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Gerasimos G. Rompotis *

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Gerasimos G. Rompotis

University of Athens MBA, National and Kapodistrian University of Athens, Greece; geras3238@yahoo.gr

Abstract

This study employs a sample of 25 active and 22 passive AI ETFs to examine a series of issues surrounding their performance, risk, pricing efficiency, persistence in possible pricing discrepancies and their impact on ETFs' performance combined with the respective impact by the intraday volatility. The relationship between AI ETFs' performance and market factors concerning size, value, profitability, investment and momentum is evaluated too. The results indicate that the passive AI ETFs have outperformed the active over their entire trade history, without however shouldering their investors with materially higher volatility. Moreover, both AI ETF groups trade at a persistent premium to their NAV. The con-current premium affects returns in a positive way, while the one-lagged premium is negatively related to return. In addition, a negative relationship between return and con-current intraday volatility and a positive (but less strong) relationship between return and one-lagged intraday volatility are revealed. Moreover, the majority of AI ETFs cannot achieve significant alphas. Finally, the market factors suggested by Fama and French (2015) and Carhart (1997) are quite capable of explaining the performance of AI ETFs.

Keywords: AI ETFs; active and passive management; performance; risk; premium

1. Introduction

Artificial intelligence (AI) refers to the capability of computers or computer-controlled robots to perform tasks that are typically related to human intelligence, including comprehension, learning, reasoning, problem solving, decision making, creativity and autonomy.

The field of AI research was founded at a workshop in the Dartmouth College in 1956, where John McCarthy coined the term "artificial intelligence". However, early efforts in the field included the development of the first chess-playing machine by the Spanish engineer Leonardo Torres y Quevedo in 1914, the creation of a digital electronic computer by Professor John Vincent Atanasoff from the Iowa State College and his graduate student Clifford Berry in 1939, the creation of artificial neurons models by McCulloch and Pitts (1943), and the publication of Alan Turing's seminal work in artificial intelligence in 1950. Turing (1950) raised the question of whether "machines can think". The development of Arthur Samuel's Checkers in 1959 was another breakthrough in the growth path of AI. That program was considered to be the world's first self-learning program.

In the early 2000s, machine learning was being used in a wide range of applications in academia and industry. The massive exploitation of machine learning tools of the 2000s was facilitated by the availability of powerful computer systems and the significant evolution in the data collection and storage process, as well as the application of solid mathematical models. However, investment in AI boomed in the 2020s. This boom led to the rapid scaling and public releases of large language models like ChatGPT. Such models show human-like traits of knowledge, perception and creativity, and have been integrated into various sectors, fueling tremendous investment in AI technology.

Apart from being in the core of the fourth industrial revolution, AI offers investors very promising investment opportunities, such as AI Exchange Traded Funds (AI ETFs). These ETFs focus on firms that, in some way, participate in the artificial intelligence sector, providing investors with diversified exposure to this fast-growing industry at a relatively low cost compared to individual stock investments. These ETFs invest in a wide range of firms that focus on robotics, self-driving vehicles, large language models generation or improving the manufacturing processes, while tapping into the prospects of a technology that has just begun to scale. In comparison to AI mutual funds and index funds, AI ETFs are more flexible due to their continuous trading, also exceling in liquidity and cost terms.

From another perspective, the term AI ETFs often refers to ETFs employing artificial intelligence algorithms to assist the selection process and the management of the underlying portfolio. However, the assistance in the portfolio selection process by AI tools does not entail that AI securities are finally selected. In any case, ETFs that are built around AI stocks are not all the same. AI ETFs differ from each other in several factors, concerning fund size, price, risk, underlying value, and dividend policies. In addition, they may invest in different stocks or indices. One key element that can differentiate AI ETFs concerns their management approach, that is, whether such ETFs adopt active or passive management techniques.[1] In fact, more AI ETFs pursue active management than those adopting a passive management approach.[2]

An important factor to consider when choosing to trade with AI ETFs is the risk of such choices. Similar to the risks of investing in general, investing in an AI ETF could result in money loses and, obviously, past performance cannot guarantee future returns. In addition, similar to any emerging technology, there is a risk that some of the respective firms may go out of business. In fact, the AI industry is a highly competitive and volatile industry, with frequent changes in the synthesis of the sector's key players. However, as already noted, due to the diversification techniques adopted by AI ETFs, these funds are considered to be less risky than investing in individual AI stocks.

In this study, we examine a series of aspects concerning trading with AI ETFs. More specifically, we gather a sample of 25 active AI ETFs and 22 passive ETFs with trade data of at least one full year up to December, 31, 2025 and focus on their performance, risk, price discrepancies between their trade prices and Net Asset Values (NAVs), the persistence in these price discrepancies and their impact on the return of AI ETFs, along with the respective impact of intraday volatility, and, finally, the relationship between AI ETFs' performance and key market factors concerning size, value, profitability and investment patterns, as prescribed by Fama and French (2015), as well as the momentum factor suggested by Carhart (1997).

The empirical results show that, on average, passive AI ETFs have performed better than the active ones at the cumulative level over their entire trade history, both in trade price and NAV terms. On the other hand, the average risk and intraday volatility records of the two groups are quite close to each other. Furthermore, active and passive AI ETFs are found to trade at an average daily premium to their NAV of 4 and 7 basis points (bps), respectively, while both groups present a premium on about 60% of their total trade history. Via regression analysis, premium is found to be quite persistent. This persistence can go back up to five trade days, at least. On the question of whether premium can affect the return of AI ETFs, the empirical analysis shows that con-current premium is more meaningful in explaining returns (in a positive way) in the case of passive ETFs than in active ETFs, while the one-lagged premium is negatively related to the returns of both ETF groups. The analysis also reveals a negative relationship between return and con-current intraday volatility, both for active and passive AI ETFs, and a positive (but less strong) relationship between return and one-lagged intraday volatility. Finally, on the relationship between AI ETFs' performance and market factors, the regression analysis reveals that only a limited number of AI ETFs produce

[1] In the overall ETF market of the United States, active ETFs outnumbered passive ETFs for the first time in 2025, with about 1,000 active ETFs being launched in this year, with only 150 launches of passive ETFs. Source: https://www.morningstar.com/funds/active-etfs-9-charts-record-year.

[2] Etf.com reports that 81 AI ETFs are currently traded in the U.S. markets, with total assets under management of $34.98B and an average expense ratio of 0.75%. 41 of these ETFs are actively managed, 27 are passive ETFs and 13 are leveraged or inverse leveraged ETFs.

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significantly positive alphas over the Russell 3000 Index. Furthermore, the performance of AI ETFs is related with the Fama and French's (2015) size factor and Carhart's (1997) momentum factor in a positive way (on average terms), while performance is negatively related with the Fama and French (2015) value and robustness factors. The impact of the conservativeness factor is less significant.

This study has been motivated by the general growing interest in AI applications and the prosperous potential of the entire AI industry for the years to come, as well as the increasing interest in AI ETFs in particular. This study is not the first to focus on AI ETFs. For instance, Wu and Chen (2022) investigate the impact of AI ETFs on their underlying stocks. Bonaparte (2024) assesses the financial opportunities arising from the new AI innovation and proposes a valuation model for the respective ETFs and stocks. Chen and Ren (2022) evaluate the performance of AI-powered mutual funds, a cousin to AI ETFs. Poutachidou and Koulis (2025) study the performance of ETFs investing in firms involved in AI technologies by considering the impact of active management. Malhotra (2025) evaluates the performance of AI (and Blockchain) ETFs trying to identify whether these funds offer opportunities for generating positive alphas.

To the best of our knowledge, no study examines the pricing efficiency of AI ETFs by focusing on the differences between the trade prices and NAVs of these funds. No study assesses the impact of these price discrepancies on the return of AI ETFs either. The impact on intraday volatility of AI ETFs has also been neglected in the relevant literature. In addition, even though the merits of active management for the performance of AI ETFs have been assessed in the literature, the impact of active management on their pricing efficiency has not been evaluated yet. Our study seeks to fill these gaps. We deem our results to be quite important given the statistically significant relationships revealed between AI ETFs' returns, premium and intraday volatility. Investors could benefit from our findings by cashing on these relationships.

The rest of the paper is organized as follows: Section 2 provides an analysis of the key findings of literature concerning AI ETFs. Section 3 describes the research methodology and the sample of our study. Section 4 discusses empirical findings. Summary and conclusions are offered in Section 5.

2. Literature Review

Several studies in literature have focused on AI ETFs examining issues that mainly concern the effect of these ETFs on their underlying stocks, the financial opportunities that are provided by investing in AI financial instruments, the evaluation of AI ETFs and mutual funds' performance, and the benefits from integrating AI tools, such as machine learning technology, into portfolio management.

Trying to identify the impact on underlying stocks, Wu and Chen (2022) assess the difference in abnormal returns of AI ETFs' constituent stocks on the inception dates of ETFs by classifying them into funds with AI names and those without AI names. The empirical evidence indicates that the underlying stocks of ETFs with AI names have larger cumulative abnormal returns over the event period than stocks selected by ETFs without AI names. The difference in cumulative abnormal returns equals 40 bps. This finding verifies the existence of a return premium associated with the name of ETFs. On the other hand, Bonaparte (2024), by examining the financial opportunities arising from the new AI innovation and introducing a valuation model for AI stocks and ETFs, reports that the AI technology significantly affects financial markets, driving revenue growth and, consequently, impacting the valuations of stocks and ETFs.

On the performance of AI funds, Chen and Ren (2022) focus on the AI-powered mutual funds finding that these funds do not outperform the market. However, by comparing AI-powered funds to non-AI-powered funds, the authors reveal that the integration of AI tools into portfolio management provides a performance advantage to the corresponding funds. The authors conclude that the outperformance of AI funds is due to their lower transaction cost, superior stock-picking capability, and reduced behavioral biases. In the same field, Day and Lin (2019) developed a robo-advisor with different machine learning and deep learning forecasting methodologies to forecast ETF trends in the stock markets of Taiwan and the U.S., highlighting the superior performance achieved

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through AI applications compared to the traditional human-related selection process. Grobys et al. (2022) report similar results using a sample of hedge funds. The authors point out that a strategy that involves longing hedge funds with highest level of automation and shorting funds with highest level of human involvement yields a highly significant return spread of at least 50 bps per month.

Zhang et al. (2023) examine the impact of robo-advisors on the returns of 798 Chinese ETFs. The empirical findings indicate that the robo-advisor can enhance ETF returns up to a certain point, also revealing that the influence of a robot advisor on the average return of ETFs is comparatively less important than that of other risk and return factors. For the robo-advisor, the most crucial factors are the risk attributes associated with the ETFs. Baek et al. (2020) examine an application of machine learning to ETFs in the U.S. market by focusing on how the changes in ETF prices are associated with expected market fundamentals, trying to detect long or short investment signals. The authors find that the high probability of an upward momentum suggests a long ETF signal, whereas the low probability of a downward momentum indicates a short ETF signal. Kovvuri et al. (2023) apply explainable artificial intelligence to global equity funds in the context of the G10 countries, seeking to define the relationship between diversification and performance for these funds. The results show that both over- and under-diversification are associated with poor performance.

Malhotra (2023) compares the monthly risk-adjusted returns of technology mutual funds and ETFs with the DJIA US Technology Index, the NASDAQ 100 Tech Index, the NYSE Arca Tech 100 Index, and the S&P 500 Information Technology Index over a period spanning from January 2010 to July 2021. The results indicate high correlation of these funds with the benchmark indexes. In addition, it is found that the technology mutual funds outperform ETFs and benchmarks in absolute and risk-adjusted performance. In the same context, Malhotra (2025) evaluates the performance and portfolio role of AI and Blockchain ETFs during the period 2010-2025. The findings show that both AI and Blockchain ETFs achieve positive alpha and high standalone returns, but also display significant downside risk. Moreover, the two ETF types are not significantly correlated to each other, neither with broad market indices, offering potential for material diversification benefits. Karoui et al. (2024) also examine the diversification benefits and the return-risk attributes of portfolios including AI stocks. By exploring the influence of risk management strategies, ranging from "buy and hold" to daily rebalancing during the period from April 30, 2021, to September 15, 2023, the results show that the AI-related stocks have outperformed in recent years, possibly signaling an "AI bubble".

Poutachidou and Koulis (2025) investigate the performance of ETFs that invest in AI stocks using a sample of 15 American AI ETFs over the period from February 1, 2019 to December 29, 2023. The authors focus on the degree of active versus passive management strategies adopted by AI ETFs. Based on the empirical results, the AI ETFs adopt highly similar investment styles, suggesting a relatively homogeneous approach to capturing AI-related market opportunities. The results also show that most of performance variation can be explained by factor exposure and asset selection, rather than by distinct or innovative active strategies. In fact, the impact of active management on excess returns is modest and statistically insignificant, suggesting that passive investment approaches may be equally or more effective in capturing returns within the AI thematic universe. Boido and Aliano (2025) also focus on the possible benefits for AI ETFs that pursue active management with a sample of 94 AI ETFs from January 2015 to September 2023. The empirical analysis across the entire period and sample reveals no clear advantage of active versus passive management neither an opposite advantage.

Belhouichet et al. (2025) assess performance persistence of AI ETFs traded on the U.S. market over the period from January 1, 2023 to June, 23 2025 in comparison to other assets including the price of West Texas Intermediate (WTI) crude oil, Bitcoin, the S&P 500 Index, 10-year US Treasury bonds, and the VIX Volatility Index. The results reveal a high degree of persistence for all return series. These findings suggest that the newly developed AI- and robotics-themed ETFs do not provide investors with additional hedging or diversification benefits compared to more traditional assets. Baldan et al. (2025) compare portfolios composed of AI ETFs and portfolios of core equity ETFs, utilizing the mean-variance models of Markowitz and finding that AI ETFs are superior to core equity ETFs in performance terms. Nonetheless, the outperformance of AI ETFs comes at the expense of increased uncertainty for the outcomes, that can be exacerbated in cases of AI inefficiencies or systemic risk spreading across the financial sector.

With respect to risk, Duppati et al. (2023) investigate if liquidity risk is priced in AI ETF equity returns and equity premiums, by also focusing on whether such relationships hold in extreme market situations, such as the pre- and post-Covid periods. The authors find that the liquidity risk is an important determinant of AI ETFs' valuations and equity premiums. It is also found that the equity premium tends to increase at the higher levels of bid-ask spread in the pre- and post-Covid periods. Finally, Deng (2025) examines whether AI-driven funds exhibit herding behavior and how they perform under different market conditions. The key findings show that the AI funds do engage in herding, as a result of "informational herding". Furthermore, a critical "AI gap" is revealed during bear markets, that is AI funds significantly underperform institutional investors due to strategic inflexibility, which prevents them from adapting herding strategies to market downturns.

From the literature review above it is concluded that a study on the possible pricing discrepancies of AI ETFs and their impact on ETFs' performance is missing. The respective impact of intraday volatility has not been examined either. An examination of these relationships from an "active versus passive management" research angle is missing too. Our study seeks to fill these gaps in the literature and provide reliable statistical evidence on whether the differences in trade prices and net asset values of AI ETFs, as well as intraday volatility, can be beneficial to investors exposed to AI ETFs.

3. Methodology

In this section, we discuss the methodology that will be used to examine the performance of AI ETFs, the existence of pricing inefficiencies, the impact of such inefficiencies in AI ETFs' performance, along with the impact of other ETF-related or market factors. The sample of the study is described in this section too.

3.1. Return and Risk Analysis

We calculate the return and risk of AI ETFs in daily percentage terms with the following formula:

$$R_i = \frac{V_{i,t} - V_{i,t-1}}{V_{i,t-1}} * 100 \tag{1}$$

where, R_i refers to the percentage return of the ETF i on day t and $V_{i,t}$ refers to the close trade price (or the NAV) of this ETF or the same day.

Next, we compute the risk of AI ETFs as the standard deviation of daily returns. Risk is measured via the following formulas:

$$\sigma^2 = \frac{\sum_{t=1}^{N}(A_i - \bar{A})^2}{N-1} \tag{2}$$

$$\text{and} \quad \sigma_A = \sqrt{\sigma_A{}^2} \tag{3}$$

where, σ^2 denotes the variance of AI ETFs' return around the average return $\bar{A}$ and σ_A expresses the risk of an AI ETF portfolio in terms of standard deviation. We also calculate the risk/return (risk/reward) ratio of AI ETFs via dividing risk by average return. In general, this ratio enables evaluating potential returns against risks when deciding on investments. A lower risk/reward ratio indicates a more favorable balance between potential gains and risks, while a higher ratio suggests increased risk relative to expected return.

Along with risk (or volatility) expressed in standard deviation terms, we calculate the intraday volatility of AI ETFs. We do so via the following formula:

$$\text{IntVol}_i = \frac{HP_{i,t} - LP_{i,t-1}}{CP_{i,t-1}} * 100 \quad (4)$$

where, IntVol_i refers to the intraday volatility of the ETF i on day t, $HP_{i,t}$ concerns the highest intraday price of this ETF on day t, $LP_{i,t}$ regards the corresponding lowest intraday price, and $CP_{i,t}$ denotes the close trade price of this ETF or the same day.

3.2. Premium Analysis

In this section we calculate the daily percentage difference between the close trade prices of AI ETFs and their net assets values. Negative percentage differences are called "discounts" to NAV and positive differences are called "premium".[3] Premium is computed via the following formula:

$$Prem_i = \frac{CP_{i,t} - NAV_{i,t}}{NAV_{i,t}} * 100 \quad (5)$$

where, $CP_{i,t}$ is as in equation (4) and $NAV_{i,t}$ is the net asset value of the AI ETF i on day t.

Apart from calculating the premium of AI ETFs, we also assess the persistence in daily premium via the following autoregressive model:

$$Prem_{i,t} = \lambda_{i,t} + \sum_{s=-1}^{s=-5} Prem_{i,s} + u_{i,t} \quad (6)$$

where, $Prem_{i,t}$ is defined as in equation (6). The model uses five lags of daily premium as independent variables. Early findings of literature on ETFs (e.g., Elton et al., 2002, and Rompotis, 2009 & 2010) report no premium persistence due to the unique "in-kind" creation and redemption mechanism of ETF shares, which helps eliminating significant and long lasting differences between the trade prices and NAVs. However, other studies (e.g., Hughen, 2003, Jares and Lavin, 2004, and Delcoure and Zhong, 2007) find evidence of premium persistence, mostly in the case of internationally-oriented ETFs. Based on these evidence, both scenarios of premium's persistence and premium's lack of persistence are possible.

3.3. Regression Analysis of Returns

In this section, we assess the impact of premium and intraday volatility of AI ETFs. We do son via the following time-series regression model:

$$R_{i,t} = \lambda_i + \lambda_{1,i} R_{i,t-1} + \lambda_{2,i} Prem_{i,t} + \lambda_{3,i} Prem_{i,t-1} + \lambda_{4,i} IntVol_{i,t} + \lambda_{5,i} IntVol_{i,t-1} + u_i \quad (7)$$

where, R_i and $Prem_i$ are as above. $IntVol_i$ is the intraday volatility of the AI ETF on day t.

The one-lagged value of return has been added to the model for control purposes. Furthermore, if the efficient market hypothesis applies to AI ETF, there will not be any consistent relationship between return and premiums and, consequently, premium cannot be indicative of future returns. However, Jares and Lavin (2004) found a strong and significantly negative relationship between return and contemporaneous premium and a significantly positive correlation between return and lagged premium. On the contrary, Cherry (2004) finds that the return of iShares (leaders in the general ETF market) is negatively related to the one-lagged discount. Rompotis (2009 & 2010) reports that, on average, the return of ETFs is positively related to the contemporaneous premium and negatively to the lagged premium. Overall, all these suggest that premiums may be significant in determining the future returns of AI ETFs and that the AI ETF prices may not be informationally efficient.

As noted by Shum et al. (2016), high intraday volatility in ETFs induces price swings, creating both risks relating to magnified losses (especially for leveraged products) and opportunities (potentially significant profits from market timing/momentum strategies), often driven by volatility in the underlying assets. Based on this reasoning, we should expect the contemporaneous and the one-lagged intraday volatility factors in model (7) to be quite significant in explaining the return of AI ETFs.

[3] For convenience, we will call both negative and positive differences between trade prices and NAVs "premium" throughout this paper.

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3.4. Performance Regression Analysis

In this section, we apply the Fama and French (2015) five-factor model, also including the Fama and French's version of Carhart's (1997) momentum factor, to assess the ability of AI ETFs to achieve any material above-market return, measure their systematic risk and assess their exposure to certain market factors such as size, value, conservativeness, robustness and momentum. The time series model applied is shown in the following equation:

$$R_i\text{-}R_f=\alpha_i+\beta_{1,i}(R_m\text{-}R_f)+\beta_{2,i}SMB+\beta_{3,i}HML+\beta_{4,i}CMA+\beta_{5,i}RMW+\beta_{6,i}MOM + u_i \quad (8)$$

where, R_i is defined as in formula (1), R_m is the daily return of the market portfolio, which is proxied by the Rusell 3000 Index,[4] R_f is the risk-free rate expressed by the one-month U.S. Treasury bill rate, SMB (Small Minus Big) is the average return on nine small-cap portfolios minus the average return on nine big-cap portfolios, and HML (High Minus Low) is the average return on two value portfolios (based on book-to-market equity values) minus the average return on two growth portfolios. SMB and HML factors have been suggested by Fama and French (1993). Moreover, CMA (Conservative Minus Aggressive) is the average return on two conservative portfolios minus the average return on two aggressive portfolios and RMW (Robust Minus Weak) is the average return on two robust operating profitability portfolios minus the average return on two weak operating profitability portfolios. These two variables have been added by Fama and French (2015) to their original model of 1993. Finally, MOM (momentum) is the average of the returns on two (big and small) high prior return portfolios minus the average of the returns on two low prior return portfolios.[5] As Malhotra (2025) notes, the inclusion of the momentum factor in the performance regression analysis is especially relevant for the AI ETFs, as the stocks underneath these funds often experience sharp valuation swings affected by technological breakthroughs, innovation cycles, and investor sentiment.

If the exposures to the six factors capture all variation in the expected returns of AI ETFs, alphas will be zero. However, Malhotra (2025) finds that the AI (and Blockchain) ETFs do generate positive alphas via applying similar regression analysis (with monthly returns instead of daily returns used in our analysis). Thus, if Malhotra's results hold in our sample too, positive and significant alphas are to be expected.

The size effect implies that small-cap stocks outperform the large ones. The book-to-market equity ratio effect captured by the HML factor shows that the average returns on stocks with high book-value to market-value equity ratios is greater than the returns on stocks with low such ratios. The Conservative Minus Aggressive and Robust Minus Weak factors correspond to the Fama and French (2015) investment and operating profitability factors. The authors consider past investment as a proxy for the expected future investment and suggest that CMA implies a negative relationship between the expected investment and the expected internal rate of return, while they reveal a negative loading for the RMW factor. Based on this finding, the excess return of AI ETFs should be affected by the profitability factor in a negative way. Finally, the existence of momentum in asset prices is an anomaly that is difficult to explain given that, as the efficient capital markets theory suggests, an increase in the price of an asset cannot be indicative of further future increases in prices.

3.5. The Sample

According to Etf.com, currently there are 81 ETFs in the U.S. that are classified as AI-related. The total assets management of these ETFs amount to $34.98B. The majority of these AI ETFs are actively

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[4] The Rusell 3000 Index measures the performance of the largest 3000 companies traded in the United States representing approximately 98% of the investable U.S. equity market. Based on this coverage of the entire U.S. stock market, we deem this index as suitable performance benchmark for our analysis.

[5] The historical daily data of risk-free rate, Fama and French five factors, and Carhart's momentum factor, are available on http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

managed (i.e., 41 funds), 27 of them pursue passive management and 13 are leveraged or inverse leveraged ETFs.

In assembling the sample of our study, we required that an AI ETF has full trading data for at least one year up to December 31, 2025. In addition, we decided to exclude the leveraged and inverse leveraged ETFs from our analysis due to their unique investing orientation, which adopts the target of achieving X times the performance of a benchmark in a positive or negative way, compared to passive ETFs that simply seek to replicate their benchmarks or the active ETFs that aim at beating the overall market. Based on our selection criteria, 25 active and 22 passive AI ETFs made the cut to our sample.

Table 1 contains information on the AI ETFs included in our sample. Information provided concerns the symbol and name of ETFs, type (i.e., active or passive), launch date, age, assets as at December 31, 2025, expense ratio, average daily volume (in shares) over the entire trade history of each ETF and ESG score.

Table 1. Profiles of ETFs. This table presents the profiles of U.S.-listed AI ETFs examined in this study. Profiles include the symbol and name of ETFs, type, launch date, age, assets ($Millions) as at December 31, 2025, expense ratio, average daily volume (in shares) over the entire trade history of each ETF and ESG score.

Symbol	Name	Type	Launch Date	Age	Assets	Exp. Ratio	Volume	ESG Score
Panel A: Active ETFs								
BAI	iShares A.I. Innovation and Tech Active ETF	Active	21 Oct 2024	1.19		0.55	1,256,185	6.30
ARKQ	ARK Autonomous Technology & Robotics ETF	Active	30 Sep 2014	11.26		0.75	146,214	6.20
IETC	iShares U.S. Tech Independence Focused ETF	Active	21 Mar 2018	7.79		0.18	24,006	6.57
AIVL	WisdomTree U.S. AI Enhanced Value Fund	Active	16 Jun 2006	19.56		0.38	42,023	6.59
AIVI	WisdomTree International AI Enhanced Value Fund	Active	16 Jun 2006	19.56		0.58	27,037	7.62
IEDI	iShares U.S. Consumer Focused ETF	Active	21 Mar 2018	7.79		0.18	4,812	6.34
AMOM	QRAFT AI-Enhanced U.S. Large Cap Momentum ETF	Active	20 May 2019	6.62		0.75	6,155	6.05
QRFT	QRAFT AI-Enhanced U.S. Large Cap ETF	Active	20 May 2019	6.62		0.75	2,691	6.25
CHAT	Roundhill Generative AI & Technology ETF	Active	18 May 2023	2.62		0.75	136,330	6.29
AIPI	REX AI Equity Premium Income ETF	Active	04 Jun 2024	1.58		0.65	118,897	6.58
ALAI	Alger AI Enablers & Adopters ETF	Active	05 Apr 2024	1.74		0.55	39,677	5.57
FDTX	Fidelity Disruptive Technology ETF	Active	12 Jun 2023	2.56		0.50	21,947	6.82
FBOT	Fidelity Disruptive Automation ETF	Active	12 Jun 2023	2.56		0.50	16,028	6.99
ECML	Euclidean Fundamental Value ETF	Active	18 May 2023	2.62		0.95	3,649	5.87
AGIX	KraneShares Artificial Intelligence & Technology ETF	Active	18 Jul 2024	1.45		0.99	19,618	6.32
AIS	VistaShares Artificial Intelligence Supercycle ETF	Active	03 Dec 2024	1.08		0.75	34,128	6.73
AIFD	TCW Artificial Intelligence ETF	Active	06 May 2024	1.65		0.75	12,253	6.75
GROZ	Zacks Focus Growth ETF	Active	05 Dec 2024	1.07		0.56	12,337	6.12
AIYY	YieldMax AI Option Income Strategy ETF	Active	27 Nov 2023	2.10		1.67	67,392	5.77
LRNZ	TrueShares Technology, AI & Deep Learning ETF	Active	28 Feb 2020	5.84		0.69	8,104	6.70
DRAI	Draco Evolution AI ETF	Active	10 Jul 2024	1.48		1.34	4,725	5.92
GPT	Intelligent Alpha Atlas ETF	Active	17 Sep 2024	1.29		0.69	9,416	6.62

NEWZ	StockSnips AI-Powered Sentiment US All Cap ETF	Active	12 Apr 2024	1.72		0.75	4,544	6.52
XDAT	Franklin Exponential Data ETF	Active	12 Jan 2021	4.97		0.50	1,496	5.89
LQAI	LG QRAFT AI-Powered U.S. Large Cap Core ETF	Active	07 Nov 2023	2.15		0.75	1,090	6.05
Mean				**4.75**		**0.70**	**80,830**	**6.38**
Min				**1.07**		**0.18**	**1,090**	**5.57**
Max				**19.56**		**1.67**	**1,256,185**	**7.62**
Panel B: Passive ETFs								
AIQ	Global X Artificial Intelligence & Technology ETF	Passive	11 May 2018	7.65		0.68	269,051	6.79
BOTZ	Global X Robotics & Artificial Intelligence ETF	Passive	12 Sep 2016	9.31		0.68	769,925	7.04
ARTY	iShares Future AI & Tech ETF	Passive	26 Jun 2018	7.52		0.47	113,206	6.35
ROBO	ROBO Global Robotics & Automation Index ETF	Passive	22 Oct 2013	12.20		0.95	145,671	6.58
ROBT	First Trust Nasdaq Artificial Intelligence & Robotics E	Passive	21 Feb 2018	7.86		0.65	41,136	6.80
IGPT	Invesco AI and Next Gen Software ETF	Passive	23 Jun 2005	20.54		0.56	64,391	6.67
DRIV	Global X Autonomous & Electric Vehicles ETF	Passive	13 Apr 2018	7.72		0.68	166,202	6.30
AIEQ	Amplify AI Powered Equity ETF	Passive	17 Oct 2017	8.21		0.75	32,166	6.23
AIVC	Amplify Bloomberg AI Value Chain ETF	Passive	08 Mar 2016	9.82		0.59	5,044	7.02
WTAI	WisdomTree Artificial Intelligence and Innovation Fun	Passive	07 Dec 2021	4.07		0.45	99,724	6.78
THNQ	ROBO Global Artificial Intelligence ETF	Passive	11 May 2020	5.64		0.68	15,448	6.64
BUZZ	VanEck Social Sentiment ETF	Passive	02 Mar 2021	4.84		0.76	77,276	4.99
XAIX	Xtrackers Artificial Intelligence and Big Data ETF	Passive	02 Aug 2024	1.41		0.35	21,284	6.84
RWEM	Rayliant Wilshire NxtGen Emerging Markets Equity E	Passive	16 Dec 2021	4.04		0.52	7,121	6.25
RWLC	Rayliant Wilshire NxtGen US Large Cap Equity ETF	Passive	16 Dec 2021	4.04		0.32	10,690	6.61
HEAL	Global X HealthTech ETF	Passive	29 Jul 2020	5.43		0.50	36,044	5.95
WISE	Themes Generative Artificial Intelligence ETF	Passive	08 Dec 2023	2.07		0.35	11,012	5.37
IBOT	Vaneck Robotics ETF	Passive	05 Apr 2023	2.74		0.47	4,213	7.55

FAI	First Trust Bloomberg Artificial Intelligence ETF	Passive	20 Nov 2024	1.11		0.65	6,382	6.81
BOTT	Themes Humanoid Robotics ETF	Passive	22 Apr 2024	1.69		0.35	2,279	N/A
KCAI	KraneShares China Alpha Index ETF	Passive	28 Aug 2024	1.34		0.79	2,336	4.17
BULD	Pacer BlueStar Engineering the Future ETF	Passive	04 May 2022	3.66		0.49	374	7.85
Mean				**6.04**		**0.58**	**86,408**	**6.46**
Min				**1.11**		**0.32**	**374**	**4.17**
Max				**20.54**		**0.95**	**769,925**	**7.85**

The passive AI ETFs are older than their active peers by about 1.3 years. The average passive AI ETF is about 6 years old, while the average active AI ETF is about 4.7 years old. The oldest AI ETF in the sample is the Invesco AI and Next Gen Software ETF (IGPT). The average active AI ETF held about $578M as at December 31, 2025. The respective figure for passive ETFs is equal to $804M. The largest ETF in the entire sample is the iShares A.I. Innovation and Tech Active ETF (BAI), with assets of $8.2B. Overall, the total assets of the 47 AI ETFs included in our sample at the end of 2025 amounted to $32.1B, that is, about 92% of total assets channeled to all AI ETFs. This percentage indicates that the sample of our study is quite representative of the AI niche of the ETF market in the United States.

Furthermore, the average expense ratio of active AI ETFs is equal to 0.70%, being larger than that of passive AI ETFs by 12 bps, which is equal to 0.58%. Notably, the largest expense ratio in the sample is equal to 1.67%, charged by the active YieldMax AI Option Income Strategy ETF. With respect to trading activity, the average daily volume of active AI ETFs amounts to 81 thousand shares. The corresponding average term for passive ETFs is slightly higher at 86 thousand shares. Finally, on the question of the ESG performance of the AI ETFs examined, the figures in Table 1 are rather modest. Active ETFs have an average ESG scores of 6.38, whereas the average ESG scores of passive AI ETFs is equal to 6.46.

4. Empirical Results

4.1. Return and Risk Analysis

Table 2 presents the return and risk of AI ETFs. Statistics reported regard average daily return, cumulative return over the entire trade history of each ETF, minimum and maximum return scores, risk estimates (i.e., standard deviation in daily returns), the risk/ return ratio, and the intraday volatility. With the exception of intraday volatility, which is computed with trade prices, all of the statistics are calculated both with trade prices and net asset values.

Table 2. Return and Risk Analysis. This table presents the trading statistics of AI ETFs over their entire trade history, which include their average daily return, cumulative return, minimum and maximum returns, risk, risk to return (reward) ratio, intraday volatility calculated as the percentage difference between the intraday highest minus the intraday lowest trade price of an ETF divided by its close trade price on day t.

Symbol	**Price Ret**	**NAV Ret**	**Price Cum**	**NAV Cum**	**Price Ret Min**	**NAV Ret Min**	**Price Ret Max**	**NAV Ret Max**	**Price Risk**	**NAV Risk**	**Price Risk/PriceRet**	**NAVRisk/NAVRet**	**IntVol**
Panel A: Active ETFs													
BAI	0.12	0.13	35.48	35.92	-7.75	-7.79	13.55	13.61	2.13	2.15	17.05	17.02	2.14
ARKQ	0.08	0.08	489.33	487.86	-10.44	-11.67	14.05	13.96	1.79	1.80	22.71	22.83	1.78

IETC	0.09	0.09	323.21	314.22	-13.26	-12.66	12.41	12.54	1.61	1.62	18.49	18.87	1.44
AIVL	0.02	0.02	131.30	131.18	-11.89	-11.74	11.37	11.60	1.22	1.25	49.77	50.14	1.08
AIVI	0.01	0.01	4.37	4.47	-13.18	-12.02	15.76	11.12	1.40	1.22	130.60	145.57	0.98
IEDI	0.05	0.05	124.90	122.49	-11.90	-12.09	8.18	8.11	1.24	1.25	25.21	25.61	0.76
AMOM	0.05	0.05	93.50	93.98	-19.39	-19.42	10.36	10.40	1.66	1.67	30.87	30.87	1.09
QRFT	0.06	0.06	149.30	149.31	-9.94	-11.55	9.62	9.65	1.29	1.32	20.42	20.73	0.67
CHAT	0.14	0.14	127.58	128.34	-8.94	-8.17	14.51	11.39	1.81	1.61	12.77	11.63	1.81
AIPI	-0.05	-0.05	-20.96	-20.95	-7.01	-6.93	10.23	10.41	1.49	1.49	-30.72	-30.89	1.44
ALAI	0.15	0.15	79.79	80.42	-7.43	-7.25	14.16	12.96	1.81	1.77	11.97	11.73	1.42
FDTX	0.09	0.08	59.66	59.96	-6.84	-6.44	11.95	11.94	1.56	1.49	18.36	17.67	1.52
FBOT	0.05	0.05	30.85	31.36	-6.42	-5.63	9.91	8.71	1.29	1.09	25.63	22.50	1.10
ECML	0.05	0.05	31.83	32.00	-6.65	-6.09	7.42	7.24	1.20	1.20	24.34	24.31	0.37
AGIX	0.12	0.12	46.39	46.61	-7.94	-7.03	11.95	11.64	1.83	1.75	15.13	14.57	1.72
AIS	0.18	0.17	50.56	50.51	-9.38	-8.51	13.61	9.19	2.19	1.88	12.42	11.06	2.10
AIFD	0.11	0.11	47.10	46.94	-7.60	-7.64	13.43	13.62	1.85	1.85	16.82	16.87	1.61
GROZ	0.07	0.07	18.07	18.24	-6.13	-6.06	11.66	11.25	1.50	1.49	20.41	20.16	1.17
AIYY	-0.41	-0.41	-91.38	-91.37	-24.36	-24.86	16.03	19.35	3.33	3.46	-8.12	-8.53	3.65
LRNZ	0.07	0.07	87.93	88.11	-11.93	-13.31	14.54	14.33	2.39	2.42	33.38	33.43	2.10
DRAI	0.05	0.05	18.99	19.05	-5.05	-5.45	5.56	5.74	1.09	1.10	20.71	20.74	0.58
GPT	0.06	0.06	19.46	19.61	-7.94	-8.04	9.57	9.51	1.29	1.30	20.26	20.29	1.05
NEWZ	0.03	0.03	9.94	10.01	-6.11	-6.21	5.40	5.46	1.03	1.02	37.80	37.21	0.51
XDAT	0.02	0.02	4.03	4.79	-8.63	-7.84	11.76	11.63	1.88	1.87	90.17	88.06	0.79
LQAI	0.09	0.09	55.27	55.27	-5.91	-5.83	9.70	9.55	1.08	1.08	12.29	12.29	0.32
Mean	**0.05**	**0.05**	**77.06**	**76.73**	**-9.68**	**-9.61**	**11.47**	**11.00**	**1.64**	**1.61**	**25.95**	**26.19**	**1.33**
Min	**-0.41**	**-0.41**	**-91.38**	**-91.37**	**-24.36**	**-24.86**	**5.40**	**5.46**	**1.03**	**1.02**	**-30.72**	**-30.89**	**0.32**
Max	**0.18**	**0.17**	**489.33**	**487.86**	**-5.05**	**-5.45**	**16.03**	**19.35**	**3.33**	**3.46**	**130.60**	**145.57**	**3.65**
Panel B: Passive ETFs													
AIQ	0.08	0.08	242.03	242.00	-9.83	-11.36	12.19	9.95	1.60	1.49	20.77	19.79	1.57
BOTZ	0.05	0.05	145.46	145.39	-12.41	-8.53	12.77	9.20	1.62	1.31	31.39	27.82	1.46
ARTY	0.05	0.05	104.07	104.65	-10.22	-9.52	13.18	13.66	1.71	1.65	32.57	31.94	1.70
ROBO	0.04	0.04	173.74	176.27	-11.16	-8.97	10.23	8.50	1.36	1.13	32.31	28.63	1.29
ROBT	0.04	0.04	72.83	73.22	-11.86	-11.32	11.64	11.50	1.60	1.57	39.48	39.09	1.50
IGPT	0.06	0.06	1,104.66	1,109.94	-11.96	-12.53	13.36	13.86	1.50	1.52	25.39	25.49	1.52
DRIV	0.05	0.05	93.61	94.87	-11.98	-11.85	11.21	10.46	1.72	1.58	35.15	33.60	1.67
AIEQ	0.04	0.04	78.93	79.00	-12.00	-12.00	11.87	12.33	1.46	1.49	37.54	37.87	1.44
AIVC	0.05	0.05	168.01	168.61	-11.62	-11.62	14.00	10.04	1.65	1.52	30.81	29.44	1.41
WTAI	0.03	0.03	17.45	17.67	-7.38	-7.23	13.09	12.65	1.91	1.78	56.14	55.98	1.63
THNQ	0.08	0.08	151.00	151.72	-6.80	-6.81	12.78	11.79	1.79	1.74	22.15	21.66	1.75
BUZZ	0.05	0.05	38.14	38.16	-7.11	-7.16	14.44	14.79	2.05	2.05	43.07	43.04	2.22
XAIX	0.12	0.12	48.02	48.18	-6.12	-5.75	11.47	9.56	1.41	1.29	11.69	10.83	1.28
RWEM	0.02	0.02	17.67	16.82	-6.32	-6.02	8.27	4.50	1.19	0.95	51.51	47.90	0.85
RWLC	0.03	0.03	32.64	33.56	-11.71	-12.94	8.79	6.31	1.11	1.00	32.49	29.74	0.83
HEAL	-0.02	-0.02	-37.45	-36.87	-6.09	-5.90	8.03	7.01	1.66	1.56	-80.33	-72.43	1.92

WISE	0.10	0.10	53.39	53.27	-6.89	-6.23	13.94	12.67	2.09	1.99	19.99	19.43	1.96
IBOT	0.07	0.07	54.35	54.15	-6.56	-6.68	11.45	12.04	1.35	1.36	18.67	18.81	0.85
FAI	0.13	0.13	36.07	36.41	-7.18	-7.09	14.36	13.87	1.92	1.88	14.77	14.44	1.32
BOTT	0.14	0.14	69.11	68.68	-7.27	-5.96	11.78	4.84	1.84	1.58	13.07	11.62	0.95
KCAI	0.08	0.08	22.51	22.35	-25.81	-25.69	6.93	6.37	2.04	1.83	24.46	23.18	0.21
BULD	0.04	0.04	30.73	30.24	-8.44	-5.70	10.61	7.54	1.73	1.55	39.19	37.94	0.36
Mean	**0.06**	**0.06**	**123.50**	**124.01**	**-9.85**	**-9.40**	**11.66**	**10.16**	**1.65**	**1.54**	**25.10**	**24.36**	**1.35**
Min	**-0.02**	**-0.02**	**-37.45**	**-36.87**	**-25.81**	**-25.69**	**6.93**	**4.50**	**1.11**	**0.95**	**-80.33**	**-72.43**	**0.21**
Max	**0.14**	**0.14**	**1,104.66**	**1,109.94**	**-6.09**	**-5.70**	**14.44**	**14.79**	**2.09**	**2.05**	**56.14**	**55.98**	**2.22**

The average daily return of active AI ETFs is equal to 5 bps, both in trade price and NAV terms. The corresponding return of passive ETFs is higher by 1 bps. At the cumulative level, passive AI ETFs have clearly outperformed active ETFs over their entire trade history by about 46-47% (for both types of returns considered). This finding supports the merit of passive strategies in the long-lasting debate in finance of “active vs passive management”. At the fund level, only 2 active ETFs and just 1 passive achieved negative cumulative returns, verifying that AI ETFs are a very promising investment choice, even though high losses are not impossible to happen, as evidenced by the minimum return records provided in Table 2.

When it comes to volatility, the average risk of active AI ETFs equals 1.64 (1.61) in trade price (NAV) terms. The respective figures for passive ETFs are 1.65 and 1.54. The comparison of active and passive ETFs shows that the return advantage of passive ETFs over the active is not attained at a cost to investors, in terms of increased risk (and increased expense ratios as shown in Table 1). This assertion is confirmed by the risk/return ratios, which are higher for active AI ETFs than passive ETFs by 85 (183) bps in trade price (NAV) terms. Overall, the combined analysis of return and risk manifests a significant advantage of passive AI ETFs against their active counterparts.

Finally, the average terms of intraday volatility for active and passive ETFs verify that the latter are not riskier than the former. The average intraday volatility of active ETFs equals 1.33 and the respective figure of passive ETFs is slightly higher (by 2 bps) at 1.35. It is worth noticing that, occasionally, intraday volatility can be either quite low or materially high, as shown by the minimum and maximum intraday volatility records for both groups. Based on these extreme records, the passively managed AI ETFs are superior to the active ones in volatility terms (i.e., they are less volatile intraday).

4.2. Premium Analysis

The pricing of AI ETFs, i.e., the differences between trade prices and NAVs, is discussed in this section. The relevant calculations are provided in Table 3. Average terms, minimum and maximum records and standard deviations are included in the table. In addition, the number and portion (%) of days with discounts and premiums are provided. The corresponding mean discounts and mean premiums are also presented. Finally, the results of model (6) on the premium persistence are discussed in this section too.

Table 3. Premium Analysis. This table presents the statistics of AI ETFs’ premium(discount) over their entire trade history, which include their average daily percentage premium (discount), minimum and maximum premiums (discounts), the standard deviation of premiums (discounts), the number and the portion of days with premiums and discounts, and the corresponding mean discount and premium. .

Symbol	Average	Min	Max	StDev	Days of Discount	Days of Premium	% of Days with Discount	% of Days with Premium	Mean Disc	Mean Prem

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Panel A: Active ETFs										
BAI	0.12	-0.31	2.23	0.17	47	251	15.772	84.228	-0.08	0.16
ARKQ	0.04	-1.88	2.50	0.26	1,246	1,584	44.028	55.972	-0.12	0.17
IETC	0.03	-2.09	1.92	0.16	712	1,242	36.438	63.562	-0.08	0.10
AIVL	-0.01	-1.47	1.91	0.11	2,835	2,081	57.669	42.331	-0.07	0.07
AIVI	0.00	-6.87	8.51	0.73	2,349	2,567	47.783	52.217	-0.49	0.46
IEDI	-0.04	-3.90	2.17	0.29	1,290	664	66.018	33.982	-0.13	0.12
AMOM	-0.03	-2.11	2.17	0.22	1,011	653	60.757	39.243	-0.13	0.12
QRFT	-0.02	-1.95	0.98	0.18	919	745	55.228	44.772	-0.10	0.08
CHAT	0.03	-2.14	1.56	0.31	296	362	44.985	55.015	-0.22	0.24
AIPI	0.09	-0.22	0.83	0.10	68	328	17.172	82.828	-0.06	0.12
ALAI	0.08	-0.57	1.25	0.17	128	309	29.291	70.709	-0.09	0.15
FDTX	0.00	-0.92	1.15	0.19	324	318	50.467	49.533	-0.14	0.14
FBOT	-0.02	-2.14	1.40	0.44	309	333	48.131	51.869	-0.36	0.29
ECML	0.01	-0.59	0.36	0.07	283	375	43.009	56.991	-0.04	0.06
AGIX	0.12	-1.42	1.62	0.31	91	275	24.863	75.137	-0.22	0.22
AIS	0.21	-1.86	2.92	0.44	67	203	24.815	75.185	-0.29	0.38
AIFD	-0.03	-0.49	0.30	0.12	247	169	59.375	40.625	-0.11	0.09
GROZ	0.04	-0.23	1.27	0.14	104	164	38.806	61.194	-0.05	0.10
AIYY	0.09	-2.45	4.75	0.53	229	296	43.619	56.381	-0.41	0.31
LRNZ	0.02	-0.51	3.17	0.22	800	668	54.496	45.504	-0.07	0.13
DRAI	0.04	-0.19	0.54	0.08	88	284	23.656	76.344	-0.05	0.07
GPT	0.05	-0.67	0.77	0.15	131	192	40.557	59.443	-0.07	0.13
NEWZ	0.09	-0.59	1.81	0.14	63	369	14.583	85.417	-0.06	0.11
XDAT	0.02	-3.99	5.50	0.49	615	632	49.318	50.682	-0.14	0.16
LQAI	-0.01	-0.54	0.54	0.08	284	255	52.690	47.310	-0.06	0.05
Mean	**0.04**	**-1.60**	**2.09**	**0.24**	**581**	**613**	**41.74**	**58.26**	**-0.15**	**0.16**
Min	**-0.04**	**-6.87**	**0.30**	**0.07**	**47**	**164**	**14.58**	**33.98**	**-0.49**	**0.05**
Max	**0.21**	**-0.19**	**8.51**	**0.73**	**2,835**	**2,567**	**66.02**	**85.42**	**-0.04**	**0.46**
Panel B: Passive ETFs										
AIQ	0.06	-2.40	1.53	0.29	719	1,200	37.467	62.533	-0.24	0.20
BOTZ	0.06	-4.75	4.56	0.57	981	1,358	41.941	58.059	-0.45	0.38
ARTY	0.14	-2.26	1.43	0.27	547	1,341	28.972	71.028	-0.18	0.27
ROBO	0.00	-4.28	3.98	0.43	1,458	1,609	47.538	52.462	-0.67	0.29
ROBT	0.12	-3.08	2.43	0.25	488	1,488	24.696	75.304	-0.17	0.22
IGPT	0.00	-4.25	4.33	0.24	2,760	2,403	53.457	46.543	-0.13	0.13
DRIV	-0.02	-7.71	2.92	0.37	1,036	903	53.430	46.570	-0.28	0.22
AIEQ	-0.02	-0.91	1.12	0.16	1,157	905	56.111	43.889	-0.13	0.11
AIVC	-0.01	-2.37	2.69	0.39	1,338	1,131	54.192	45.808	-0.28	0.31
WTAI	0.13	-3.21	5.54	0.53	354	665	34.740	65.260	-0.23	0.31
THNQ	0.04	-1.20	0.81	0.22	563	856	39.676	60.324	-0.17	0.18
BUZZ	-0.04	-2.92	2.50	0.16	742	472	61.120	38.880	-0.10	0.06
XAIX	0.15	-0.59	1.45	0.18	57	298	16.056	83.944	-0.11	0.20

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RWEM	0.09	-6.35	7.28	0.98	457	557	45.069	54.931	-0.61	0.64
RWLC	-0.10	-3.59	4.47	0.50	644	370	63.511	36.489	-0.35	0.32
HEAL	-0.13	-1.61	1.03	0.36	878	485	64.417	35.583	-0.36	0.22
WISE	0.17	-1.40	0.93	0.23	109	408	21.083	78.917	-0.17	0.25
IBOT	0.23	-0.44	0.74	0.14	24	663	3.493	96.507	-0.10	0.25
FAI	0.16	-0.35	0.88	0.15	27	250	9.747	90.253	-0.07	0.19
BOTT	0.34	-2.17	5.52	0.59	83	343	19.484	80.516	-0.40	0.52
KCAI	0.09	-3.71	13.28	1.16	159	178	47.181	52.819	-0.36	0.48
BULD	-0.02	-9.33	6.28	1.00	418	500	45.534	54.466	-0.53	0.38
Mean	**0.07**	**-3.13**	**3.44**	**0.42**	**682**	**836**	**39.50**	**60.50**	**-0.28**	**0.28**
Min	**-0.13**	**-9.33**	**0.74**	**0.14**	**24**	**178**	**3.49**	**35.58**	**-0.67**	**0.06**
Max	**0.34**	**-0.35**	**13.28**	**1.16**	**2,760**	**2,403**	**64.42**	**96.51**	**-0.07**	**0.64**

The average active AI ETF trades at premium of 4 bps over its entire trade history, while the average premium of passive AI ETFs is slightly higher at 7 bps. At the fund level, 8 out of 25 active ETFs and 9 out of 22 passive ETFs trade at a discount. Furthermore, quite high daily discounts or premiums are to be expected when trading with AI ETFs, as verified by the minimum and maximum scores in Table 3. In this respect, the extreme discounts or premiums are higher for passive ETFs than those of active ETFs, showing that the arbitrage mechanism inherent to ETFs, which helps minimizing the differences between their trade prices and NAVs, works better for active AI ETFs than for their passive peers.

On the variation in daily premiums or discounts, the relevant standard deviations in Table 3 indicate that pricing discrepancies are not that volatile. However, they are more volatile for passive AI ETFs than for the active ones (i.e., 0.42 vs 0.24, respectively).

Overall, the analysis of pricing efficiency so far shows that the active AI ETFs trade closer to their underlying values compared to the passive AI ETFs. This evidence could be critical for investors forming their ETF investment choices based on the criterion of proximity between the value of ETF shares and that of the underlying assets.

Furthermore, as shown in Table 3, both active and passive AI ETFs are more prone to trading at a premium instead of a discount. On about 60% of total trade history, active and passive AI ETFs present a premium at the end of the trade day, while discounts are presented on about 40% of days. In the case of active (passive) ETFs, the respective mean discount amounts to 15 (28) bps, while their mean premium is equal to 16 (28) bps. These statistics verify the superiority of active AI ETFs in trading closer to their NAVs.

The estimates of model (6) on premium persistence are found in Table 4. Regarding the one-lagged premium of active AI ETFs, just 7 significantly positive estimates and only 1 significantly negative coefficients are obtained. In the case of passive AI ETFs, 11 estimates are significantly positive. Moreover, most of the two-lagged premium estimates are positive and significant (17 and 16 for active and passive AI ETFs, respectively), while no significantly negative estimate is produced. The influence of the three-lagged premium is less strong, but still significantly positive for 11 active and 14 passive AI ETFs. Even weaker, but still positive, is the impact of the four-lagged premium for 10 active ETFs and 11 passive. Finally, in 9 cases, the five-lagged premium is positive and significant for active ETFs and in 1 case significantly negative. For passive AI ETFs, the five-lagged premium offers 15 out of 22 significantly positive coefficients.

Table 4. Premium Persistence Regression Analysis. This table presents the results of an autoregressive model via which the premium of each AI ETF is regressed on its lagged values up to five days. The estimation period of each AI ETF spans from its launch date up to December 31, 2025 (see Table 1 for launch dates). a indicates statistical significance at 1%; b indicates statistical significance at 5%; c indicates statistical significance at 10%.

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Symbol	const	t-Stat	Pr(-1)	t-Stat	Pr(-2)	t-Stat	Pr(-3)	t-Stat	Pr(-4)	t-Stat	Pr(-5)	t-Stat	R^2	Obs
Panel A: Active ETFs														
BAI	0.13[a]	6.06	-0.02	-0.31	0.15[b]	2.03	-0.04	-0.56	0.00	0.01	-0.10	-1.41	0.12	293
ARKQ	0.03[a]	6.07	0.05	1.16	0.10[c]	1.89	0.03	0.79	0.08[c]	1.90	0.03	0.76	0.13	2,825
IETC	0.02[a]	4.61	0.07	0.68	0.01	0.27	0.13[a]	2.98	0.07	1.45	-0.01	-0.08	0.13	1,949
AIVL	-0.01[a]	-3.35	0.08	1.19	0.13[a]	3.22	0.12[a]	2.68	0.05	1.12	0.01	0.30	0.15	4,911
AIVI	0.00	0.28	0.03	0.86	0.09[a]	2.60	0.11[a]	3.43	0.07	1.61	0.08[b]	2.25	0.14	4,911
IEDI	-0.02[a]	-3.49	0.31[a]	2.62	0.08	1.28	0.05	0.62	-0.04	-0.46	0.06	0.67	0.23	1,949
AMOM	-0.02[a]	-2.60	0.08	1.01	0.10[a]	2.73	0.12[b]	2.08	0.14[a]	3.50	0.08[b]	2.24	0.19	1,659
QRFT	-0.01[b]	-2.43	0.07	1.17	0.07[b]	2.15	0.17[a]	4.42	0.10[b]	2.56	0.11[a]	2.85	0.19	1,659
CHAT	0.02	1.24	0.10	1.38	0.13[b]	2.49	0.09	1.13	0.05	1.34	0.05	1.02	0.16	653
AIPI	0.06[a]	5.72	0.11[b]	2.11	0.08	1.42	0.15[a]	2.63	0.00	0.03	0.05	0.98	0.15	391
ALAI	0.03[b]	2.48	0.06	0.79	0.25[a]	2.88	0.07	1.16	0.05	0.91	0.1[b]	2.05	0.24	432
FDTX	0.00	0.08	0.10	1.39	0.25[a]	5.03	0.09[c]	1.91	0.18[a]	4.39	0.09	1.57	0.35	637
FBOT	-0.01	-0.78	0.15[a]	2.72	0.10[b]	2.16	0.15[a]	3.04	0.09[c]	1.95	0.04	0.81	0.22	637
ECML	0.01[c]	1.95	0.09[b]	2.33	0.14[a]	3.51	0.08[c]	1.91	0.08[c]	1.83	0.16[a]	3.81	0.21	653
AGIX	0.06[a]	3.13	0.20[a]	3.71	0.13[b]	2.40	0.09	1.49	0.14[b]	2.42	-0.04	-0.77	0.23	361
AIS	0.13[b]	2.17	0.12	0.99	0.19[a]	3.04	0.03	0.25	-0.07	-1.16	0.13	1.57	0.17	265
AIFD	-0.01	-1.49	0.19[a]	3.95	0.09[c]	1.88	0.13[b]	2.57	0.19[a]	3.62	0.11[b]	2.13	0.36	411
GROZ	0.04[a]	3.30	0.09	1.43	0.10	1.38	0.02	0.32	-0.04	-0.62	0.06	0.89	0.12	263
AIYY	0.07[a]	2.64	0.00	0.00	0.03	0.80	0.05	1.42	0.08[b]	2.09	0.06	0.83	0.11	520
LRNZ	0.01	1.52	0.07	0.92	0.21[a]	3.04	0.17[a]	2.61	0.15	1.47	0.16[c]	1.99	0.37	1,463
DRAI	0.03[a]	5.49	-0.02	-0.37	0.10[c]	1.78	0.00	0.00	-0.01	-0.26	0.13[b]	2.43	0.12	367
GPT	0.02[c]	1.93	-0.01	-0.06	0.28[a]	3.08	0.08	0.76	0.19[c]	1.87	0.06	0.68	0.28	318
NEWZ	0.10[a]	7.35	-0.09[c]	-1.88	-0.05	-0.95	-0.02	-0.43	0.05	0.95	-0.02	-0.31	0.11	427
XDAT	0.02	1.04	0.17[a]	5.95	0.01	0.18	0.00	0.01	-0.01	-0.38	-0.09[a]	-2.88	0.14	1,242
LQAI	0.00	-1.14	0.10	1.21	0.05	1.27	0.07	1.36	0.05	1.18	0.09[b]	2.33	0.14	534
Mean	**0.03**	**1.67**	**0.08**	**1.40**	**0.11**	**2.06**	**0.08**	**1.54**	**0.07**	**1.33**	**0.06**	**1.07**	**0.19**	**1,189**
Min	**-0.02**	**-3.49**	**-0.09**	**-1.88**	**-0.05**	**-0.95**	**-0.04**	**-0.56**	**-0.07**	**-1.16**	**-0.10**	**-2.88**	**0.11**	**263**
Max	**0.13**	**7.35**	**0.31**	**5.95**	**0.28**	**5.03**	**0.17**	**4.42**	**0.19**	**4.39**	**0.16**	**3.81**	**0.37**	**4,911**
Panel B: Passive ETFs														
AIQ	0.03[a]	3.63	0.12[a]	2.85	0.13[a]	4.14	0.02	0.65	0.05	1.60	0.15[a]	4.35	0.19	1,914
BOTZ	0.03[b]	2.40	0.04	0.90	0.13[a]	3.94	0.08[b]	2.31	0.07[b]	2.43	0.08[a]	2.78	0.15	2,334
ARTY	0.02[a]	3.67	0.20[a]	3.22	0.17[a]	4.33	0.14[a]	3.18	0.15[a]	3.80	0.16[a]	4.43	0.51	1,883
ROBO	0.00	-0.09	0.08[c]	1.92	0.19[a]	6.13	0.11[a]	3.18	0.09[a]	3.30	0.11[a]	4.38	0.23	3,062
ROBT	0.04[a]	4.11	0.09	1.14	0.13[a]	3.92	0.12[a]	3.99	0.18[a]	5.37	0.17[a]	4.29	0.31	1,971
IGPT	0.00	-0.69	-0.07	-0.81	0.01	0.32	0.10[c]	1.66	0.10[c]	1.81	0.07[b]	2.09	0.13	5,158
DRIV	-0.02[c]	-1.85	0.03	0.38	0.11[c]	1.98	0.11[b]	2.41	0.10[b]	2.48	0.06	1.31	0.15	1,934
AIEQ	-0.01[a]	-2.73	0.07	1.64	0.14[a]	4.17	0.06[c]	1.87	0.03	0.97	0.12[a]	3.51	0.16	2,057
AIVC	0.00	-0.24	0.18[a]	4.93	0.19[a]	6.61	0.12[a]	3.71	0.16[a]	6.53	0.13[a]	4.92	0.43	2,464
WTAI	0.10[a]	5.15	0.10[a]	3.03	-0.05	-1.56	0.08[b]	2.25	0.05	1.39	0.05	1.46	0.12	1,014
THNQ	0.01[c]	1.82	0.19[a]	4.72	0.15[a]	4.47	0.18[a]	5.35	0.13[a]	4.54	0.12[a]	4.42	0.44	1,414
BUZZ	-0.03[a]	-5.35	-0.11	-0.72	0.02	0.39	0.08[b]	2.29	0.07[b]	2.01	0.05[c]	1.74	0.12	1,209

XAIX	0.06[b]	2.46	0.05	0.50	0.30[a]	4.04	0.03	0.24	0.08	1.20	0.16[b]	2.15	0.27	350
RWEM	0.03	1.13	0.20[b]	2.32	0.15[b]	2.16	0.06	0.90	0.00	0.02	0.20[a]	3.69	0.26	1,009
RWLC	-0.04[a]	-2.76	0.19[c]	1.81	0.13[b]	2.58	0.05	0.67	0.11	1.49	0.11[b]	2.54	0.25	1,009
HEAL	-0.04[a]	-4.63	0.11[a]	3.00	0.19[a]	5.90	0.12[a]	3.53	0.17[a]	4.87	0.11[a]	3.79	0.33	1,358
WISE	0.08[a]	4.88	0.07	1.52	0.14[a]	3.15	0.11[b]	2.29	0.10[b]	2.07	0.11[b]	2.41	0.20	512
IBOT	0.18[a]	9.69	-0.01	-0.33	0.09[b]	2.28	0.11[a]	2.68	0.02	0.41	0.02	0.51	0.12	682
FAI	0.11[a]	5.37	0.10[c]	1.72	0.10	1.55	0.10	1.46	-0.03	-0.51	0.06	0.93	0.14	272
BOTT	0.30[a]	3.98	-0.13	-1.23	0.13[c]	1.95	0.02	0.19	0.05	0.67	0.07	1.13	0.14	421
KCAI	0.08	1.15	0.26	1.31	0.16	0.95	0.09	0.59	-0.06	-0.39	0.00	-0.04	0.23	332
BULD	-0.01	-0.26	0.38[a]	2.64	0.19[b]	2.59	-0.06	-0.85	-0.09	-1.62	-0.02	-0.32	0.31	913
Mean	**0.04**	**1.40**	**0.10**	**1.66**	**0.13**	**3.00**	**0.08**	**2.02**	**0.07**	**2.02**	**0.10**	**2.57**	**0.24**	**1,512**
Min	**-0.04**	**-5.35**	**-0.13**	**-1.23**	**-0.05**	**-1.56**	**-0.06**	**-0.85**	**-0.09**	**-1.62**	**-0.02**	**-0.32**	**0.12**	**272**
Max	**0.30**	**9.69**	**0.38**	**4.93**	**0.30**	**6.61**	**0.18**	**5.35**	**0.18**	**6.53**	**0.20**	**4.92**	**0.51**	**5,158**

Overall, the results of model (6) indicate that the premium (discount) of trade prices for AI ETFs is quite persistent on a daily (and more than daily) basis. Given the positive sign for the majority of statistically significant estimates of the premium's five lagged values considered in the regression model, the premium (or discount) of an AI ETF on one day is likely to continue up to five days, at least, based on our research approach. To our view, profitable investing strategies could be built on this evidence concerning premium persistence by executing efficient arbitrage techniques from the one trade day to the next.

4.3. Regression Analysis of Returns

The results of model (7) on the impact of premium and intraday volatility on returns are presented in Table 5. First, with respect to the relationship between current and lagged returns, 5 significantly negative and 1 positive and significant estimates are obtained for active ETFs. In the case of passive AI ETFs, 10 coefficients are significantly positive and one is negative and significant. These results indicate that there is no monotonic relationship between current and lagged returns for all AI ETFs.

Table 5. Return Regression Analysis. This table presents the results of a regression model via which the returns each AI ETF is regressed on its one-lagged value, the con-current and the one-lagged premium, and the con-current and the one-lagged intraday volatility. The estimation period of each AI ETF spans from its launch date up to December 31, 2025 (see Table 1 for launch dates). a indicates statistical significance at 1%; b indicates statistical significance at 5%; c indicates statistical significance at 10%. .

Symbol	const	t-Stat	Ret(-1)	t-Stat	Pr(-1)	t-Stat	Pr(-2)	t-Stat	IntVol	t-Stat	IntVol(-1)	t-Stat	R^2	Obs
Panel A: Active ETFs														
BAI	0.72	1.02	-0.06	-0.62	-1.05	-1.00	-0.81	-1.28	-0.45	-1.42	0.28[c]	1.73	0.18	296
ARKQ	0.41[a]	4.33	-0.03	-1.09	-0.17	-1.51	-0.87[a]	-7.68	-0.39[a]	-6.32	0.23[a]	5.23	0.16	2,828
IETC	0.38[a]	2.68	-0.12[a]	-2.90	-0.51[c]	-1.70	-0.22	-0.78	-0.39[a]	-3.91	0.21[a]	3.57	0.17	1,952
AIVL	0.07[c]	1.78	-0.08[b]	-2.30	-1.61[a]	-4.02	-0.15	-0.45	-0.08[b]	-2.25	0.02	0.78	0.14	4,914
AIVI	0.04	1.12	0.05[b]	2.17	1.17[a]	29.41	-0.37[a]	-6.92	-0.21[a]	-4.25	0.17[a]	3.76	0.50	4,914
IEDI	0.17[b]	2.09	-0.10[b]	-2.02	0.26[b]	2.33	-0.50[a]	-3.52	-0.27[a]	-2.79	0.11	1.43	0.14	1,952
AMOM	0.35[a]	3.61	-0.10[b]	-2.58	0.35	1.30	-0.36	-0.97	-0.40[a]	-3.26	0.13[c]	1.77	0.17	1,662
QRFT	0.29[a]	6.90	-0.13[a]	-5.22	-0.32[c]	-1.88	-0.18	-1.05	-0.47[a]	-12.28	0.13[a]	3.23	0.20	1,662
CHAT	0.07	0.26	0.07	1.37	3.82[a]	10.21	-1.64[a]	-6.09	-0.23[c]	-1.81	0.23[b]	2.38	0.57	656

AIPI	0.25	0.94	-0.08	-1.00	-0.98	-1.11	-0.87	-1.43	-0.52[a]	-2.87	0.42[a]	3.21	0.22	394
ALAI	0.32	0.96	-0.04	-0.49	2.04[b]	2.11	-1.87[c]	-1.81	-0.35	-1.48	0.22[b]	2.03	0.19	435
FDTX	0.16	0.36	0.03	0.36	3.55[a]	9.54	-2.23[a]	-5.16	-0.19	-0.71	0.15	0.94	0.30	640
FBOT	-0.18	-0.68	0.11	1.46	2.19[a]	12.77	-0.72[a]	-3.75	0.12	0.51	0.11	0.82	0.59	640
ECML	0.04	0.44	0.01	0.18	-0.47	-0.28	-0.03	-0.03	0.14	0.66	-0.08	-0.67	0.11	656
AGIX	0.58	1.64	0.00	0.02	1.32[a]	4.59	-1.68[a]	-3.39	-0.51[a]	-3.06	0.26	1.62	0.30	364
AIS	-0.03	-0.19	0.05	0.83	3.81[a]	18.02	-1.86[a]	-6.60	-0.14[b]	-2.13	0.03	0.47	0.67	268
AIFD	0.32	0.78	-0.08	-1.04	-0.37	-0.43	-0.99	-1.27	-0.30	-1.27	0.15	1.30	0.15	414
GROZ	0.09	0.26	-0.15	-1.55	0.90	1.63	-1.29[a]	-2.84	-0.12	-0.45	0.13	1.03	0.14	266
AIYY	0.98[c]	1.69	-0.07	-1.43	-0.51	-1.10	0.15	0.52	-0.48[a]	-2.72	0.10	0.91	0.19	523
LRNZ	0.48[a]	3.01	0.00	0.12	-0.47	-0.99	0.64[c]	1.67	-0.25[a]	-3.38	0.06	1.08	0.13	1,466
DRAI	0.22[b]	2.20	-0.08	-1.36	-0.57	-0.44	-0.48	-0.62	-0.24	-1.62	0.03	0.43	0.14	370
GPT	0.17	0.97	-0.05	-0.58	-0.16	-0.52	-0.15	-0.39	-0.02	-0.08	-0.07	-0.61	0.11	321
NEWZ	0.13	0.94	-0.04	-0.62	0.97[b]	2.24	-0.79[a]	-2.79	-0.33	-1.41	0.10	0.60	0.16	430
XDAT	0.13	1.32	0.00	-0.01	0.14	1.52	-0.95[a]	-5.32	-0.06	-0.54	-0.06	-0.80	0.16	1,245
LQAI	0.05	0.47	-0.10	-1.07	-0.34	-0.63	-1.09[b]	-2.21	-0.23	-1.59	0.34	1.36	0.15	537
Mean	**0.25**	**1.55**	**-0.04**	**-0.77**	**0.52**	**3.20**	**-0.77**	**-2.57**	**-0.25**	**-2.42**	**0.14**	**1.50**	**0.24**	**1,192**
Min	**-0.18**	**-0.68**	**-0.15**	**-5.22**	**-1.61**	**-4.02**	**-2.23**	**-7.68**	**-0.52**	**-12.28**	**-0.08**	**-0.80**	**0.11**	**266**
Max	**0.98**	**6.90**	**0.11**	**2.17**	**3.82**	**29.41**	**0.64**	**1.67**	**0.14**	**0.66**	**0.42**	**5.23**	**0.67**	**4,914**
Panel B: Passive ETFs														
AIQ	0.14	0.85	-0.04	-0.96	2.49[a]	9.45	-0.95[a]	-4.18	-0.36[a]	-3.81	0.26[a]	4.40	0.35	1,917
BOTZ	-0.06	-0.94	0.10[a]	3.49	2.09[a]	30.18	-0.65[a]	-8.51	-0.14[a]	-3.14	0.16[a]	3.81	0.67	2,337
ARTY	0.21	0.98	0.00	-0.06	2.31[a]	9.39	-1.73[a]	-7.19	-0.31[a]	-2.86	0.17[b]	2.38	0.23	1,886
ROBO	0.01	0.17	0.19[a]	7.68	2.32[a]	36.28	-1.13[a]	-14.81	-0.07[b]	-2.57	0.09[a]	3.49	0.61	3,065
ROBT	0.30	1.59	-0.05	-1.19	1.06[a]	3.88	-0.98[a]	-4.73	-0.39[a]	-3.49	0.21[a]	2.83	0.18	1,974
IGPT	0.24[a]	4.30	-0.06[a]	-2.69	-0.32[b]	-2.27	-0.75[a]	-5.50	-0.13[a]	-3.30	0.01	0.46	0.14	5,162
DRIV	0.23	1.64	0.00	-0.01	2.32[a]	5.79	-0.68[b]	-2.56	-0.35[a]	-4.16	0.27[a]	3.48	0.39	1,937
AIEQ	0.26[c]	1.89	-0.07	-1.37	-1.07[a]	-3.91	-0.13	-0.49	-0.32[a]	-2.85	0.15[b]	2.08	0.15	2,060
AIVC	0.18[b]	2.58	0.12[a]	3.92	2.20[b]	15.47	-1.65[a]	-13.16	-0.11[b]	-2.50	0.02	0.61	0.34	2,467
WTAI	0.00	-0.01	0.08[b]	2.02	1.22[a]	6.14	-0.93[a]	-7.07	-0.11	-0.77	0.11	1.30	0.25	1,017
THNQ	0.38[c]	1.82	0.06[c]	1.72	2.96[a]	7.97	-2.05[a]	-7.29	-0.32[a]	-3.19	0.12[c]	1.75	0.25	1,417
BUZZ	0.32	1.24	0.00	0.07	0.74[c]	1.91	-0.78[a]	-2.92	-0.26[a]	-2.66	0.14[c]	1.94	0.13	1,212
XAIX	0.04	0.18	0.16[b]	2.59	4.95[a]	6.34	-3.55[a]	-6.25	-0.20[c]	-1.72	0.10	1.42	0.53	353
RWEM	0.01	0.34	0.12[a]	3.34	0.83[a]	13.17	-0.69[a]	-12.45	-0.04	-1.29	0.04	1.14	0.56	1,012
RWLC	0.08	1.56	0.07[c]	1.83	0.93[a]	7.52	-0.89[a]	-9.77	-0.11	-1.11	0.06	1.44	0.30	1,012
HEAL	0.01	0.06	0.06[b]	1.96	1.93[a]	13.46	-1.07[a]	-7.60	0.01	0.17	0.03	0.66	0.26	1,361
WISE	-0.16	-0.58	0.03	0.60	4.33[a]	8.47	-1.45[a]	-2.96	-0.18	-1.44	0.08	0.92	0.34	515
IBOT	-0.25	-1.19	-0.06	-0.91	0.94	1.64	0.65	1.61	-0.17	-0.67	0.12	1.01	0.13	685
FAI	0.12	0.32	-0.10	-0.95	2.34[b]	2.17	-2.30[a]	-2.54	-0.12	-0.53	0.13	0.99	0.18	275
BOTT	-0.30[b]	-2.34	-0.02	-0.30	2.04[a]	12.32	-0.04	-0.19	-0.20[a]	-2.05	-0.06	-0.67	0.55	424
KCAI	0.12	1.07	0.02	0.37	0.94[a]	9.12	-0.68[a]	-6.25	-0.07	-0.39	-0.22	-1.23	0.32	335
BULD	0.10[c]	1.68	0.07[c]	1.89	0.80[a]	8.96	-0.90[a]	-11.65	-0.20[c]	-1.77	0.02	0.23	0.32	916
Mean	**0.09**	**0.78**	**0.03**	**1.05**	**1.74**	**9.25**	**-1.06**	**-6.20**	**-0.19**	**-2.10**	**0.09**	**1.57**	**0.33**	**1,512**

Min	**-0.30**	**-2.34**	**-0.10**	**-2.69**	**-1.07**	**-3.91**	**-3.55**	**-14.81**	**-0.39**	**-4.16**	**-0.22**	**-1.23**	**0.13**	**272**
Max	**0.38**	**4.30**	**0.19**	**7.68**	**4.95**	**36.28**	**0.65**	**1.61**	**0.01**	**0.17**	**0.27**	**4.40**	**0.67**	**5,158**

When it comes to con-current premium, this factor has 8 and 2 significantly positive and negative estimates respectively in the case of active ETFs. In the case of passive ETFs, 19 (2) positive (negative) and significant coefficients are obtained. These results reveal a significant relationship between current return and premium, especially for the passive AI ETFs. On the other hand, the relationship between current return and lagged premium is rather negative. In the case of active ETFs, 13 estimates are significantly negative (and only 1 is significantly positive), while the passive ETFs have 19 significantly negative coefficients and none significantly positive.

A negative impact of the current intraday volatility on current return is revealed too. 13 and 14 coefficients are significantly negative for active and passive ETFs, respectively, while no positive and significant estimate is produced by the model. The opposite relationship applies to the lagged intraday volatility, at least for 9 active and 9 passive ETFs.

Overall, the results of model (7) indicate that factors such as the current and lagged premium, the current and lagged intraday volatility, and, to some extent, the lagged returns, can be quite important when trying to detect factors that can affect the return of AI ETFs' returns. We deem that the positive relationship (on average) between return and premium, the negative relationship between return and lagged premium, and the opposite patterns found between return and intraday volatility could be the basis for prosperous investing strategies.

4.4. Performance Regression Analysis

The results of model (8) are discussed in this section. The model has been applied both with trade price and NAV returns. The estimates of the first version of the model are provided in Table 6.1. We begin our analysis by noting that the majority of the AI ETFs examined cannot achieve material alphas against the selected market index. In the case of active ETFs, only 4 significantly positive alphas are provided by the regression model and 4 significantly negative. In the case of passive ETFs, only 3 funds achieve positive and significant alphas, while no one presents significantly negative alphas. Overall, these results indicate that, on average, the AI ETFs rather go with the flow, without beating the market, neither being inferior to it. Our evidence challenges the findings of Malhotra (2025), who reports that the AI ETFs can provide their investors with positive and significant alphas.

Table 6.1. Performance Regression Analysis (Price Returns). This table presents the results of a six-factor performance regression model via which the daily excess return of AI ETFs (calculated in close trade prices terms) is regressed on the excess return of the Russell 3000 Index, and the Fama and French (2015) SMB (small minus big) factor, HML (high minus low book-to-price ratio) factor, CMA (conservative minus aggressive) factor, RMW (robust minus weak) factor, and Carhart's MOM (momentum) factor. The estimation period of each AI ETF spans from its launch date up to December 31, 2025 (see Table 1 for launch dates). a indicates statistical significance at 1%; b indicates statistical significance at 5%; c indicates statistical significance at 10%.

Symbol	**const**	**t-Stat**	**Mkt**	**t-Stat**	**SMB**	**t-Stat**	**HML**	**t-Stat**	**CMA**	**t-Stat**	**RMW**	**t-Stat**	**MOM**	**t-Stat**	**R^2**	**Obs**
Panel A: Active ETFs																
BAI	0.06	1.14	1.26[a]	26.97	0.18[b]	2.08	-0.77[a]	-10.27	0.08	0.74	-0.32[a]	-3.20	0.44[a]	7.36	0.87	297
ARKQ	0.03[c]	1.80	1.11[a]	44.81	0.52[a]	15.23	-0.32[a]	-9.60	-0.23[a]	-4.16	-0.53[a]	-13.28	-0.01	-0.72	0.77	2,829
IETC	0.02[b]	2.17	1.14[a]	133.71	-0.10[a]	-6.22	-0.36[a]	-24.40	-0.17[a]	-7.01	0.00	-0.24	0.05[a]	5.62	0.92	1,953
AIVL	-0.01[b]	-2.30	0.86[a]	89.87	0.01	0.53	0.19[a]	13.19	0.21[a]	9.16	0.13[a]	7.96	-0.15[a]	-17.44	0.91	4,915
AIVI	-0.03[b]	-2.54	0.91[a]	96.02	-0.09[a]	-4.96	0.16[a]	9.39	0.14[a]	4.50	-0.02	-0.90	-0.05[a]	-4.63	0.71	4,915
IEDI	0.00	-0.01	0.86[a]	54.51	0.16[a]	6.50	-0.15[a]	-6.32	-0.03	-0.74	0.20[a]	7.02	-0.03[c]	-1.84	0.81	1,953

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AMOM	-0.01	-0.42	1.04[a]	43.60	0.11[a]	3.09	-0.19[a]	-5.15	-0.03	-0.54	-0.18[a]	-3.01	0.35[a]	18.46	0.77	1,663
QRFT	0.01	0.79	0.93[a]	76.17	0.04[b]	2.24	-0.16[a]	-8.17	-0.01	-0.44	-0.04	-1.58	0.11[a]	9.80	0.92	1,663
CHAT	0.03	1.04	1.41[a]	32.18	-0.01	-0.19	-0.54[a]	-6.73	-0.15	-1.12	-0.24[a]	-2.73	0.20[a]	2.73	0.81	657
AIPI	-0.14[a]	-3.38	0.95[a]	22.65	-0.07	-1.03	-0.26[a]	-4.05	0.16[c]	1.89	-0.37[a]	-4.11	0.21[a]	4.06	0.74	395
ALAI	0.06[b]	2.18	1.31[a]	41.50	0.01	0.18	-0.60[a]	-12.38	0.11[c]	1.70	0.00	-0.06	0.44[a]	11.37	0.90	436
FDTX	-0.02	-0.80	1.25[a]	34.18	-0.06	-1.21	-0.34[a]	-7.04	-0.17[b]	-2.26	-0.42[a]	-6.66	0.18[a]	5.10	0.86	641
FBOT	-0.02	-0.97	1.03[a]	36.60	0.19[a]	4.26	-0.29[a]	-6.63	0.06	1.02	-0.12	-2.13	0.05	1.44	0.78	641
ECML	0.00	0.18	0.93[a]	45.33	0.77[a]	24.05	0.26[a]	8.30	0.07[c]	1.77	0.49[a]	12.30	-0.05[b]	-2.07	0.87	657
AGIX	0.03	0.85	1.18[a]	31.71	0.15[b]	2.34	-0.64[a]	-10.91	-0.06	-0.76	-0.36[a]	-4.47	0.22[a]	4.72	0.88	365
AIS	0.12[c]	1.93	1.27[a]	19.89	0.25[c]	1.82	-0.70[a]	-4.54	0.32	1.19	-0.33[c]	-1.89	0.23	1.64	0.79	269
AIFD	0.01	0.32	1.33[a]	30.71	0.07	1.08	-0.59[a]	-8.91	0.05	0.48	-0.12	-1.31	0.33[a]	5.28	0.89	415
GROZ	0.03	1.49	1.12[a]	57.43	-0.03	-0.75	-0.37[a]	-10.78	0.05	1.03	0.04	0.95	0.20[a]	7.82	0.96	267
AIYY	-0.49[a]	-4.03	1.17[a]	8.54	0.91[a]	4.21	-0.52[b]	-2.49	0.48[c]	1.70	-1.10[a]	-3.95	-0.08	-0.49	0.35	524
LRNZ	0.03	1.28	1.03[a]	49.77	0.22[a]	5.38	-0.64[a]	-18.18	-0.65[a]	-11.28	-1.03[a]	-20.60	-0.04[c]	-1.87	0.83	1,467
DRAI	0.02	0.57	0.60[a]	6.21	0.25[b]	2.57	-0.37[a]	-4.67	0.09	1.04	0.04	0.43	0.04	0.48	0.58	371
GPT	0.01	0.15	0.88[a]	13.92	-0.03	-0.25	-0.18[c]	-1.91	0.19	1.50	-0.24[b]	-2.26	0.01	0.11	0.75	322
NEWZ	-0.03	-1.18	0.74[a]	15.48	0.17[b]	2.61	0.06	1.18	0.07	1.23	-0.20[a]	-3.29	0.15[a]	3.89	0.75	431
XDAT	0.00	-0.12	1.01[a]	32.33	-0.01	-0.32	-0.42[a]	-11.33	-0.51[a]	-8.70	-0.61[a]	-9.91	0.04	1.48	0.78	1,246
LQAI	0.00	-0.36	0.99[a]	63.63	-0.06[b]	-2.62	-0.02	-0.75	-0.04	-1.14	-0.12[a]	-3.72	0.08[a]	4.35	0.92	538
Mean	**-0.01**	**-0.01**	**1.05**	**44.31**	**0.14**	**2.42**	**-0.31**	**-5.73**	**0.00**	**-0.37**	**-0.22**	**-2.43**	**0.12**	**2.66**	**0.80**	**1,193**
Min	**-0.49**	**-4.03**	**0.60**	**6.21**	**-0.10**	**-6.22**	**-0.77**	**-24.40**	**-0.65**	**-11.28**	**-1.10**	**-20.60**	**-0.15**	**-17.44**	**0.35**	**267**
Max	**0.12**	**2.18**	**1.41**	**133.71**	**0.91**	**24.05**	**0.26**	**13.19**	**0.48**	**9.16**	**0.49**	**12.30**	**0.44**	**18.46**	**0.96**	**4,915**
Panel B: Passive ETFs																
AIQ	0.02	1.57	1.04[a]	90.99	0.05[b]	2.26	-0.33[a]	-16.84	-0.26[a]	-7.84	-0.21[a]	-7.49	0.00	0.03	0.86	1,918
BOTZ	-0.01	-0.45	1.12[a]	53.54	0.18[a]	5.62	-0.20[a]	-6.78	-0.11[b]	-2.23	-0.22[a]	-5.88	-0.04[c]	-1.95	0.79	2,338
ARTY	0.00	0.23	1.05[a]	43.52	0.28[a]	9.32	-0.33[a]	-8.82	-0.08	-1.14	-0.40[a]	-10.34	-0.02	-1.34	0.83	1,887
ROBO	0.00	-0.37	1.03[a]	74.09	0.30[a]	15.08	-0.16[a]	-8.49	0.02	0.70	-0.14[a]	-4.98	-0.06[a]	-4.91	0.83	3,066
ROBT	-0.01	-0.61	1.04[a]	92.93	0.36[a]	16.31	-0.24[a]	-12.30	-0.06[b]	-2.00	-0.28[a]	-10.48	-0.04[a]	-3.31	0.87	1,975
IGPT	0.02[b]	2.34	0.96[a]	51.70	0.29[a]	11.41	-0.42[a]	-18.17	-0.26[a]	-6.77	-0.47[a]	-15.10	0.12[a]	8.64	0.79	5,163
DRIV	0.00	-0.09	1.10[a]	33.50	0.32[a]	7.33	-0.13[a]	-3.17	0.06	0.98	-0.17[a]	-4.40	-0.13[a]	-4.66	0.78	1,938
AIEQ	-0.01	-0.72	0.99[a]	55.33	0.23[a]	7.41	-0.19[a]	-7.84	-0.01	-0.13	-0.31[a]	-10.90	0.05[b]	2.29	0.85	2,061
AIVC	0.00	0.26	0.98[a]	36.41	0.17[a]	5.17	-0.34[a]	-8.88	-0.18[a]	-2.82	-0.67[a]	-17.46	-0.03	-1.43	0.73	2,468
WTAI	0.00	-0.14	1.17[a]	29.09	0.25[a]	4.35	-0.28[a]	-5.06	-0.15[c]	-1.92	-0.57[a]	-8.04	0.19[a]	5.25	0.76	1,018
THNQ	0.03[b]	2.05	1.14[a]	72.77	0.11[a]	4.31	-0.39[a]	-17.14	-0.30[a]	-8.58	-0.58[a]	-18.71	-0.02	-1.13	0.89	1,418
BUZZ	0.02	0.68	1.28[a]	54.50	0.24[a]	6.17	-0.18[a]	-5.06	-0.33[a]	-6.54	-0.81[a]	-18.19	-0.02	-0.91	0.85	1,213
XAIX	0.02	0.92	1.10[a]	50.98	-0.07[c]	-1.85	-0.23[a]	-6.73	-0.06	-1.36	-0.22[a]	-4.68	0.09[a]	3.25	0.93	354
RWEM	-0.01	-0.46	0.56[a]	20.64	-0.02	-0.50	0.02	0.50	0.07	1.24	-0.12[b]	-2.32	0.03	1.02	0.36	1,013
RWLC	0.01	0.33	0.76[a]	42.20	0.00	0.04	-0.03	-1.09	0.08[b]	2.07	-0.03	-0.73	0.13[a]	6.77	0.69	1,013
HEAL	-0.04	-1.58	0.78[a]	30.08	0.54[a]	12.64	-0.43[a]	-10.78	0.02	0.27	-0.57[a]	-11.31	-0.08[a]	-3.15	0.71	1,362
WISE	0.01	0.15	1.30[a]	25.47	0.36[a]	4.52	-0.54[a]	-7.00	0.11	1.01	-0.84[a]	-8.11	0.15[b]	2.41	0.77	516
IBOT	-0.01	-0.57	1.16[a]	39.54	0.19[a]	4.13	-0.19[a]	-4.27	0.05	0.84	0.00	0.08	0.05	1.41	0.77	686
FAI	0.06[c]	1.73	1.25[a]	34.93	0.06	0.95	-0.71[a]	-11.29	0.00	-0.03	-0.22[a]	-2.97	0.18[a]	4.01	0.91	276
BOTT	0.02	0.42	1.17[a]	21.22	0.26[a]	2.80	-0.29[a]	-3.45	0.22[c]	1.94	-0.34[a]	-2.95	0.18[b]	2.64	0.69	425

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KCAI	0.13	1.56	0.21[b]	2.48	-0.04	-0.26	-0.10	-0.74	0.14	0.75	-0.18	-1.01	-0.27[b]	-2.55	0.17	336
BULD	-0.01	-0.23	0.99[a]	24.76	0.46[a]	6.38	-0.16[b]	-2.53	-0.03	-0.31	-0.17[b]	-2.11	0.12[a]	2.82	0.55	917
Mean	**0.01**	**0.32**	**1.01**	**44.58**	**0.21**	**5.62**	**-0.27**	**-7.54**	**-0.05**	**-1.45**	**-0.34**	**-7.64**	**0.03**	**0.69**	**0.74**	**1,512**
Min	**-0.04**	**-1.58**	**0.21**	**2.48**	**-0.07**	**-1.85**	**-0.71**	**-18.17**	**-0.33**	**-8.58**	**-0.84**	**-18.71**	**-0.27**	**-4.91**	**0.17**	**272**
Max	**0.13**	**2.34**	**1.30**	**92.93**	**0.54**	**16.31**	**0.02**	**0.50**	**0.22**	**2.07**	**0.00**	**0.08**	**0.19**	**8.64**	**0.93**	**5,158**

On the systematic risk of AI ETFs, an average beta of 1.05 is estimated for active ETFs, while the respective average coefficient for passive is equal to 1.01. All individual betas are statistically significant and positive. Moreover, 15 active ETFs have betas that are higher than unity, implying that they move more aggressively relative to the market index. 14 passive ETFs do so too. Aggressiveness helps funds realizing more gains during bull markets, but punishes them with greater losses during bear markets.

Regarding the size factor, 13 active AI ETFs present significantly positive estimates and only 3 present negative and significant SMB estimates. In the case of passive ETFs, 17 out of 22 SMB estimates are positive and significant, and only 1 is significantly negative. These results establish a positive relationship between the performance of AI ETFs and the size factor suggested by Fama and French (1993) for the stock market in the U.S.

On the value factor suggested by Fama and French (1993), the results indicate a negative impact on AI ETFs' performance by this element. In particular, 20 HML estimates are negative and significant in the case of active ETFs and only 3 are positive and significant. The corresponding numbers for passive AI ETFs are 19 and 0.

As far as the conservativeness factor of Fama and French (2015) is concerned, the results in Table 6.1 reveal a rather weak and unsystematic influence on AI ETFs' return. The average CMA coefficient of active ETFs is equal to zero, while the respective average term of passive ETFs is equal to -0.05. At the fund level, 6 active AI ETFs present significantly positive estimates and 5 funds have significantly negative CMA estimates. The respective numbers for passive ETFs are 8 and 2.

Contrary to conservativeness, the robustness factor offers quite significant estimates, both for active and passive ETFs. More specifically, 15 coefficients are significantly negative in the case of active ETFs and only 3 are positive and significant. In the case of passive ETFs, 19 estimates are negative and significant and none is significantly positive. Overall, these results accentuate a clear negative impact by the robustness factor on the performance of AI ETFs in the U.S.

Finally, the impact of the momentum factor included in model (8) is positive for the majority of the AI ETFs examined, (i.e., for 15 active ETFs and 9 passive ETFs), while 11 ETFs present significantly negative MOM coefficients (5 active and 6 passive).

To summarize our results, we note that the model applied can sufficiently explain the performance of AI ETFs traded on the U.S. stock market. Most of the variables included in the model produce statistically significant estimates, either negative or positive, but at the average level, performance is found to be related with the size and momentum factors in a positive fashion, while the influence of the value and robustness factors on performance is negative. Finally, the contribution of the conservativeness factor to AI ETFs' performance is less significant.

Before concluding this section, we should remind that the analysis above concerns the results of model (8) obtained when the return of AI ETFs calculated in trade price terms is the dependent variable of the model. Table 6.2 reports the corresponding results when ETF returns included in the model have been calculated with net asset values. By comparing the results in Tables 6.1 and 6.2 we observe the proximity between the two sets of estimates. Therefore, the inferences drawn via analyzing trade price returns still hold in the case of NAV returns.

Table 6.2. Performance Regression Analysis (NAVs). This table presents the results of a six-factor performance regression model via which the daily excess return of AI ETFs (calculated in net asset values terms) is regressed on the excess return of the Russell 3000 Index, and the Fama and French (2015) SMB (small minus big) factor, HML (high minus low book-to-price ratio) factor, CMA (conservative minus aggressive) factor, RMW (robust

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minus weak) factor, and Carhart's MOM (momentum) factor. The estimation period of each AI ETF spans from its launch date up to December 31, 2025 (see Table 1 for launch dates). a indicates statistical significance at 1%; b indicates statistical significance at 5%; c indicates statistical significance at 10%. .

Symbol	const	t-Stat	Mkt	t-Stat	SMB	t-Stat	HML	t-Stat	CMA	t-Stat	RMW	t-Stat	MOM	t-Stat	R^2	Obs
Panel A: Active ETFs																
BAI	0.05	1.14	1.30^{a}	28.75	0.12	1.39	-0.77^{a}	-10.52	0.05	0.44	-0.30^{a}	-3.04	0.46^{a}	7.97	0.88	297
ARKQ	0.03^{c}	1.84	1.16^{a}	55.23	0.53^{a}	17.67	-0.31^{a}	-10.42	-0.24^{a}	-4.81	-0.52^{a}	-14.00	-0.01	-0.50	0.81	2,829
IETC	0.02^{b}	2.16	1.16^{a}	81.22	-0.10^{a}	-4.91	-0.35^{a}	-17.54	-0.20^{a}	-5.48	0.01	0.29	0.06^{a}	5.76	0.94	1,953
AIVL	-0.01^{b}	-2.50	0.88^{a}	92.15	0.00	-0.17	0.21^{a}	14.26	0.21^{a}	9.09	0.13^{a}	7.91	-0.15^{a}	-18.80	0.92	4,915
AIVI	-0.01	-0.80	0.45^{a}	15.42	-0.08^{c}	-1.65	0.13^{a}	2.79	0.04	0.56	-0.09^{c}	-1.78	-0.10^{a}	-4.07	0.27	4,915
IEDI	0.00	-0.28	0.90^{a}	67.84	0.16^{a}	7.76	-0.16^{a}	-7.27	-0.05	-1.28	0.24^{a}	9.57	-0.02	-1.51	0.87	1,953
AMOM	-0.01	-0.55	1.08^{a}	72.30	0.05^{c}	1.81	-0.19^{a}	-7.31	-0.01	-0.32	-0.18^{a}	-4.80	0.34^{a}	20.87	0.80	1,663
QRFT	0.01	0.71	0.97^{a}	157.90	0.01	0.87	-0.14^{a}	-12.92	-0.03	-1.61	-0.03^{b}	-2.02	0.11^{a}	15.96	0.95	1,663
CHAT	0.04	1.25	1.22^{a}	23.26	-0.03	-0.39	-0.48^{a}	-5.98	-0.23^{c}	-1.69	-0.18^{c}	-1.97	0.19^{b}	2.59	0.77	657
AIPI	-0.14^{a}	-3.43	0.96^{a}	23.24	-0.09	-1.27	-0.28^{a}	-4.34	0.17^{c}	1.99	-0.38^{a}	-4.29	0.19^{a}	3.76	0.75	395
ALAI	0.06^{b}	2.38	1.27^{a}	43.81	0.01	0.28	-0.60^{a}	-13.59	0.10^{c}	1.75	-0.03	-0.56	0.44^{a}	12.46	0.91	436
FDTX	-0.02	-0.75	1.20^{a}	34.59	-0.07	-1.43	-0.33^{a}	-7.11	-0.23^{a}	-3.47	-0.42^{a}	-6.92	0.14^{a}	4.17	0.86	641
FBOT	-0.02	-0.68	0.82^{a}	24.50	0.08	1.52	-0.20^{a}	-4.15	-0.08	-1.11	-0.07	-1.05	-0.02	-0.39	0.64	641
ECML	0.00	0.16	0.93^{a}	45.45	0.77^{a}	24.03	0.27^{a}	8.58	0.07	1.60	0.49^{a}	12.27	-0.05^{c}	-1.91	0.87	657
AGIX	0.03	0.89	1.17^{a}	35.10	0.06	1.08	-0.52^{a}	-9.91	0.00	0.07	-0.36^{a}	-5.04	0.20^{a}	4.76	0.89	365
AIS	0.12^{c}	1.99	0.99^{a}	10.99	0.23^{c}	1.71	-0.63^{a}	-4.17	0.32	1.26	-0.33^{c}	-1.92	0.24^{c}	1.77	0.73	269
AIFD	0.01	0.37	1.34^{a}	29.38	0.07	1.03	-0.61^{a}	-8.84	0.06	0.66	-0.10	-1.21	0.32^{a}	5.29	0.89	415
GROZ	0.03^{c}	1.70	1.12^{a}	66.67	-0.03	-0.93	-0.36^{a}	-12.08	0.02	0.48	0.04	1.04	0.20^{a}	9.02	0.97	267
AIYY	-0.49^{a}	-3.85	1.19^{a}	8.33	0.94^{a}	4.19	-0.59^{a}	-2.72	0.45	1.54	-1.23^{a}	-4.27	-0.11	-0.63	0.36	524
LRNZ	0.03	1.20	1.10^{a}	46.32	0.17^{a}	3.99	-0.61^{a}	-16.72	-0.65^{a}	-9.73	-1.03^{a}	-19.51	-0.04^{c}	-1.65	0.84	1,467
DRAI	0.02	0.58	0.60^{a}	6.11	0.24^{b}	2.42	-0.37^{a}	-4.53	0.09	0.98	0.02	0.28	0.02	0.29	0.59	371
GPT	0.01	0.19	0.88^{a}	13.76	-0.03	-0.21	-0.19^{b}	-2.00	0.26^{b}	2.08	-0.26^{b}	-2.49	0.01	0.19	0.75	322
NEWZ	-0.03	-1.31	0.75^{a}	15.47	0.18^{a}	2.76	0.06	1.10	0.08	1.56	-0.17^{a}	-3.04	0.16^{a}	4.41	0.79	431
XDAT	-0.01	-0.26	1.08^{a}	52.76	-0.02	-0.65	-0.41^{a}	-13.73	-0.54^{a}	-12.34	-0.60^{a}	-15.63	0.03	1.34	0.86	1,246
LQAI	-0.01	-0.42	1.00^{a}	68.84	-0.07^{a}	-2.95	-0.01	-0.56	-0.03	-1.18	-0.12^{a}	-4.02	0.08^{a}	4.75	0.93	538
Mean	**-0.01**	**0.07**	**1.02**	**44.78**	**0.12**	**2.32**	**-0.30**	**-5.99**	**-0.02**	**-0.76**	**-0.22**	**-2.65**	**0.11**	**3.04**	**0.79**	**1,193**
Min	**-0.49**	**-3.85**	**0.45**	**6.11**	**-0.10**	**-4.91**	**-0.77**	**-17.54**	**-0.65**	**-12.34**	**-1.23**	**-19.51**	**-0.15**	**-18.80**	**0.27**	**267**
Max	**0.12**	**2.38**	**1.34**	**157.90**	**0.94**	**24.03**	**0.27**	**14.26**	**0.45**	**9.09**	**0.49**	**12.27**	**0.46**	**20.87**	**0.97**	**4,915**
Panel B: Passive ETFs																
AIQ	0.02^{c}	1.81	1.00^{a}	104.38	0.01	0.55	-0.26^{a}	-16.15	-0.29^{a}	-10.66	-0.17^{a}	-7.22	0.01	0.90	0.89	1,918
BOTZ	0.01	0.43	0.70^{a}	42.14	0.14^{a}	4.59	-0.15^{a}	-5.24	-0.14^{a}	-3.07	-0.26^{a}	-6.77	-0.04^{b}	-2.05	0.53	2,338
ARTY	0.01	0.33	0.99^{a}	36.30	0.25^{a}	7.64	-0.33^{a}	-8.52	-0.08	-1.07	-0.41^{a}	-10.87	-0.04^{b}	-2.19	0.82	1,887
ROBO	0.01	0.52	0.72^{a}	34.80	0.27^{a}	10.33	-0.12^{a}	-4.72	-0.03	-0.69	-0.15^{a}	-4.57	-0.08^{a}	-4.84	0.65	3,066
ROBT	-0.01	-0.74	1.04^{a}	67.81	0.33^{a}	12.28	-0.25^{a}	-11.23	-0.05	-1.14	-0.26^{a}	-9.02	-0.05^{a}	-4.00	0.89	1,975
IGPT	0.02^{b}	2.41	1.02^{a}	86.55	0.29^{a}	17.40	-0.42^{a}	-21.75	-0.25^{a}	-7.24	-0.43^{a}	-17.85	0.12^{a}	9.55	0.85	5,163
DRIV	0.00	-0.01	1.01^{a}	44.79	0.32^{a}	10.18	-0.06^{c}	-1.71	-0.05	-0.89	-0.15^{a}	-3.72	-0.09^{a}	-4.61	0.78	1,938
AIEQ	-0.01	-0.88	1.03^{a}	62.42	0.26^{a}	10.35	-0.19^{a}	-8.71	-0.02	-0.43	-0.28^{a}	-10.71	0.06^{a}	2.82	0.87	2,061

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AIVC	0.01	0.41	0.87[a]	35.10	0.18[a]	5.33	-0.33[a]	-9.70	-0.20[a]	-3.46	-0.62[a]	-17.23	-0.03	-1.32	0.72	2,468
WTAI	-0.01	-0.23	1.13[a]	37.69	0.20[a]	4.08	-0.27[a]	-5.84	-0.20[a]	-3.06	-0.48[a]	-8.35	0.12[a]	3.98	0.81	1,018
THNQ	0.03[b]	2.24	1.10[a]	76.00	0.10[a]	4.21	-0.37[a]	-17.60	-0.31[a]	-9.43	-0.57[a]	-19.88	-0.02	-1.26	0.90	1,418
BUZZ	0.02	0.69	1.29[a]	57.15	0.24[a]	6.47	-0.19[a]	-5.49	-0.34[a]	-6.91	-0.79[a]	-18.60	-0.02	-0.85	0.86	1,213
XAIX	0.02	1.08	1.00[a]	46.13	-0.07[c]	-1.88	-0.19[a]	-5.62	-0.08[c]	-1.78	-0.22[a]	-4.76	0.10[a]	3.66	0.92	354
RWEM	-0.01	-0.20	0.21[a]	7.18	-0.07	-1.32	0.11[b]	2.47	-0.11[c]	-1.76	-0.15[a]	-2.71	0.01	0.30	0.18	1,013
RWLC	0.01	0.65	0.77[a]	78.94	-0.02	-0.94	0.00	-0.07	0.02	1.09	-0.03[c]	-1.73	0.13[a]	12.46	0.89	1,013
HEAL	-0.04[c]	-1.75	0.74[a]	29.80	0.53[a]	13.37	-0.40[a]	-10.90	-0.02	-0.28	-0.54[a]	-11.85	-0.08[a]	-3.05	0.73	1,362
WISE	0.01	0.25	1.22[a]	25.01	0.41[a]	5.25	-0.52[a]	-7.03	0.09	0.88	-0.77[a]	-7.77	0.17[a]	2.87	0.77	516
IBOT	-0.02	-0.62	1.18[a]	41.78	0.17[a]	3.92	-0.20[a]	-4.66	0.08	1.41	0.01	0.26	0.05	1.46	0.79	686
FAI	0.06[c]	1.72	1.25[a]	24.19	-0.01	-0.06	-0.65[a]	-8.61	0.00	-0.04	-0.24[a]	-2.72	0.16[a]	3.19	0.92	276
BOTT	0.04	0.66	0.76[a]	12.33	0.31[a]	3.08	-0.18[c]	-1.94	0.08	0.64	-0.26[b]	-2.04	0.25[a]	3.34	0.46	425
KCAI	0.14[b]	2.10	0.27[c]	1.79	0.07	0.61	-0.21[c]	-1.95	0.20	1.34	0.05	0.34	-0.08	-0.91	0.13	336
BULD	-0.01	-0.48	0.98[a]	24.44	0.38	7.40	-0.19[a]	-3.59	-0.13[c]	-1.73	-0.15[b]	-2.55	-0.03	-0.75	0.72	917
Mean	**0.01**	**0.47**	**0.92**	**44.40**	**0.20**	**5.58**	**-0.24**	**-7.21**	**-0.08**	**-2.20**	**-0.31**	**-7.74**	**0.03**	**0.85**	**0.73**	**1,512**
Min	**-0.04**	**-1.75**	**0.21**	**1.79**	**-0.07**	**-1.88**	**-0.65**	**-21.75**	**-0.34**	**-10.66**	**-0.79**	**-19.88**	**-0.09**	**-4.84**	**0.13**	**272**
Max	**0.14**	**2.41**	**1.29**	**104.38**	**0.53**	**17.40**	**0.11**	**2.47**	**0.20**	**1.41**	**0.05**	**0.34**	**0.25**	**12.46**	**0.92**	**5,158**

5. Conclusion

Artificial Intelligence provides very prosperous investment opportunities for investors, also assisting financial managers in the securities selection process and portfolio management. The current study focuses on an investment product that has been attracting the interest of investors over the recent years. This product is the AI ETFs, namely, ETFs that invest in companies that are somehow involved in artificial intelligence.

In our analysis, we adopt an "active vs passive" research stance. In doing so, we select 25 active and 22 passive AI ETFs with full trade data at least for 2025. Several issues are addressed in our study, concerning the return and risk of AI ETFs, their pricing efficiency, or (in other words) the divergence between the trade prices of these ETFs and their NAVs, the persistence in these differences, and the impact of pricing inefficiency and intraday volatility in ETF prices on returns. The relationship between AI ETFs' performance and market factors regarding size, value, profitability, investment and momentum is evaluated too.

The empirical findings indicate the passive AI ETFs have outperformed their active peers as they have achieved considerably higher cumulative returns than them over their entire trade history. At the same time, the risk figures of the two groups approximate each other. Achieving significantly higher cumulative returns with the same level of risk constitutes a clear advantage of passive AI ETFs over the active ones. On the other hand, the active AI ETFs are better than the passive at trading close to their underlying assets' value. In any case, both ETF groups trade, on average, at a premium to their NAVs. Premium for both groups is found to be quite persistent up to five trade days, possibly showing that investors could cash on this premium persistence.

On the question of whether premium is a material factor to consider when trying to determine the returns of AI ETFs, the empirical results reveal a positive relationship between current premium and current returns, especially for passive AI ETFs. On the other hand, the lagged premium is negatively related to return, both for active and passive AI ETFs. Moreover, a negative relationship between return and con-current intraday volatility is accentuated. This finding concerns both active and passive AI ETFs. A positive but weaker relationship between return and one-lagged intraday volatility is revealed too.

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Finally, the regression analysis on the relationship between ETFs' performance and the market factors finds that only a small number of AI ETFs can achieve positive and significant alphas over the Russell 3000 Index, which has been used as the market proxy index. In addition, positive relationships are found between the performance of AI ETFs and the size and momentum factors. The opposite is the case for the value and robustness factors. On the other hand, the effect of the conservativeness factor on ETFs' performance is less significant.

Overall, our study provides useful empirical insights on a growing investment tool. To our view, the comprehensive study of AI ETFs' performance, risk and pricing efficiency, as well as the accentuation of several factors that can be significant in determining the return of these ETFs should be quite helpful to a range of agents including ETF investors, assets managers and ETF issuers.

References

Baek, S., K.Y. Lee, M. Uctum, and S.H. Oh. (2020). Robo-Advisors: Machine Learning in Trend-Following ETF Investments. Sustainability 12, (16), 1-15.

Baldan, C., Sapienza, E., and Zen, F. (2025). Artificial Intelligence (AI) in Exchange-Traded Funds: A Quantitative Modelling Approach Using the Markowitz Portfolio Theory. Working Paper, Department of Economics and Management "DSEA", University of Padova, Retrieved from file:///C:/Users/User/Downloads/ssrn-5604632.pdf on January 18, 2026.

Belhouichet, F., Caporale, G.M., and Gil-Alana, L.A., (2025). Persistence in Stock Returns: Robotics and AI ETFs Versus Other Assets. *Journal of Risk and Financial Management*, 18(11), 1-13.

Boido, C., and Aliano, M. (2025). Artificial Intelligence Exchange-Traded Funds: The Intersection of Finance, Technology and Sustainability. *Journal of Asset Management*, 26(4), 345-354.

Bonaparte, Y. (2024). Artificial Intelligence in Finance: Valuations and Opportunities. *Finance Research Letters*, 60, 1-5.

Carhart, M.M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, 52(1), 57-82.

Chen, R., and Ren, J. (2022). Do AI-Powered Mutual Funds Perform Better?. *Finance Research Letters*, 47(A), 1-7.

Cherry, J. (2004). The Limits of Arbitrage: Evidence from Exchange Traded Funds", Working Paper, University of California-Berkeley, Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=628061.

Day, M.Y., and Lin, J.T. (2019). Artificial Intelligence for ETF Market Prediction and Portfolio Optimization. In Proceedings of the 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, 1026–1033.

Delcoure, N., and Zhong, M. (2007). On the Premiums of iShares. *Journal of Empirical Finance*, 14(2), 168-195.

Deng, W. (2025). Informational Herding and Conditional Performance of AI-Driven ETFs: A Comparative Analysis with Institutional Investors. *Sage Open*, 15(4), 1-17.

Duppati, G., Sonono, E., Musvoto, W., Scrimgeour, F., and Tiwari, A.K. (2023). Is Liquidity Risk Priced in Artificial Intelligence ETFs?. *Australasian Accounting, Business and Finance Journal*, 17(3), 62-80.

Elton, E.J., Gruber, M.J., Comer, G., and Li, K. (2002) Spiders: Where are the Bugs?. *Journal of Business* 75(3), 453-473.

Fama, E.F., and French, K.R. (1993), Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, 33(1), 3-56.

Fama, E.F., and French, K.R. (2015). A Five-Factor Asset Pricing Model. *Journal of Financial Economics*, 116(1), 1-22.

Grobys, K., J.W. Kolari, and J. Niang. (2022). Man versus Machine: On Artificial Intelligence and Hedge Funds Performance. Applied Economics 54(40): 4632-4646.

Hughen, C.J. (2003) How Effective is Arbitrage of Foreign Stocks? The Case of the Malaysia Exchange Traded Fund. *Multinational Business Review*, 11, 17-27.

Jares, T.E., and Lavin, A.M. (2004). Japan and Hong Kong Exchange-Traded Funds (ETFs): Discounts, Returns, and Trading Strategies. *Journal of Financial Service Research*, 25(1), 57-69.

Karoui, A.T., Sayari, S., Dammak, W., and Jeribi, A. (2024). Unveiling Outperformance: A Portfolio Analysis of Top AI-Related Stocks Against IT Indices and Robotics ETFs. *Risks*, 12(3), 52.

Kovvuri, V.R.R., Fu, H., Fan, X., and Seisenberger, M. (2023). Fund Performance Evaluation with Explainable Artificial Intelligence. *Finance Research Letters* 58, 1-9.

Malhotra, D.K. (2023). Market Timing, Selectivity, and Performance of Technology Exchange-Traded Funds and Mutual Funds. *Journal of Beta Investment Strategies*, 14(1), 42-53.

Malhotra, D.K. (2025). Unpacking Alpha in Innovation-Driven ETFs: A Comparative Study of Artificial Intelligence and Blockchain Funds. *Journal of Risk and Financial Management*, 18(12), 1-19.

McCulloch, W.S., and Pitts, W. (1943). A Logical Calculus of the Ideas Immanent in Nervous Activity. *Bulletin of Mathematical Biophysics*, 5(4), 115-133.

Poutachidou, N., and Koulis, A. (2025). The Investment Styles and Performance of AI-Related ETFs: Analyzing the impact of active management. *FinTech*, 4, 1-17.

Rompotis, G.G. (2009). Premiums and Returns of iShares. *The Journal of Beta Investment Strategies*, (1), 135-143.

Rompotis, G.G. (2010). Does Premium Impact ETF Returns? Evidence from iShares. *Journal of Asset Management*, 11(4), 298-308.

Shum, P.M., Hejazi, W., Haryanto, E., and Rodier, A. (2016). Intraday Share Price Volatility and Leveraged ETF Rebalancing. *European Finance Review*, 20(6) 2379-2409.

Turing, A.M. (1950). Computing Machinery and Intelligence. *Mind*, 49, 433-460.

Wu, C.C., and Chen, W.P. (2022). What's an AI Name Worth? The Impact of AI ETFs on their Underlying Stocks. *Finance Research Letters*, 46, 1-7.

Zhang, B., Z. Chen, W. Li, and J. Li. (2023). The Robo-Advisor for ETF Funds in China: Influences and Determinants. *Procedia Computer Science*, 221, 1029-1035.