	0.173*	0.209**	0.205**	5.347	0.598	-22.510	58.543	463	75.292
	(0.376)	(0.153)	(0.094)	(0.095)	(0.093)						
7	0.923**	0.198	0.181*	0.200**	0.196**	5.279	0.606	-23.310	59.707	463	75.300
	(0.371)	(0.155)	(0.093)	(0.093)	(0.091)						
8	0.962***	0.274*	0.259***	0.258***	0.256***	4.997	0.667	-22.045	53.154	463	75.303
	(0.340)	(0.147)	(0.082)	(0.080)	(0.079)						
9	0.970***	0.311**	0.296***	0.283***	0.280***	4.787	0.702	-23.627	52.011	463	75.313
	(0.321)	(0.142)	(0.092)	(0.089)	(0.088)						
10	1.249***	0.661***	0.648***	0.601***	0.599***	4.503	0.961	-23.838	42.636	464	75.364
	(0.301)	(0.182)	(0.146)	(0.139)	(0.140)						
H-L	2.108***	2.608***	2.643***	2.313***	2.320***	7.726	0.945	-38.027	67.362		
	(0.607)	(0.499)	(0.453)	(0.382)	(0.385)						

Table 3: **Fund Characteristics**

This table reports the fund characteristics by AMLT and examines the determinants of AMLT. Panel A summarizes the average characteristics of portfolios of mutual funds sorted according to the most recent AMLT measure. The differences in characteristics are computed on a quarterly basis using Newey-West standard errors with a lag length of four quarters. Panel B presents the determinants of AMLT. The regressions include time fixed effects. Standard errors are clustered by fund and are shown in parentheses. The significance levels are abbreviated with asterisks: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A – Fund Characteristics by AMLT

Portfolio	AMLT	AMLT_tilt	Exp ratio	Turnover	Fund age	TNA	TNA family	Past perf	Total risk	β_{MKT}	Idio vol	Active share
1	-1.357	-0.365	1.218	0.715	15.246	1,708	50,376	0.651	5.582	1.152	1.687	0.850
2	-0.692	-0.179	1.121	0.665	16.090	2,061	60,642	0.717	5.096	1.080	1.333	0.780
3	-0.428	-0.108	1.069	0.643	16.388	2,437	67,462	0.706	4.905	1.048	1.206	0.739
4	-0.245	-0.059	1.010	0.611	16.413	3,440	79,641	0.720	4.782	1.027	1.098	0.677
5	-0.102	-0.023	0.934	0.567	16.157	3,768	90,158	0.724	4.700	1.012	1.028	0.609
6	0.016	0.007	0.848	0.506	15.525	3,601	77,758	0.728	4.644	1.005	0.944	0.545
7	0.122	0.033	0.892	0.530	15.553	2,424	60,632	0.716	4.618	0.996	0.951	0.594
8	0.259	0.069	1.003	0.595	15.786	1,912	54,472	0.717	4.649	0.993	1.045	0.700
9	0.451	0.119	1.041	0.594	15.469	1,763	48,417	0.733	4.719	1.001	1.108	0.748
10	0.872	0.233	1.085	0.578	14.614	1,482	39,533	0.773	4.813	1.009	1.229	0.816
H-L	2.229***	0.599***	-0.133***	-0.137***	-0.632***	-226*	-10,843***	0.121	-0.768***	-0.144***	-0.458***	-0.034***
	(0.098)	(0.023)	(0.011)	(0.024)	(0.228)	(118.681)	(3,899.061)	(0.083)	(0.146)	(0.032)	(0.035)	(0.005)

Panel B – Determinants of AMLT

Dependent Variable:		$AMLT_t$	
Model:	(1)	(2)	(3)
Exp ratio$_t$	-0.148***	-0.168***	-0.241***
	(0.018)	(0.018)	(0.018)
Log(TNA$_t$)	-0.023***	-0.020***	-0.024***
	(0.005)	(0.005)	(0.005)
Log(TNA family$_t$)	0.002	0.003	0.001
	(0.003)	(0.003)	(0.003)
Turnover$_t$	-0.094***	-0.093***	-0.141***
	(0.015)	(0.015)	(0.016)
Fund age$_t$	0.000	0.000	0.001***
	(0.001)	(0.001)	(0.001)
Ret$_t$	0.043***	0.035***	0.004**
	(0.006)	(0.006)	(0.002)
Total risk$_t$	-0.107***	-0.122***	-0.061***
	(0.007)	(0.009)	(0.004)
Size score$_t$		-0.061***	-0.032***
		(0.010)	(0.009)
Value score$_t$		0.096***	0.112***
		(0.018)	(0.018)
Momentum score$_t$		0.005	0.052***
		(0.014)	(0.013)
US recession$_t$			-0.095***
			(0.012)
High VIX$_t$			0.098***
			(0.007)
Time fixed effects	Yes	Yes	
Observations	141,067	141,067	141,067
Adjusted R^2	0.114	0.124	0.073

Table 4: **Transition Matrix**

This table reports the transition probabilities for mutual funds sorted in quintiles based on their AMLT over the horizon of one, two, and four quarters in Panel A, B, and C, respectively. Column (2) to (6) report the transition probabilities. Column (7) reports the attrition rate. Column (8) reports the difference in transition probability between the quintile on the diagonal and any other quintile. The last row reports the difference in attrition between portfolio five and portfolio one. Differences are computed on a quarterly basis using Newey-West standard errors with a lag length of four quarters. All probabilities are expressed in %. The significance levels are abbreviated with asterisks: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A – One quarter ahead

	Portfolio$_{t+1}$							
Portfolio$_t$	1	2	3	4	5	Attrition	Δ Off-Diag	
1	65.1	19.8	6.3	4.0	3.1	1.9	56.8***	(0.021)
2	20.0	41.1	21.1	10.8	5.4	2.0	26.8***	(0.020)
3	6.5	21.6	40.4	22.0	8.1	1.9	25.9***	(0.019)
4	4.0	10.6	22.6	40.5	20.8	1.7	26.0***	(0.020)
5	3.2	5.3	8.0	21.1	61.1	1.7	51.7***	(0.022)
						-0.4***		
						(0.001)		

Panel B – Two quarter ahead

	Portfolio$_{t+2}$							
Portfolio$_t$	1	2	3	4	5	Attrition	Δ Off-Diag	
1	55.9	20.8	8.4	6.2	5.3	3.4	45.7***	(0.024)
2	21.1	33.5	20.8	13.2	8.2	3.2	17.6***	(0.020)
3	8.7	21.3	34.9	21.8	10.4	3.0	19.3***	(0.019)
4	6.1	13.1	22.3	33.8	21.7	3.0	17.9***	(0.019)
5	5.4	8.2	10.5	21.9	51.3	2.9	39.9***	(0.024)
						-0.7***		
						(0.002)		

Panel C – One year ahead

	Portfolio$_{t+4}$							
Portfolio$_t$	1	2	3	4	5	Attrition	Δ Off-Diag	
1	47.2	20.6	10.2	8.1	7.2	6.8	35.7***	(0.021)
2	21.4	29.1	18.9	14.3	10.3	6.0	12.8***	(0.014)
3	10.5	19.3	30.8	21.5	12.1	5.8	15.0***	(0.019)
4	7.8	14.3	22.0	29.1	21.2	5.5	12.8***	(0.013)
5	7.4	10.8	12.2	21.0	43.4	5.2	30.5***	(0.023)
						-1.6***		
						(0.004)		

Table 5: **AMLT and Future Fund Performance: Portfolio Approach**

This table reports the abnormal monthly returns of portfolios of mutual funds sorted according to the most recent AMLT measure. Panel A and B summarize the intercepts from factor regressions based on the CAPM ("CAPM-α"), the Fama-French three-factor model ("FF-α"), the Carhart four-factor model ("Carhart-α"), and Pastor-Stambaugh five-factor model ("PS-α"). All returns are expressed in % per month. In Panel A (B) AMLT is computed using a symmetric (asymmetric) transformation of the ML signal. The significance levels are abbreviated with asterisks: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A – AMLT

Portfolio	1	2	3	4	5	6	7	8	9	10	H-L
CAPM-α	-0.120	-0.038	-0.017	-0.022	-0.003	-0.008	0.012	0.018	0.055	0.118*	0.237***
	(0.089)	(0.061)	(0.050)	(0.041)	(0.036)	(0.034)	(0.035)	(0.041)	(0.050)	(0.067)	(0.081)
FF-α	-0.133**	-0.047	-0.023	-0.027	-0.007	-0.011	0.008	0.014	0.048	0.107***	0.240***
	(0.066)	(0.045)	(0.038)	(0.031)	(0.028)	(0.026)	(0.025)	(0.028)	(0.031)	(0.040)	(0.079)
Carhart-α	-0.108*	-0.046	-0.028	-0.033	-0.013	-0.018	0.003	0.006	0.040	0.090**	0.198**
	(0.065)	(0.046)	(0.039)	(0.031)	(0.028)	(0.026)	(0.025)	(0.028)	(0.031)	(0.040)	(0.077)
PS-α	-0.113*	-0.049	-0.029	-0.035	-0.014	-0.020	0.001	0.004	0.038	0.089**	0.201***
	(0.063)	(0.044)	(0.038)	(0.031)	(0.028)	(0.025)	(0.025)	(0.028)	(0.031)	(0.039)	(0.076)

Panel B – AMLT_long

Portfolio	1	2	3	4	5	6	7	8	9	10	H-L
CAPM-α	-0.121	-0.038	-0.028	-0.016	0.000	-0.016	0.000	0.030	0.062	0.121**	0.242***
	(0.082)	(0.060)	(0.049)	(0.042)	(0.038)	(0.037)	(0.038)	(0.043)	(0.050)	(0.061)	(0.080)
FF-α	-0.132**	-0.046	-0.035	-0.021	-0.005	-0.020	-0.005	0.024	0.055*	0.113***	0.245***
	(0.063)	(0.046)	(0.036)	(0.031)	(0.028)	(0.027)	(0.026)	(0.028)	(0.031)	(0.041)	(0.078)
Carhart-α	-0.107*	-0.045	-0.040	-0.026	-0.009	-0.028	-0.010	0.015	0.045	0.097**	0.204***
	(0.062)	(0.046)	(0.036)	(0.031)	(0.028)	(0.027)	(0.026)	(0.028)	(0.031)	(0.041)	(0.075)
PS-α	-0.112*	-0.048	-0.042	-0.028	-0.010	-0.029	-0.011	0.013	0.044	0.096**	0.208***
	(0.061)	(0.045)	(0.036)	(0.031)	(0.028)	(0.027)	(0.026)	(0.027)	(0.031)	(0.040)	(0.075)

Table 6: **AMLT and Future Fund Performance: Multivariate Regressions**

This table reports monthly predictive regressions of fund returns on the most recent AMLT and on additional lagged control variables from January 2002 to December 2022. We report raw returns as well as performance measures based on the CAPM ("CAPM-α"), the Fama-French three-factor model ("FF-α"), and the Carhart four-factor model ("Carhart-α"). The abnormal returns are estimated as the return of a fund minus the fitted return for the various models using the factor loadings estimated over the prior 36 months. The regressions include time and style fixed effects. Standard errors are clustered by fund and are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variables:	Raw return$_t$	CAPM-α_t	FF-α_t	Carhart-α_t
Model:	(1)	(2)	(3)	(4)
AMLT$_{t-1}$	0.055***	0.045***	0.051***	0.055***
	(0.007)	(0.007)	(0.006)	(0.006)
Ret$_{t-1}$	0.044***	0.005	-0.001	0.006
	(0.008)	(0.007)	(0.007)	(0.007)
Exp ratio$_{t-1}$	-1.044***	-1.120***	-1.151***	-1.097***
	(0.113)	(0.123)	(0.105)	(0.101)
Log(TNA)$_{t-1}$	-0.004*	-0.001	-0.002	-0.004***
	(0.002)	(0.002)	(0.002)	(0.002)
Turnover$_{t-1}$	-0.035***	-0.026***	-0.043***	-0.060***
	(0.007)	(0.008)	(0.007)	(0.007)
Fund age$_{t-1}$	0.001***	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Time fixed effects	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Observations	417,034	408,163	408,163	408,163
Adjusted R^2	0.851	0.118	0.075	0.078

Table 7: **AMLT and Future Fund Performance: Performance Decomposition**

The table reports monthly predictive regressions of characteristic selectivity ("CS"), characteristic timing ("CT"), average style ("AS"), expense ratio ("Exp Ratio"), and return gap ("RG") on the most recent AMLT and on additional lagged control variables from January 2002 to December 2022. The "CS", "CT", and "AS" measures are based on Daniel et al. (1997), where the benchmarks are formed based on the market capitalization, dividend yield, and prior 12-month return. The "RG" measure is based on Kacperczyk et al. (2008). In Panel A, we present univariate regressions omitting control variables. In Panel B, we include the same control variables as in Table 6. Because Exp Ratio is highly persistent, we omit lagged Exp Ratio as control in Column (4). The regressions include time and style fixed effects. Standard errors are clustered by fund and are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A – Univariate Regression

Dependent Variables:	CS_t	CT_t	AS_t	Exp $Ratio_t$	RG_t
Model:	(1)	(2)	(3)	(4)	(5)
$AMLT_{t-1}$	0.050***	0.001	0.008***	-0.006***	0.008**
	(0.006)	(0.002)	(0.003)	(0.001)	(0.004)
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	434,065	420,089	420,089	433,522	418,959
Adjusted R^2	0.063	0.084	0.952	0.219	0.031

Panel B – Multivariate Regression

Dependent Variables:	CS_t	CT_t	AS_t	Exp $Ratio_t$	RG_t
Model:	(1)	(2)	(3)	(4)	(5)
$AMLT_{t-1}$	0.043***	0.002	0.009***	-0.005***	0.003
	(0.006)	(0.002)	(0.003)	(0.001)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	417,034	410,614	410,614	416,902	406,228
Adjusted R^2	0.065	0.085	0.952	0.330	0.032

Table 8: **AMLT and Future Fund Performance: Longer-term Performance**

This table reports longer-term monthly predictive regressions of fund returns on AMLT and on additional lagged control variables from January 2002 to December 2022. The dependent variable is abnormal returns with respect to the four-factor model of Carhart ("Carhart-α"). Column (1), (2), (3), and (4) consider a predictive horizon of one quarter, two quarters, one year, and two years, respectively. Abnormal returns are estimated as the return of a fund minus the fitted return using the factor loadings estimated over the prior 36 months. The regressions include time and style fixed effects. Standard errors are clustered by fund and are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variables:	Carhart-α_t	Carhart-α_{t+1}	Carhart-α_{t+4}	Carhart-α_{t+8}
Model:	(1)	(2)	(3)	(4)
AMLT_{t-1}	0.055***	0.033***	0.041***	0.031***
	(0.006)	(0.006)	(0.006)	(0.006)
Ret_{t-1}	0.006	0.038***	0.043***	-0.006
	(0.007)	(0.008)	(0.008)	(0.010)
Exp ratio_{t-1}	-1.097***	-1.176***	-1.070***	-1.041***
	(0.101)	(0.097)	(0.092)	(0.109)
Log(TNA)_{t-1}	-0.004***	-0.005***	-0.004**	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Turnover_{t-1}	-0.060***	-0.041***	-0.037***	-0.037***
	(0.007)	(0.006)	(0.007)	(0.007)
Fund age_{t-1}	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Time fixed effects	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Observations	408,163	399,791	372,937	337,799
Adjusted R^2	0.078	0.077	0.081	0.084

Table 9: **AMLT and Future Fund Performance: Market Conditions**

This table reports monthly predictive regressions of fund returns on the most recent AMLT interacted with market conditions, and on additional lagged control variables from January 2002 to December 2022. The dependent variable is abnormal returns with respect to the four-factor model of Carhart ("Carhart-α"). Abnormal returns are estimated as the return of a fund minus the fitted return using the factor loadings estimated over the prior 36 months. "High" is a dummy turning one if a market proxy in a given month is above the full sample median. In column (1), we condition on investor sentiment from Baker and Wurgler (2007) ("Sentiment"). In column (2) and (3), we condition on the monthly VIX index of implied volatilities of S&P 500 index options ("VIX") and market illiquidity ("Market illiquidity"), defined as the equally-weighted average of stock-level Amihud (2002) illiquidity for all NYSE/AMEX stocks in a month (Avramov et al., 2016), respectively. The regressions include time and style fixed effects. Standard errors are clustered by fund and are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variables:	Carhart-α_t		
Market states:	Sentiment	VIX	Market Illiquidity
Model:	(1)	(2)	(3)
AMLT_{t-1}	0.039***	0.017***	0.032***
	(0.008)	(0.007)	(0.007)
$\text{AMLT}_{t-1} \times \text{High}_t$	0.033***	0.071***	0.046***
	(0.010)	(0.012)	(0.011)
Ret_{t-1}	0.006	0.006	0.006
	(0.007)	(0.007)	(0.007)
Exp ratio_{t-1}	-1.098***	-1.102***	-1.097***
	(0.101)	(0.101)	(0.101)
Log(TNA)_{t-1}	-0.005***	-0.004**	-0.004***
	(0.002)	(0.002)	(0.002)
Turnover_{t-1}	-0.060***	-0.059***	-0.060***
	(0.007)	(0.007)	(0.007)
Fund age_{t-1}	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Time fixed effects	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes
Observations	408,163	408,163	408,163
Adjusted R^2	0.078	0.079	0.078

Table 10: **AMLT and Future Fund Performance: Fund Styles**

This table reports monthly predictive regressions of fund returns on the most recent AMLT and on additional lagged control variables from January 2002 to December 2022, estimated separately for groups of funds with different styles. The dependent variable is abnormal returns with respect to the four-factor model of Carhart ("Carhart-α"). Abnormal returns are estimated as the return of a fund minus the fitted return using the factor loadings estimated over the prior 36 months. At the beginning of each quarter, funds are are assigned to one out of four styles. Funds are first categorized into two groups based on a size score. Within each size group, funds are categorized into two groups based on a value score. The size (value) score of a fund corresponds to the average quintile number of firms' market values (book-to-market ratio) using NYSE cutoff levels. The regressions include time and style fixed effects. Standard errors are clustered by fund and are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variables:	Carhart-α_t			
Sample:	Small Value	Small Growth	Large Value	Large Growth
Model:	(1)	(2)	(3)	(4)
$AMLT_{t-1}$	0.039***	0.071***	0.044***	0.048***
	(0.010)	(0.010)	(0.010)	(0.012)
Ret_{t-1}	0.011	0.028*	-0.003	-0.021
	(0.018)	(0.014)	(0.016)	(0.014)
Exp $ratio_{t-1}$	-1.016***	-0.608***	-1.461***	-1.456***
	(0.215)	(0.213)	(0.166)	(0.188)
$Log(TNA)_{t-1}$	-0.009**	-0.008*	-0.006**	-0.002
	(0.004)	(0.004)	(0.002)	(0.003)
$Turnover_{t-1}$	-0.042***	-0.090***	-0.037***	-0.031**
	(0.015)	(0.012)	(0.010)	(0.012)
Fund age_{t-1}	0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Time fixed effects	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Observations	100,673	102,696	102,305	102,489
Adjusted R^2	0.149	0.225	0.110	0.085

Table 11: **AMLT and Volume of Information**

Panel A reports quarterly regressions of active portfolio tilt towards stocks with many signals ("ATILT_N.Signals") on AMLT and additional control variables from 2002 to 2022. Panel B, reports monthly predictive regressions of fund returns on the most recent AMLT interacted with holdings-based information proxies, and on additional lagged control variables from January 2002 to December 2022. The dependent variable is abnormal returns with respect to the four-factor model of Carhart ("Carhart-α"). Abnormal returns are estimated as the return of a fund minus the fitted return using the factor loadings estimated over the prior 36 months. "High info" is a dummy turning one if the holding-size weighted-average of firm-level number of available signals is above the cross-sectional median. The regressions include time and style fixed effects. Standard errors are clustered by fund and are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A – AMLT and Active Portfolio Tilt

Dependent Variables:	ATILT_N.Signals$_t$	
Model:	(1)	(2)
AMLT$_t$	0.208***	0.204***
	(0.009)	(0.009)
Exp ratio$_t$		-0.098***
		(0.015)
Log(TNA$_t$)		-0.003
		(0.004)
Turnover$_t$		0.045***
		(0.013)
Fund age$_t$		0.000
		(0.000)
Ret$_t$		-0.005
		(0.004)
Style fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Observations	145,741	141,068
Adjusted R^2	0.109	0.117

Panel B – Performance Regression

Dependent Variables:	Carhart-α_t	
Model:	(1)	(2)
AMLT_{t-1}	0.057***	0.047***
	(0.007)	(0.007)
High info_{t-1}	0.023***	0.020***
	(0.006)	(0.006)
$\text{AMLT}_{t-1} \times \text{High info}_{t-1}$	0.021*	0.021**
	(0.011)	(0.011)
Ret_{t-1}		0.006
		(0.007)
Exp ratio_{t-1}		-1.082***
		(0.101)
Log(TNA)_{t-1}		-0.004**
		(0.002)
Turnover_{t-1}		-0.060***
		(0.007)
Fund age_{t-1}		0.000
		(0.000)
Style fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Observations	415,044	408,163
Adjusted R^2	0.077	0.078

Table 12: **AMLT and Future Fund Performance: Alternative ML Model, and Quantitative vs. Textual Information Inputs**

This table reports monthly predictive regressions of fund returns on the most recent AMLT based on different predictive models and on additional lagged control variables from January 2002 to December 2022. The dependent variable is abnormal returns with respect to the four-factor model of Carhart ("Carhart-α"). Abnormal returns are estimated as the return of a fund minus the fitted return using the factor loadings estimated over the prior 36 months. We consider three alternative models. In column (2), the ML signal is derived from an Elastic-Net model using the full set of predictors. In columns (3) and (4), we use a DNN model, estimating the ML signal using only quantitative data in column (3) and only textual data in column (4). The regressions include time and style fixed effects. Standard errors are clustered by fund and are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variables:	Carhart-α_t			
Model:	(1)	(2)	(3)	(4)
AMLT_{t-1}	0.055***			
	(0.006)			
AMLT_ENet_{t-1}		0.027***		
		(0.006)		
AMLT_quant_{t-1}			0.028***	
			(0.005)	
AMLT_text_{t-1}				0.017***
				(0.006)
Ret_{t-1}	0.006	0.008	0.007	0.008
	(0.007)	(0.007)	(0.007)	(0.007)
Exp ratio_{t-1}	-1.097***	-1.153***	-1.151***	-1.182***
	(0.101)	(0.101)	(0.101)	(0.100)
Log(TNA)_{t-1}	-0.004***	-0.005***	-0.005***	-0.005***
	(0.002)	(0.002)	(0.002)	(0.002)
Turnover_{t-1}	-0.060***	-0.063***	-0.062***	-0.065***
	(0.007)	(0.007)	(0.007)	(0.007)
Fund age_{t-1}	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Time fixed effects	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Observations	408,163	408,163	408,163	408,163
Adjusted R^2	0.078	0.078	0.078	0.078

Table 13: **AMLT and Self-designated AI Funds and Quant Funds**

This table reports quarterly regressions of AMLT on self-designated fund strategy, AI funds, and Quant funds, along with additional control variables from 2002 to 2022. In columns (1) and (4), AMLT is based on the full set of information inputs. In columns (2) and (5), AMLT_quant is computed using only quantitative information inputs. In columns (3) and (6), AMLT_text is computed using only textual information inputs. The main independent variables are dummies that turn one if a fund is identified as an AI fund or Quant fund, and zero otherwise. We identify five funds that include the term "AI" in their fund name and 41 through online searches. We identify 46 funds that include the term "quant" or "quantitative" in their fund name. The regressions include time and style fixed effects. Standard errors are clustered by fund and are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variables:	$AMLT_t$	$AMLT_quant_t$	$AMLT_text_t$	$AMLT_t$	$AMLT_quant_t$	$AMLT_text_t$
Model:	(1)	(2)	(3)	(4)	(5)	(6)
AI $fund_t$	0.679***	0.692***	0.495***			
	(0.035)	(0.041)	(0.042)			
Quant $fund_t$				0.157***	0.191***	0.048
				(0.050)	(0.052)	(0.037)
Exp $ratio_t$	-0.171***	-0.173***	-0.133***	-0.172***	-0.174***	-0.135***
	(0.019)	(0.020)	(0.016)	(0.019)	(0.020)	(0.016)
$Log(TNA_t)$	-0.019***	-0.016***	-0.022***	-0.020***	-0.016***	-0.022***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)
$Turnover_t$	-0.117***	-0.124***	-0.074***	-0.119***	-0.126***	-0.074***
	(0.016)	(0.017)	(0.014)	(0.016)	(0.017)	(0.014)
Fund age_t	0.000	0.000	0.001	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ret_t	0.039***	0.046***	0.015***	0.039***	0.046***	0.015***
	(0.005)	(0.006)	(0.004)	(0.005)	(0.006)	(0.004)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	141,068	141,068	141,068	141,068	141,068	141,068
Adjusted R^2	0.096	0.086	0.059	0.091	0.081	0.055

Table 14: **AMLT and Employee AI Talent**

This table reports the relationship between AI talent and AMLT, as well as the predictive power of AI talent and AMLT for mutual fund performance. Panel A presents quarterly regressions of AMLT on AI talent and on additional control variables from 2002 to 2022. The main dependent variable is defined as the share of employees of an ADV that has AI talent ("Share_Core AI"). An employee is defined as having AI talent, if they list one out of the four AI core skills in their profile: Artificial Intelligence, Machine Learning, Natural Language Processing, and Computer Vision. The regressions include time and style fixed effects. Panel B presents monthly predictive regressions of fund returns on the most recent AMLT, Share_Core AI, and on additional lagged control variables from 2002 to 2022. The dependent variable is abnormal returns with respect to the four-factor model of Carhart ("Carhart-α"). Abnormal returns are estimated as the return of a fund minus the fitted return using the factor loadings estimated over the prior 36 months. The regressions include time and style fixed effects. Standard errors are clustered by fund and are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A – AMLT and Employee AI talent

Dependent Variable:	$AMLT_t$	
Model:	(1)	(2)
$Share_Core\ AI_t$	2.428***	1.227**
	(0.487)	(0.516)
$\log(\text{Nr of profiles}_t)$		0.018
		(0.011)
Exp ratio_t		-0.160***
		(0.037)
$\text{Log(TNA}_t)$		-0.020**
		(0.009)
Turnover_t		-0.153***
		(0.030)
Fund age_t		0.001
		(0.001)
Ret_t		0.034***
		(0.010)
$\log(\text{Nr of profiles}_t)$		0.018
		(0.011)
Time fixed effects	Yes	Yes
Style fixed effects	Yes	Yes
Observations	35,113	34,074
Adjusted R^2	0.005	0.083

Panel B – Performance Regression

Dependent Variable:	Carhart-α_t	
Model:	(1)	(2)
AMLT_{t-1}		0.073***
		(0.011)
$\text{Share_Core AI}_{t-1}$	0.742*	0.656
	(0.428)	(0.430)
Ret_{t-1}	0.009	0.006
	(0.012)	(0.012)
Exp ratio_{t-1}	-1.867***	-1.729***
	(0.276)	(0.280)
Log(TNA)_{t-1}	-0.008**	-0.007*
	(0.004)	(0.004)
Turnover_{t-1}	-0.066***	-0.056***
	(0.014)	(0.014)
Fund age_{t-1}	0.000	0.000
	(0.000)	(0.000)
$\log(\text{Nr of profiles}_{t-1})$	-0.014***	-0.015***
	(0.005)	(0.005)
Time fixed effects	Yes	Yes
Style fixed effects	Yes	Yes
Observations	98,684	98,684
Adjusted R^2	0.076	0.077