



# **Implications of AI Usage for Financial Stability: Evidence from AI-driven Investment Funds Identified by GenAI amid Interest Rate Hikes**

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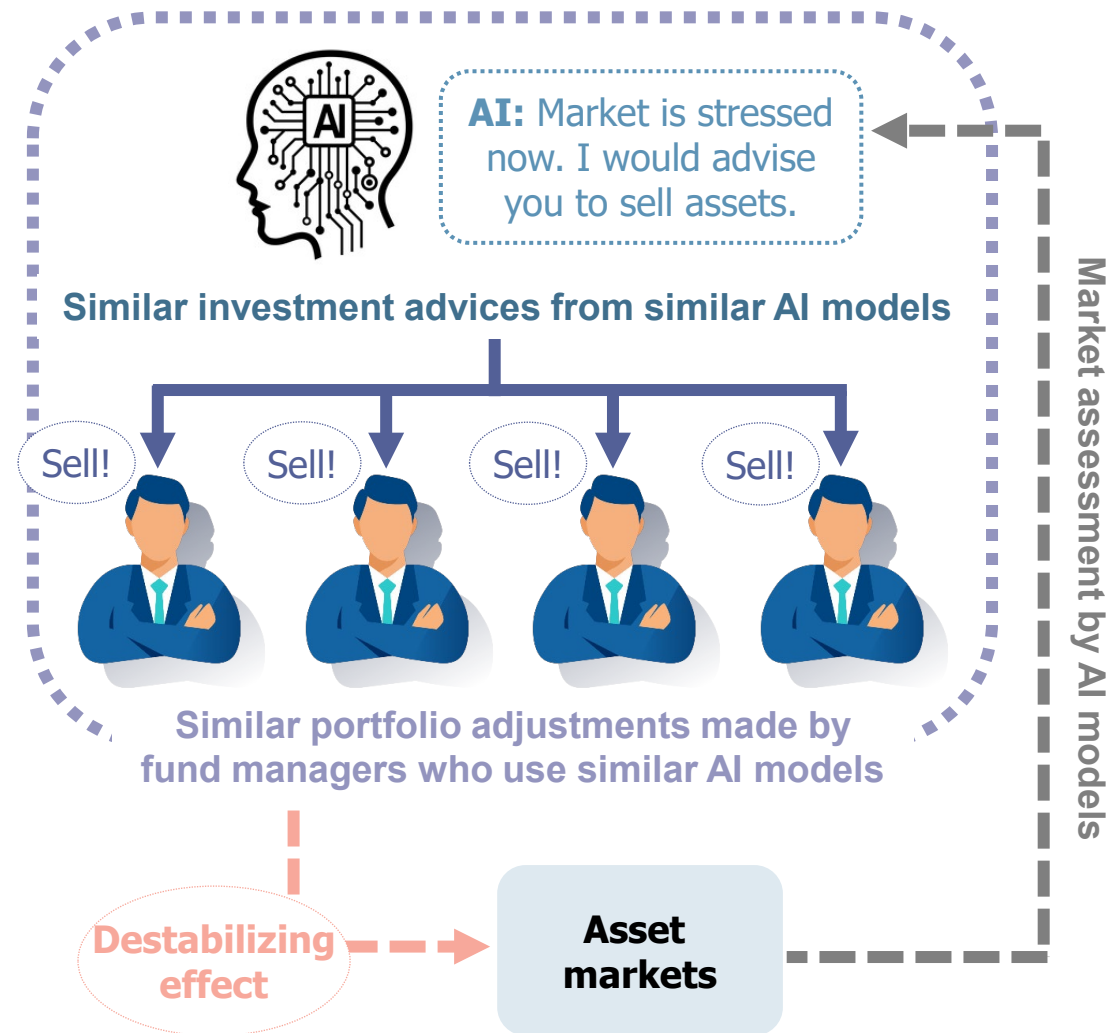
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# Background and Motivation

- The potential for a widespread use of similar AI models by investors would be a concern ([Financial Stability Board, 2024](#)).
- For instance, fund managers may apply AI to similar investment strategies.
- These similar applications of AI could increase the trading correlation among fund managers.
- In stressed times, AI could advise fund managers to sell off assets simultaneously, potentially deepening the market downturn.



# Research Questions



1. Does the use of AI by investment funds increase the trading correlation among them?
2. If yes, does the increased trading correlation result from the common use of AI by investment funds, e.g. applying AI to similar investment strategies?
3. Does the common use of AI by investment funds lead to collective asset sales among them in periods of market stress?

# Data Collection: AI Applications of Funds



- To answer these questions, we first needed to identify AI applications of investment funds:
  - Compiled a sample of 87,090 equity open-ended funds which represents 70% of the total assets of the same fund type in 2023.
  - Downloaded their prospectuses from the Morningstar Document Library. Each prospectus usually discloses the fund's investment strategies and AI applications.
  - Analyzed these prospectuses to identify investment funds' use of AI in the following steps.



# Step 1: Keyword Screening on Fund Prospectuses

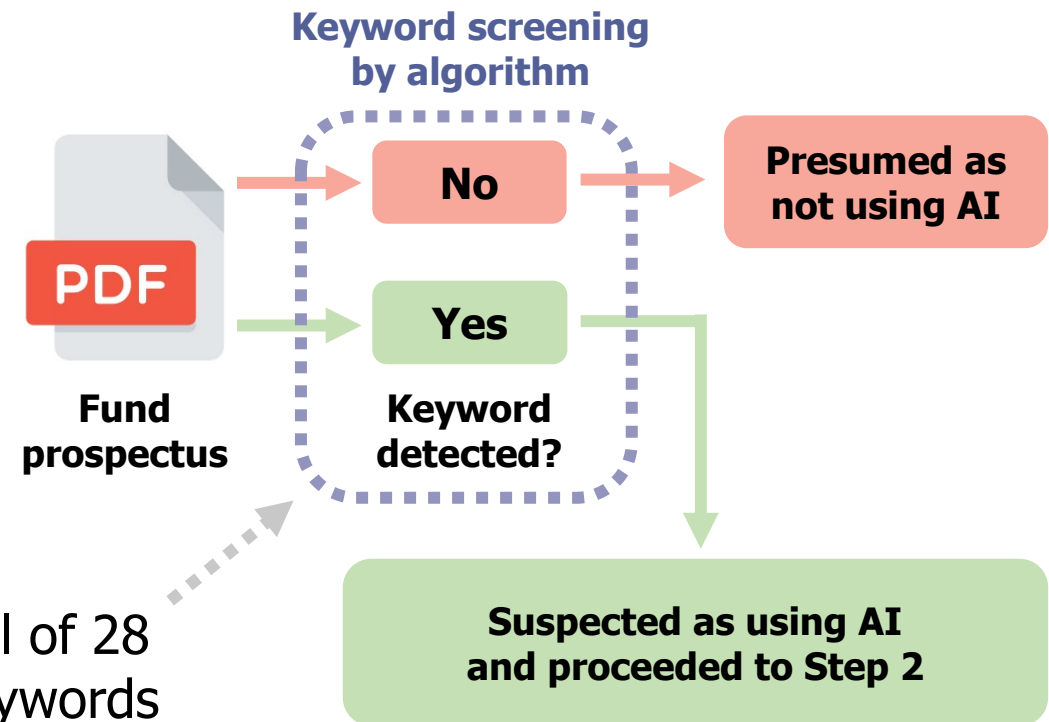
- We established a bank of keywords related to AI subfields shown below:

## English version of keywords

<i>artificial intelligence</i>	<i>supervised learning</i>
<i>AI</i>	<i>semi-supervised learning</i>
<i>machine learning</i>	<i>cluster analysis</i>
<i>deep learning</i>	<i>swarm</i>
<i>decision tree</i>	<i>sentiment analysis</i>
<i>neural network</i>	<i>textual model</i>
<i>natural language processing</i>	<i>text mining</i>
<i>reinforcement learning</i>	<i>attention mechanism</i>
<i>unsupervised learning</i>	<i>cognitive computing</i>

- The prospectuses were written in a total of 28 languages. We used the language of keywords aligned with that of each prospectus.

- We selected 16,529 funds whose prospectus contains at least one keyword and proceeded to Step 2.





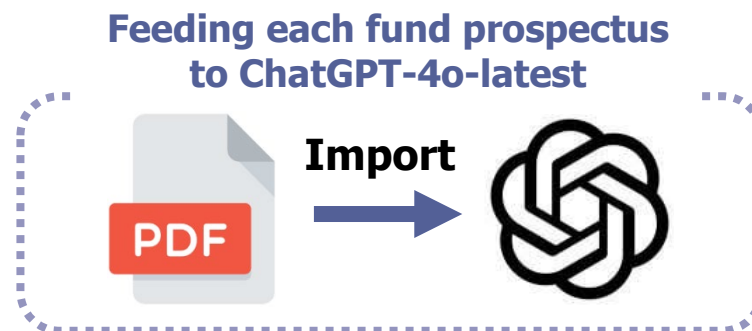
## Step 2: Analysis of Fund Prospectuses

- However, these keywords may not truly indicate that the fund uses AI for making investment decisions.
- We reviewed a sample of prospectuses and found that some keywords were mentioned only for describing issues irrelevant to AI applications, including:
  - a) Background information, e.g. trends associated with the growing use of AI
  - b) Profile of fund managers, e.g. their AI-related experience or education
  - c) Funds' investment focus on securities exposed to the AI sector.
- Therefore, we needed to analyze each prospectus to ensure more accurate identification of funds' AI applications.



## Step 2: Analysis of Fund Prospectuses (cont.)

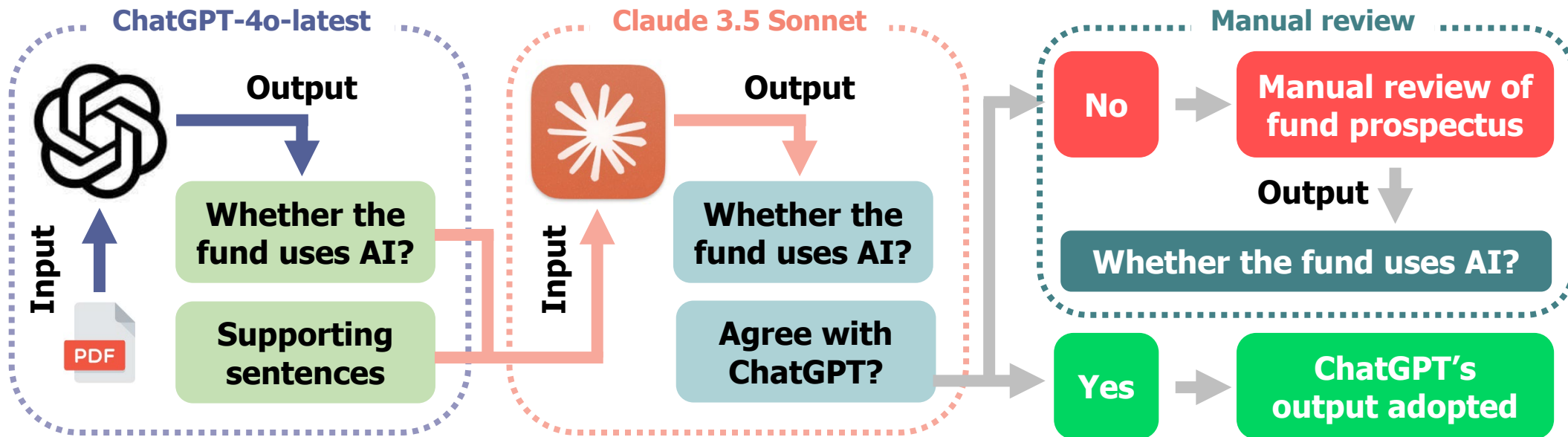
- However, we encountered two technical issues as follows:
  - a) Large volume: 16,529 prospectuses containing keywords were pending for review.
  - b) Multiple language: A total of 28 languages were in use across prospectuses.
- To address these issues, we utilized **ChatGPT-4o-latest** to analyse these prospectuses for us. We commanded it to:
  - a) Determine whether the fund uses AI for investment decision-making; and
  - b) Extract sentences from the prospectus to support its identification.
- For validation, we manually reviewed a sample of ChatGPT's outputs. The results indicated that ChatGPT almost perfectly identified the AI usage of funds.





# Step 3: Validation of ChatGPT's Outputs

- We also imported all ChatGPT's outputs to Claude 3.5 Sonnet for review:
  - a) If Claude agreed with ChatGPT, we adopted ChatGPT's judgement;
  - b) Otherwise, we manually reviewed the prospectus and re-classified the fund ourselves.
- The validation results revealed that the error rate of ChatGPT was about 1%.

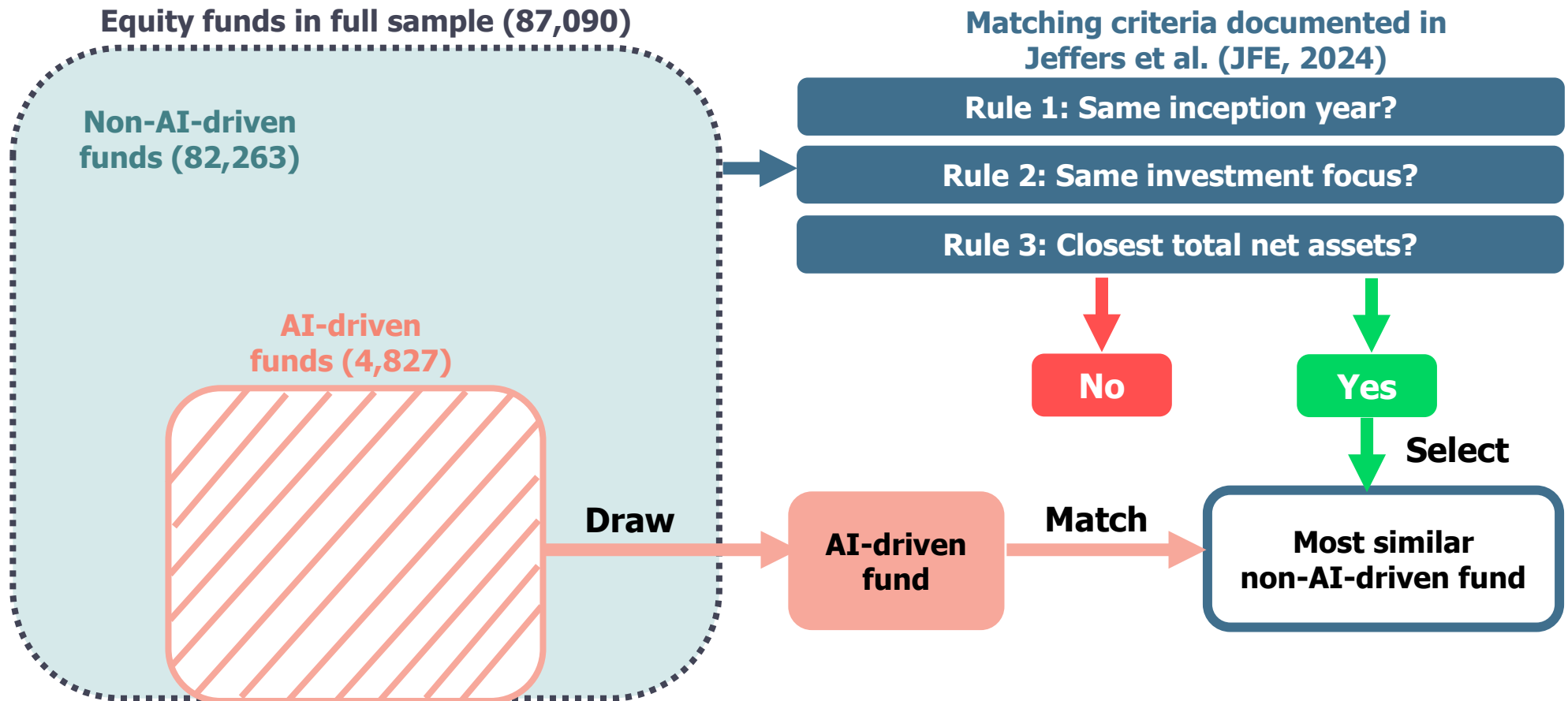






# Construction of the Matched Sample

- We used the approach inspired by Jeffers et al. (JFE, 2024) to match 2,698 AI-driven funds with 2,374 non-AI-driven funds with replacement.



# Overview of the Panel Dataset



- **Panel Data (Fund-Time-Asset Level):**
  - 1) Source: Morningstar Direct and Morningstar Document Library
  - 2) Fund: 2,698 AI-driven funds and 2,374 non-AI-driven funds
  - 3) Time: Monthly frequency; January 2022 to June 2024
  - 4) Asset: 35,806 assets held by funds (incl. cash-like assets, risky assets, derivatives)
- **Main Variables:**
  - 1) Fund's portfolio change: Log change in the number of shares of each asset held by each fund
  - 2) Fund's size: Each fund's total net assets (in USD) in log
  - 3) Fund's age: Each fund's age (in year) in log
  - 4) Fund's return: Each fund's monthly gross return (%)
  - 5) Fund's AI usage: Dummy variable equal to 1 for AI-driven fund; or 0 otherwise



# Question 1: Hypothesis and Methodology

- We considered Equation (1) for estimating the trading correlation within AI-driven funds and that within non-AI-driven funds.
- For asset  $k$  held by fund  $i$  in month  $t$ :

$$\Delta \log(1 + \text{Share}_{i,k,t}) = \beta_1 \times \Delta \log \left( 1 + \sum_{j \neq i, AI_i = AI_j} \text{Share}_{j,k,t} \right) + \beta_2 \times \Delta \log \left( 1 + \sum_{j \neq i, AI_i = AI_j} \text{Share}_{j,k,t} \right) \times AI_i + \text{Size}_{i,t-1} + \text{Age}_{i,t-1} + \text{Return}_{i,t-1} + \theta_i + \theta_k + \theta_t + \varepsilon_{i,k,t} \quad (1)$$

Log change in the number of shares of asset  $k$  held by fund  $i$  in month  $t$

Log changes in the total number of shares of asset  $k$  held by all funds  $j \neq i$  on the condition that  $AI_i = AI_j$

= 1 if fund  $i$  is AI-driven; or 0 otherwise.

- $\beta_1$  indicates the trading correlation within non-AI-driven funds.
- $\beta_1 + \beta_2$  indicates the trading correlation within AI-driven funds.
- Hypothesis (1):**  $\beta_2 > 0$  if the use of AI by funds can increase their trading correlation.



# Question 1: Empirical Results

	$\Delta \log(1 + \text{Share}_{i,k,t})$			
	Full matched sample	Of which: Cash-like assets only	Of which: Risky assets only	Of which: Derivatives only
$\beta_1$	0.14***	0.09***	0.23***	0.12***
$\beta_2$	<b>0.04***</b>	<b>0.01***</b>	<b>0.03***</b>	<b>0.08***</b>
Fund FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Asset FE	Yes	Yes	Yes	Yes
No. of Obs.	41,601,089	8,238,709	21,591,193	11,771,187
No. of funds	5,072	4,993	5,072	3,601
No. of assets	35,806	4,124	25,953	5,729

Note: \*\*\*, \*\*, and \* indicate significance at the 1%, 5% and 10% levels, respectively

Our findings support Hypothesis (1):

- **The trading correlation among AI-driven funds is significantly higher** compared to that of non-AI-driven funds ( $\beta_2 > 0$ ).
- Results demonstrate **robustness across various asset class**, including:
  - Cash-like assets: Currencies, MMFs, US Treasuries, etc.
  - Risky assets: Stocks, corporate bonds, non-MMF mutual funds, etc.
  - Derivatives: Forwards, futures, swaps, warrants, etc.



# Question 2: Hypothesis and Methodology

We examined whether the increased trading correlation was attributable to funds' common use of AI.

- We utilised ChatGPT to analyze fund prospectuses to identify their various AI applications:
  - a) Asset value prediction (*AVP*);
  - b) Market sentiment analysis (*MSA*);
  - c) Thematic screening (*TS*); and
  - d) ESG risk analysis (*ERA*).
- Some funds implemented a multiple of these "AI-driven investment strategies".

88%



**Asset value prediction:**  
Using AI/machine learning (ML)-powered quantitative models to predict asset values, often to identify undervalued assets for investment

15%



**Market sentiment analysis:**  
Using natural language processing (NLP)-powered models to gauge market sentiment, often to facilitate momentum trading

52%



**Thematic screening:**  
Identifying assets under specific investment themes through NLP-powered textual analysis of documents related to the assets

3%



**ESG risk analysis:**  
Assessing the ESG risks of assets through NLP-powered textual analysis of documents related to the assets

## Question 2: Hypothesis and Methodology (cont.)



- We considered Equation (2) to estimate the trading correlations for different groups of AI-driven funds.
- For asset  $k$  held by AI-driven fund  $i$  in month  $t$ :

$$\begin{aligned} \Delta \log(1 + \text{Share}_{i,k,t}) = & \pi_1 \times \Delta \log \left( 1 + \sum_{j \neq i, \text{AVP}_j=1} \text{Share}_{j,k,t} \right) \times \text{AVP}_i + \pi_2 \times \Delta \log \left( 1 + \sum_{j \neq i, \text{AVP}_j=0} \text{Share}_{j,k,t} \right) \times \text{AVP}_i + \\ & \pi_3 \times \Delta \log \left( 1 + \sum_{j \neq i, \text{MSA}_j=1} \text{Share}_{j,k,t} \right) \times \text{MSA}_i + \pi_4 \times \Delta \log \left( 1 + \sum_{j \neq i, \text{MSA}_j=0} \text{Share}_{j,k,t} \right) \times \text{MSA}_i + \\ & \pi_5 \times \Delta \log \left( 1 + \sum_{j \neq i, \text{OTH}_j=1} \text{Share}_{j,k,t} \right) \times \text{OTH}_i + \pi_6 \times \Delta \log \left( 1 + \sum_{j \neq i, \text{OTH}_j=0} \text{Share}_{j,k,t} \right) \times \text{OTH}_i + \\ & \text{Size}_{i,t-1} + \text{Age}_{i,t-1} + \text{Return}_{i,t-1} + \theta_i + \theta_k + \theta_t + \varepsilon_{i,k,t} \end{aligned} \quad (2)$$

- AVP<sub>i</sub>** denotes the dummy variable equal to 1 if fund  $i$  uses AI for **asset value prediction**
- MSA<sub>i</sub>** denotes the dummy variable equal to 1 if fund  $i$  uses AI for **market sentiment analysis**
- OTH<sub>i</sub>** denotes the dummy variable equal to 1 if fund  $i$  uses AI for **other strategies**.



# Question 2: Hypothesis and Methodology (cont.)

- We considered Equation (2) to estimate the impact of different groups of AI-driven funds.
- For asset  $k$  held by AI-driven fund

Log change in the total number of shares of asset  $k$  held by all funds  $j \neq i$  which use AI for asset value prediction ( $AVP_j = 1$ )

$$\Delta \log(1 + \text{Share}_{i,k,t}) = \pi_1 \times \Delta \log \left( 1 + \sum_{j \neq i, AVP_j=1} \text{Share}_{j,k,t} \right) \times AVP_i + \pi_2 \times \Delta \log \left( 1 + \sum_{j \neq i, AVP_j=0} \text{Share}_{j,k,t} \right) \times AVP_i + \pi_3 \times \Delta \log \left( 1 + \sum_{j \neq i, MSA_j=0} \text{Share}_{j,k,t} \right) \times MSA_i + \pi_4 \times \Delta \log \left( 1 + \sum_{j \neq i, MSA_j=1} \text{Share}_{j,k,t} \right) \times MSA_i + \pi_5 \times \Delta \log \left( 1 + \sum_{j \neq i, OTH_j=0} \text{Share}_{j,k,t} \right) \times OTH_i + \pi_6 \times \Delta \log \left( 1 + \sum_{j \neq i, OTH_j=1} \text{Share}_{j,k,t} \right) \times OTH_i + \text{Size}_{i,t-1} + \text{Age}_{i,t-1} + \text{Return}_{i,t-1} + \sigma_i + \sigma_k + \sigma_t + \epsilon_{i,k,t} \quad (2)$$

Log change in the total number of shares of asset  $k$  held by all funds  $j \neq i$  which use AI **NOT** for asset value prediction ( $AVP_j = 0$ )

- $AVP_i$  denotes the dummy variable equal to 1 if fund  $i$  uses AI for **asset value prediction**
- $MSA_i$  denotes the dummy variable equal to 1 if fund  $i$  uses AI for **market sentiment analysis**
- $OTH_i$  denotes the dummy variable equal to 1 if fund  $i$  uses AI for **other strategies**.

## Question 2: Hypothesis and Methodology (cont.)



- The following matrix illustrates how to interpret the estimated coefficients:

Trading correlation between fund $i$ and funds $j \neq i$		Funds $j \neq i$ that use AI for		
		Asset value prediction	Market sentiment analysis	Other strategies
Fund $i$ that uses AI for	Asset value prediction	$\pi_1$	$\pi_2$	$\pi_2$
	Market sentiment analysis	$\pi_4$	$\pi_3$	$\pi_4$
	Other strategies	$\pi_6$	$\pi_6$	$\pi_5$

- Hypothesis (2):**  $\pi_1 > \pi_2$ ;  $\pi_3 > \pi_4$ ; and  $\pi_5 > \pi_6$ , if trading correlations are stronger among funds that apply AI to the same investment strategy.
- $\pi_2, \pi_4, \pi_6 \leq 0$ , if the investment decisions are divergent among funds that use AI differently.





# Question 2: Empirical Results

	$\Delta \log(1 + \text{Share}_{i,k,t})$			
	Full matched sample	Cash-like assets only	Risky assets only	Derivatives only
$\pi_1$	<b>0.20***</b>	<b>0.08***</b>	<b>0.19***</b>	<b>0.25***</b>
$\pi_2$	-0.03***	-0.02***	0.01***	-0.04***
$\pi_3$	<b>0.13***</b>	<b>0.09***</b>	<b>0.18***</b>	<b>0.14***</b>
$\pi_4$	-0.11***	-0.04***	-0.14***	-0.15***
$\pi_5$	<b>0.02</b>	<b>0.01</b>	<b>0.03</b>	<b>0.02</b>
$\pi_6$	-0.01	-0.01	-0.04	-0.01
Fund, time, asset FEs	Yes	Yes	Yes	Yes
No. of Obs.	21,819,354	4,991,875	10,867,962	5,959,517
No. of funds	2,698	2,692	2,698	2,106
No. of assets	14,473	2,232	11,476	765

Note: \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5% and 10% levels, respectively

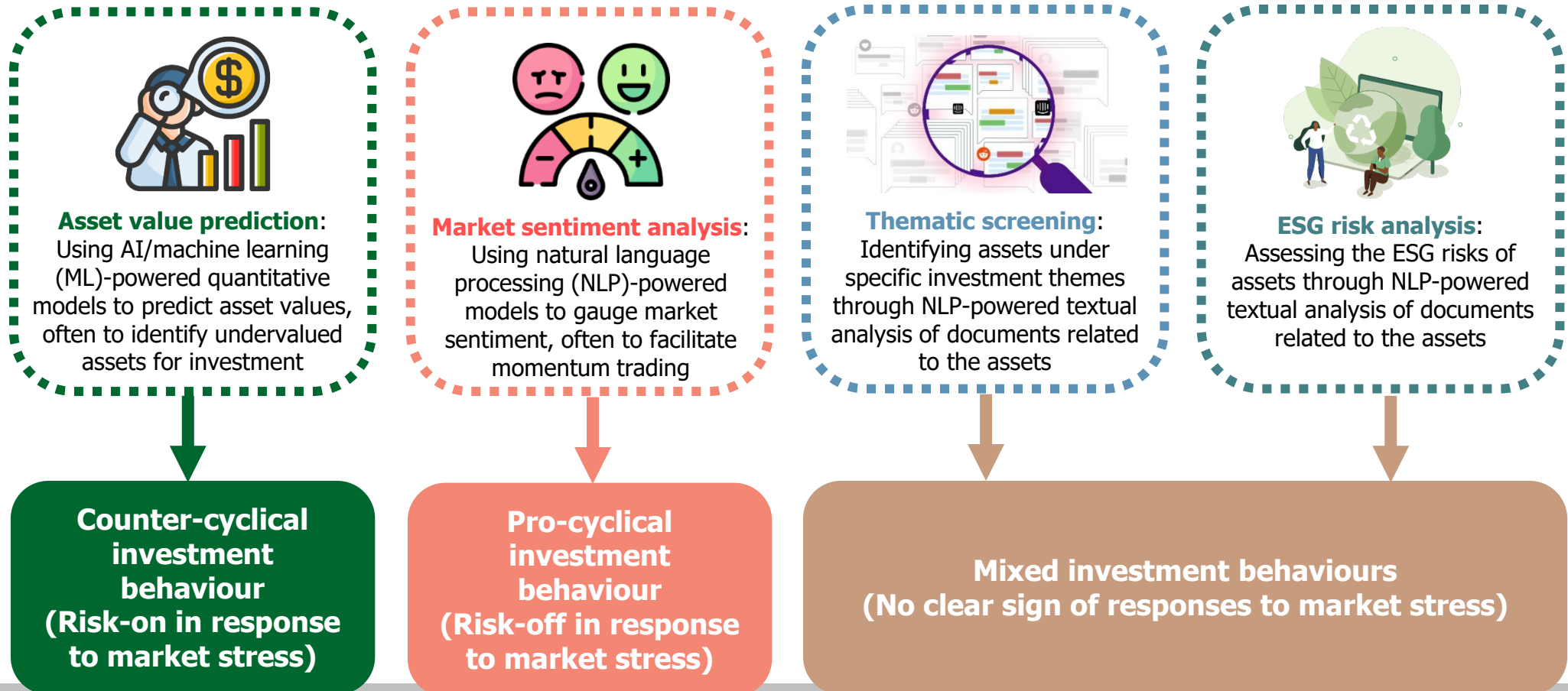
Our results largely support Hypothesis (2):

- **Trading correlations among funds that use AI for the same strategies are largely positive:**
  - a) asset value prediction ( $\pi_1 > 0$ )
  - b) market sentiment analysis ( $\pi_3 > 0$ ).
- **Trading correlations among funds that use AI differently are mostly zero or negative ( $\pi_2 \leq 0$ ;  $\pi_4 \leq 0$  ;  $\pi_6 \leq 0$ ).**
- However, trading correlations among funds that use AI for other strategies are insignificant ( $\pi_5 = 0$ ).



# Question 3: Hypothesis and Methodology

- We examined how AI-driven funds respond to market stress. Their responses may be varied with different investment strategies.





# Question 3: Hypothesis and Methodology (cont.)

- We considered Equation (3) to estimate the portfolio adjustments of funds in response to market stress.

- For asset  $k$  held by fund  $i$  in month  $t$ :

=1 if asset  $k$  is cash-like assets (e.g., currencies, MMFs, US Treasuries, etc.); or =0 otherwise.

$$\Delta \log(1 + \text{Share}_{i,k,t}) = \beta_1 \times \text{Stress}_t \times (1 - \text{AI}_i) \times \text{Cash}_k + \beta_2 \times \text{Stress}_t \times (1 - \text{AI}_i) \times \text{Risky}_k +$$

$$\pi_1 \times \text{Stress}_t \times \text{AVP}_i \times \text{Cash}_k + \pi_2 \times \text{Stress}_t \times \text{AVP}_i \times \text{Risky}_k +$$

$$\pi_3 \times \text{Stress}_t \times \text{MSA}_i \times \text{Cash}_k + \pi_4 \times \text{Stress}_t \times \text{MSA}_i \times \text{Risky}_k +$$

$$\pi_5 \times \text{Stress}_t \times \text{OTH}_i \times \text{Cash}_k + \pi_6 \times \text{Stress}_t \times \text{OTH}_i \times \text{Risky}_k +$$

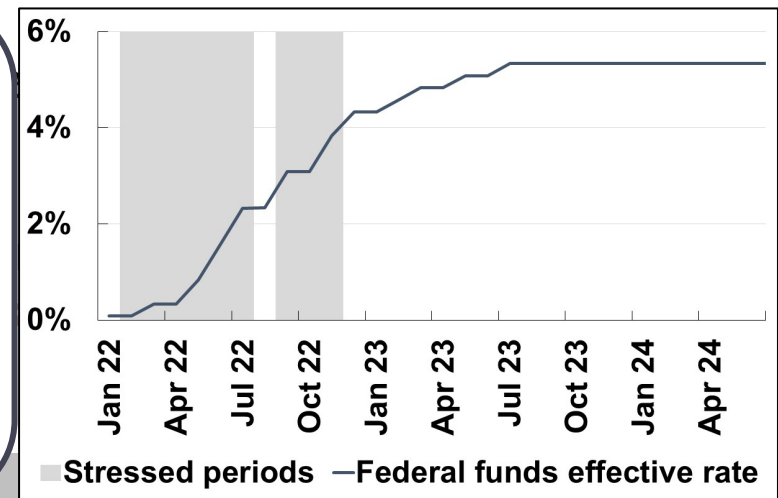
$$\text{Size}_{i,t-1} + \text{Age}_{i,t-1} + \text{Return}_{i,t-1} + \theta_i + \theta_k + \varepsilon_{i,k,t}$$

=1 if asset  $k$  is risky assets (e.g., stocks, corporate bonds, non-MMF mutual funds, etc.); or =0 otherwise.

(3)

=1 if the average of the end-of-day Chicago Board Options Exchange's Volatility Index (VIX) for month  $t$  exceeds the upper quantile of the sample; or 0 otherwise.

- This measure is inspired by a substantial body of literature, e.g., Converse et al. (RFS, 2023) and Goldstein et al. (JFS, 2017), etc.
- The stressed periods (grey-shaded area, RHS chart) predominantly cover the hawkish pivot by the US FOMC in early 2022 and the subsequent interest rate hikes of 50 and 75 basis points.





# Question 3: Hypothesis and Methodology (cont.)

- We considered Equation (3) to estimate the portfolio adjustments of funds in response to market stress.

- For asset  $k$  held by fund  $i$  in month  $t$ :

$$\Delta \log(1 + \text{Share}_{i,k,t}) = \beta_1 \times \text{Stress}_t \times (1 - \text{AI}_i) \times \text{Cash}_k + \beta_2 \times \text{Stress}_t \times (1 - \text{AI}_i) \times \text{Risky}_k +$$

$$\pi_1 \times \text{Stress}_t \times \text{AVP}_i \times \text{Cash}_k + \pi_2 \times \text{Stress}_t \times \text{AVP}_i \times \text{Risky}_k +$$

$$\pi_3 \times \text{Stress}_t \times \text{MSA}_i \times \text{Cash}_k + \pi_4 \times \text{Stress}_t \times \text{MSA}_i \times \text{Risky}_k +$$

$$\pi_5 \times \text{Stress}_t \times \text{OTH}_i \times \text{Cash}_k + \pi_6 \times \text{Stress}_t \times \text{OTH}_i \times \text{Risky}_k +$$

$$\text{Size}_{i,t-1} + \text{Age}_{i,t-1} + \text{Return}_{i,t-1} + \theta_i + \theta_k + \varepsilon_{i,k,t}$$

(3)

=1 if asset  $k$  is cash-like assets (e.g., currencies, MMFs, US Treasuries, etc.); or =0 otherwise.

=1 if asset  $k$  is risky assets (e.g., stocks, corporate bonds, non-MMF mutual funds, etc.); or =0 otherwise.

- $\beta_1$  and  $\beta_2$  indicate the percentage change in the amount of **cash-like** and **risky assets**, respectively, held by **non-AI-driven funds** in response to market stress.
- $\pi_1, \pi_2, \pi_3, \pi_4, \pi_5$  and  $\pi_6$  indicate the corresponding changes for funds that use AI for **asset value prediction**, **market sentiment analysis**, and **other strategies**.

# Question 3: Hypothesis and Methodology (cont.)



- Funds may adjust their holdings of (a) cash-like assets and (b) risky assets differently in response to market stress, depending on their investment cyclicality:
  - a) Cash-like assets: ↓ if counter-cyclical; ↑ if pro-cyclical
  - b) Risky assets: ↑ if counter-cyclical; ↓ if pro-cyclical
  - c) Derivatives: The adjustment may be ambiguous as the purpose of using them is unknown.
- **Hypothesis (3):**
  - Funds that use AI for asset value prediction:  $\pi_1 < 0$ ; and  $\pi_2 > 0$  (counter-cyclical)
  - Funds that use AI for market sentiment analysis:  $\pi_3 > 0$ ; and  $\pi_4 < 0$  (pro-cyclical)
  - Funds that use AI for other strategies:  $\pi_5 = 0$ ; and  $\pi_6 = 0$  (mixed)



# Question 3: Empirical Results

	$\Delta \log(1 + \text{Share}_{i,k,t})$		
Stress <sub>t</sub> defined by	VIX	St. Louis Fed FSI	US OFR FSI
$\beta_1$	-0.06***	0.04***	-0.07***
$\beta_2$	-0.02***	0.08***	0.01***
$\pi_1$	<b>-0.03***</b>	<b>-0.02***</b>	<b>-0.09***</b>
$\pi_2$	<b>0.02***</b>	<b>0.09***</b>	<b>0.06***</b>
$\pi_3$	<b>0.04***</b>	<b>0.00</b>	<b>0.00</b>
$\pi_4$	<b>-0.11***</b>	<b>-0.11***</b>	<b>-0.11***</b>
$\pi_5$	-0.01	0.01	-0.01
$\pi_6$	-0.01	-0.01	-0.01
$\pi_4 - \beta_2$	<b>-0.08***</b>	<b>-0.19***</b>	<b>-0.12***</b>
Fund and asset FEs	Yes	Yes	Yes
No. of obs.	29,829,902	29,829,902	29,829,902
No. of funds	5,072	5,072	5,072
No. of assets	30,077	30,077	30,077

Note: \*\*\*, \*\*, and \* indicate significance at the 1%, 5% and 10% levels, respectively

Our findings support Hypothesis (3):

- **Funds that use AI for asset value prediction:**
  - Counter-cyclical investment behaviour ( $\pi_1 < 0$ ;  $\pi_2 > 0$ )
- **Funds that use AI for market sentiment analysis:**
  - Pro-cyclical investment behaviour ( $\pi_3 > 0$ ;  $\pi_4 < 0$ )
  - More pro-cyclical than non-AI-driven funds ( $\pi_4 - \beta_2 < 0$ )
- **Funds that use AI for other strategies:**
  - Mixed investment behaviours ( $\pi_5 = 0$ ;  $\pi_6 = 0$ )

# Conclusion and Implications



- **This study empirically shows that:**
  - The use of AI by funds increases the trading correlation among them, on the condition that they apply AI to similar investment strategies.
  - However, their similar applications of AI do not necessarily lead to collective asset sales in times of market stress, as their responses to market stress are varied significantly with their strategies.
- **These findings carry two policy implications for financial stability:**
  - Risks associated with the use of AI should be evaluated using a nuanced approach that acknowledges the heterogeneity of AI applications to diverse investment strategies.
  - Among these investment strategies, the pro-cyclical ones identified in this study may warrant closer monitoring in the future.



- **Our results should be interpreted with caution due to the following limitations:**
  - a) The identification of AI usage for each fund was solely based on prospectuses**, without guarantee that these disclosures were accurate.
    - However, it is common for academic literature to rely on fund prospectuses for collecting qualitative data on fund characteristics:
      - e.g. Andrikogiannopoulou et al. (2023), Birk et al. (2024), Kostovetsky & Warner (2020) and Alda et al. (2022)
  - b) Funds' investment decision-making processes might still involve a certain degree of human judgement.**
    - Therefore, our estimations reflect the impacts of the "partial" usage of AI by investment funds, rather than "full" usage of AI.





*Thank you for your attention!*



# Appendix 1 - Summary Statistics

	Mean	SD	25pt	50pt	75pt	Obs.
$\Delta \log(1 + \text{Share}_{i,k,t})$	-0.03	4.27	0.00	0.00	0.00	41,601,089
$\Delta \log(1 + \sum_{j \neq i, AI_j = AI_i} \text{Share}_{j,k,t})$	-0.07	2.96	-0.39	0.00	0.27	41,601,089
$AI_i$	0.55	0.50	0.00	1.00	1.00	41,601,089
$1 - AI_i$	0.45	0.50	0.00	0.00	1.00	41,601,089
$\text{Size}_{i,t-1}$	14.41	3.44	11.92	15.07	17.13	41,601,089
$\text{Age}_{i,t-1}$	1.44	0.54	1.07	1.50	1.87	41,601,089
$\text{Return}_{i,t-1}$	0.04	6.25	-3.77	0.04	4.01	41,601,089
$AVP_i$	0.82	0.39	1.00	1.00	1.00	21,819,354
$MSA_i$	0.33	0.47	0.00	0.00	1.00	21,819,354
$OTH_i$	0.49	0.50	0.00	0.00	1.00	21,819,354
$\Delta \log(1 + \sum_{j \neq i, AVP_j = 1} \text{Share}_{j,k,t})$	-0.09	3.36	-0.53	0.00	0.37	21,819,354
$\Delta \log(1 + \sum_{j \neq i, AVP_j = 0} \text{Share}_{j,k,t})$	-0.04	4.06	-0.19	0.00	0.20	21,819,354
$\Delta \log(1 + \sum_{j \neq i, MSA_j = 1} \text{Share}_{j,k,t})$	-0.06	3.45	-0.38	0.00	0.30	21,819,354
$\Delta \log(1 + \sum_{j \neq i, MSA_j = 0} \text{Share}_{j,k,t})$	-0.06	3.27	-0.50	0.00	0.38	21,819,354
$\Delta \log(1 + \sum_{j \neq i, OTH_j = 1} \text{Share}_{j,k,t})$	-0.04	3.67	-0.37	0.00	0.31	21,819,354
$\Delta \log(1 + \sum_{j \neq i, OTH_j = 0} \text{Share}_{j,k,t})$	-0.12	3.48	-0.56	0.00	0.37	21,819,354
$\text{Stress}_t$	0.25	0.43	0.00	0.00	1.00	29,829,902
$\text{Cash}_k$	0.28	0.45	0.00	0.00	1.00	29,829,902
$\text{Risky}_k$	0.72	0.45	0.00	1.00	1.00	29,829,902

# Appendix 2 - Regression Results for Equation (1)



	$\Delta \log(1 + \text{Share}_{i,k,t})$			
	(1) Full matched sample	(2) Of which: Cash-like assets	(3) Of which: Risky assets	(4) Of which: Derivatives
$\Delta \log \left( 1 + \sum_{j \neq i, AI_j = AI_i} \text{Share}_{j,k,t} \right)$	0.14***	0.09***	0.23***	0.12***
$\Delta \log \left( 1 + \sum_{j \neq i, AI_j = AI_i} \text{Share}_{j,k,t} \right) \times AI_i$	0.04***	0.01***	0.03***	0.08***
$\text{Size}_{i,t-1}$	0.001**	-0.00	0.00***	-0.00***
$\text{Age}_{i,t-1}$	-0.11***	-0.05***	-0.06***	-0.31***
$\text{Return}_{i,t-1}$	0.00***	0.00***	0.00***	0.01***
Wald test: $\beta_1 + \beta_2$	0.18***	0.10***	0.26***	0.20***
Fixed effects:				
Funds	Yes	Yes	Yes	Yes
Assets	Yes	Yes	Yes	Yes
Months	Yes	Yes	Yes	Yes
No. of funds	5,072	4,993	5,072	3,601
No. of assets	35,806	4,124	25,953	5,729
No. of months	30	30	30	30
No. of observations	41,601,089	8,238,709	21,591,193	11,771,187

**Note:** \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5% and 10% levels, respectively

# Appendix 3 - Regression Results for Equation (2)



	$\Delta \log(1 + \text{Share}_{i,k,t})$			
	(1) Full matched sample	(2) Of which: Cash- like assets	(3) Of which: Risky Assets	(4) Of which: Derivatives
$\Delta \log \left( 1 + \sum_{j \neq i, AVP_j=1} \text{Share}_{j,k,t} \right) \times AVP_i$	0.20***	0.08***	0.19***	0.25***
$\Delta \log \left( 1 + \sum_{j \neq i, AVP_j=0} \text{Share}_{j,k,t} \right) \times AVP_i$	-0.03***	-0.02***	0.01***	-0.04***
$\Delta \log \left( 1 + \sum_{j \neq i, MSA_j=1} \text{Share}_{j,k,t} \right) \times MSA_i$	0.13***	0.09***	0.18***	0.14***
$\Delta \log \left( 1 + \sum_{j \neq i, MSA_j=0} \text{Share}_{j,k,t} \right) \times MSA_i$	-0.11***	-0.04***	-0.14***	-0.15***
$\Delta \log \left( 1 + \sum_{j \neq i, OTH_j=1} \text{Share}_{j,k,t} \right) \times OTH_i$	0.02	0.01	0.03	0.02
$\Delta \log \left( 1 + \sum_{j \neq i, OTH_j=0} \text{Share}_{j,k,t} \right) \times OTH_i$	-0.01	-0.01	-0.04	-0.01
<b>Size</b> <sub><i>i,t-1</i></sub>	0.00	0.00**	0.00***	-0.01***
<b>Age</b> <sub><i>i,t-1</i></sub>	-0.07***	-0.05***	0.01*	-0.26***
<b>Return</b> <sub><i>i,t-1</i></sub>	0.00***	0.01***	0.00***	0.01***
Wald test: $\pi_1 - \pi_2$	0.23***	0.10***	0.18***	0.29***
Wald test: $\pi_3 - \pi_4$	0.24***	0.13***	0.32***	0.29***
Wald test: $\pi_5 - \pi_6$	0.03	0.02	0.07	0.03
Fixed effects:				
Funds	Yes	Yes	Yes	Yes
Assets	Yes	Yes	Yes	Yes
Months	Yes	Yes	Yes	Yes
No. of funds	2,698	2,692	2,698	2,106
No. of assets	14,473	2,232	11,476	765
No. of months	30	30	30	30
No. of observations	21,819,354	4,991,875	10,867,962	5,959,517

**Note:** \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5% and 10% levels, respectively

# Appendix 4 - Regression Results for Equation (3)



	$\Delta \log(1 + \text{Share}_{i,k,t})$		
	(1)	(2)	(3)
Stress <sub>t</sub> defined by	VIX	SLFFSI	OFRFSI
<b>Stress<sub>t</sub> × Cash<sub>k</sub> × (1 – AI<sub>i</sub>)</b>	-0.06***	0.04***	-0.07***
<b>Stress<sub>t</sub> × Risky<sub>k</sub> × (1 – AI<sub>i</sub>)</b>	-0.02***	0.08***	0.01***
<b>Stress<sub>t</sub> × Cash<sub>k</sub> × AVP<sub>i</sub></b>	-0.03***	-0.02***	-0.09***
<b>Stress<sub>t</sub> × Risky<sub>k</sub> × AVP<sub>i</sub></b>	0.02***	0.09***	0.06***
<b>Stress<sub>t</sub> × Cash<sub>k</sub> × MSA<sub>i</sub></b>	0.04***	0.00	0.00
<b>Stress<sub>t</sub> × Risky<sub>k</sub> × MSA<sub>i</sub></b>	-0.11***	-0.11***	-0.11***
<b>Stress<sub>t</sub> × Cash<sub>k</sub> × OTH<sub>i</sub></b>	-0.01	0.01	-0.01
<b>Stress<sub>t</sub> × Risky<sub>k</sub> × OTH<sub>i</sub></b>	-0.01	-0.01	-0.01
<b>Size<sub>i,t-1</sub></b>	0.00***	0.00***	0.00***
<b>Age<sub>i,t-1</sub></b>	-0.36***	-0.26***	-0.34***
<b>Return<sub>i,t-1</sub></b>	0.00***	0.00***	0.00***
Wald test: $\pi_4 - \beta_2$	-0.09***	-0.19***	-0.12***
Fixed effects:			
Funds	Yes	Yes	Yes
Assets	Yes	Yes	Yes
Months	No	No	No
No. of funds	5,072	5,072	5,072
No. of assets	30,077	30,077	30,077
No. of months	30	30	30
No. of observations	29,829,902	29,829,902	29,829,902

**Note:** \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5% and 10% levels, respectively



# Appendix 5: Examples of ChatGPT's analysis on non-English prospectuses

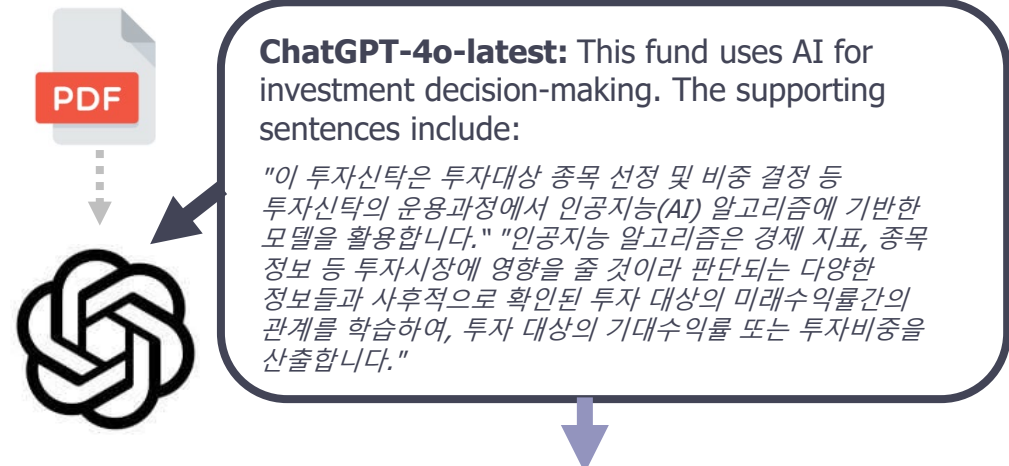
- ChatGPT-4o-latest was excellent in comprehending content in a variety of languages.

## Example 1: Simplified Chinese prospectus



**Google translate to English:** The investment strategy of this fund is growth-oriented. By building a multi-factor quantitative investment model, the fund selects stocks with high performance, good quality and reasonable pricing to build an investment portfolio. The fund manager will also introduce quantitative and price factors mined based on deep learning models and other machine learning models to identify trading signals.

## Example 2: Korean prospectus



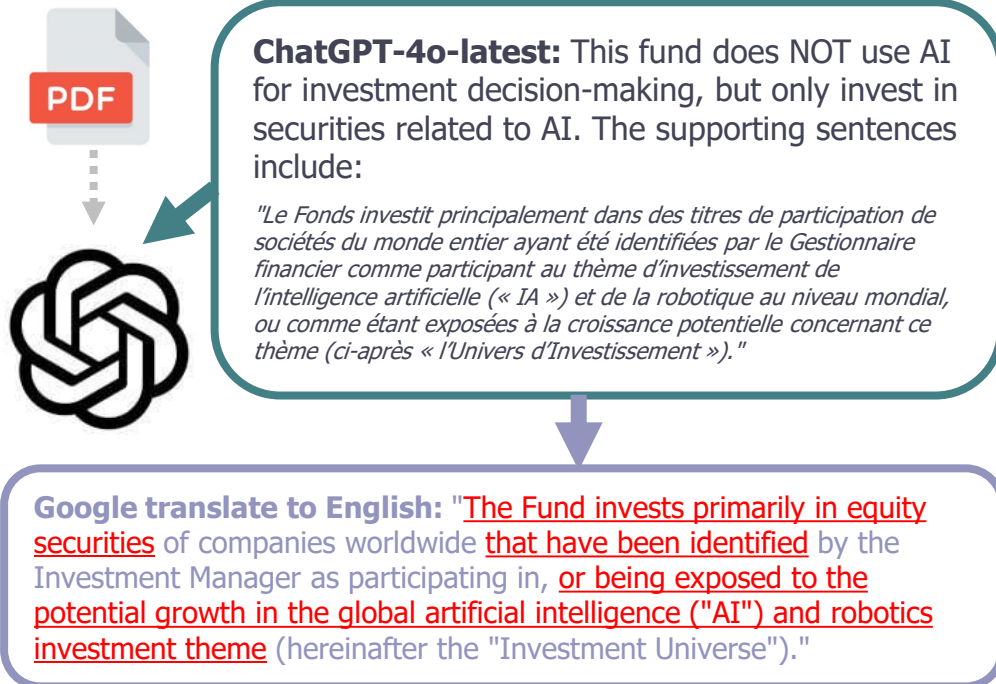
**Google translate to English:** "This investment trust utilizes a model based on an artificial intelligence (AI) algorithm in the investment trust management process, such as selecting investment target stocks and determining weights." "The AI algorithm learns the relationship between various information that is judged to have an impact on the investment market, such as economic indicators and stock information, and the future return rate of the investment target confirmed afterward, and calculates the expected return rate or investment weight of the investment target."



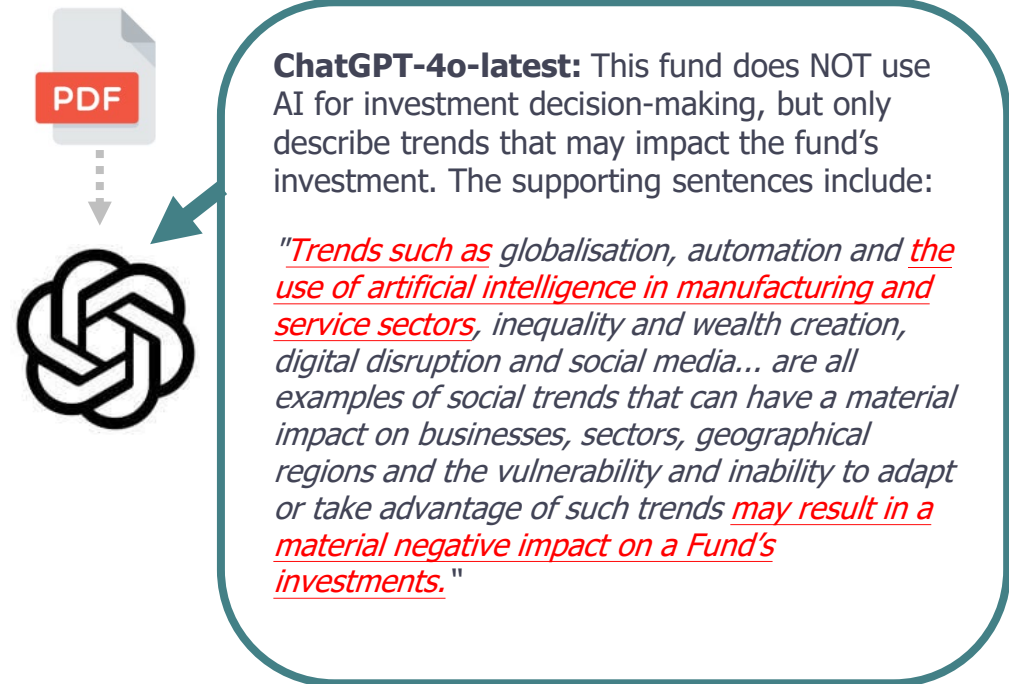
# Appendix 6: Examples of ChatGPT's analysis on prospectuses without mentions of funds' AI usage

- ChatGPT-4o-latest demonstrates a understanding of prospectus content, capably making well-informed judgement on each fund's application of AI.

## Example 1: Fund's investment focus



## Example 2: AI-related market trends

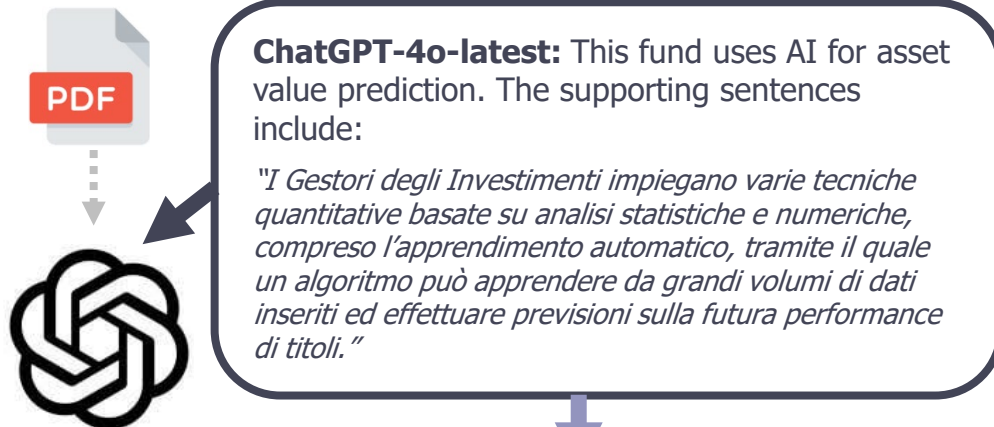




# Appendix 7: Examples of ChatGPT identifying funds that use AI for asset value prediction

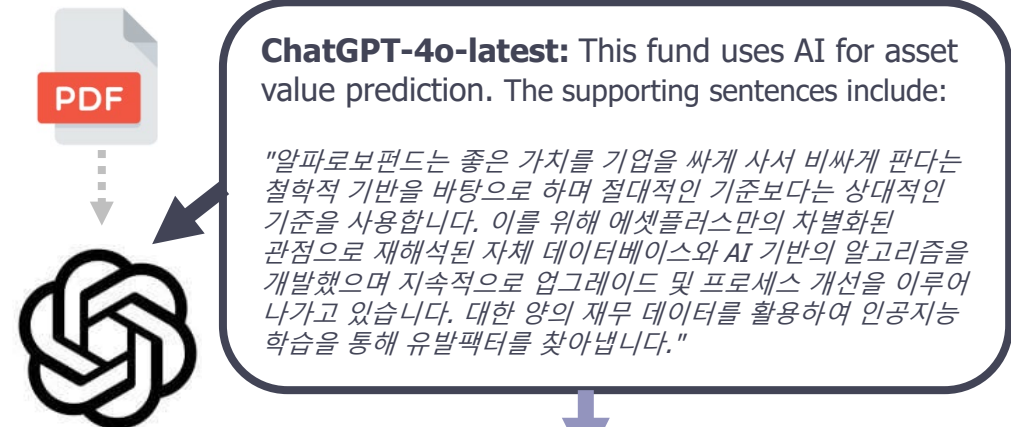
- Some funds apply AI to asset value prediction, often to identify undervalued assets for investment.

## Example 1:



**Google translate to English:** "The Investment Managers employ a variety of quantitative techniques based on statistical and numerical analysis, including machine learning, whereby an algorithm can learn from large volumes of input data and make predictions about the future performance of securities."

## Example 2:



**Google translate to English:** "Alpha Robo Fund is based on the philosophical foundation of buying good value companies cheaply and selling them expensively, and uses relative criteria rather than absolute criteria. To this end, we have developed our own database and AI-based algorithms that have been reinterpreted from Asset Plus's unique perspective, and we are continuously upgrading and improving the process. We use a vast amount of financial data to find trigger factors through AI learning."





# Appendix 8: Examples of ChatGPT identifying funds that use AI for market sentiment analysis

- Some funds apply AI to market sentiment analysis, often to facilitate momentum trading strategies.

## Example 1:



**ChatGPT-4o-latest:** This fund uses AI for market sentiment analysis. The supporting sentences include:

*"The strategy is based on the application of a number of advanced quantitative methodologies and techniques, including natural language processing.*

- *First, market news items are retrieved from a general news feed and quantified using tailor-made natural language processing methods;*
- *Second, proprietary dynamic agent-based models are applied to extract market sentiment from this quantified market news; and*
- *Third, customized algorithms are applied to this market sentiment to determine the expected impact of market news on the development of future prices. The estimation may be used to facilitate momentum trading strategies.*

## Example 2:



**ChatGPT-4o-latest:** This fund uses AI for market sentiment analysis. The supporting sentences include:

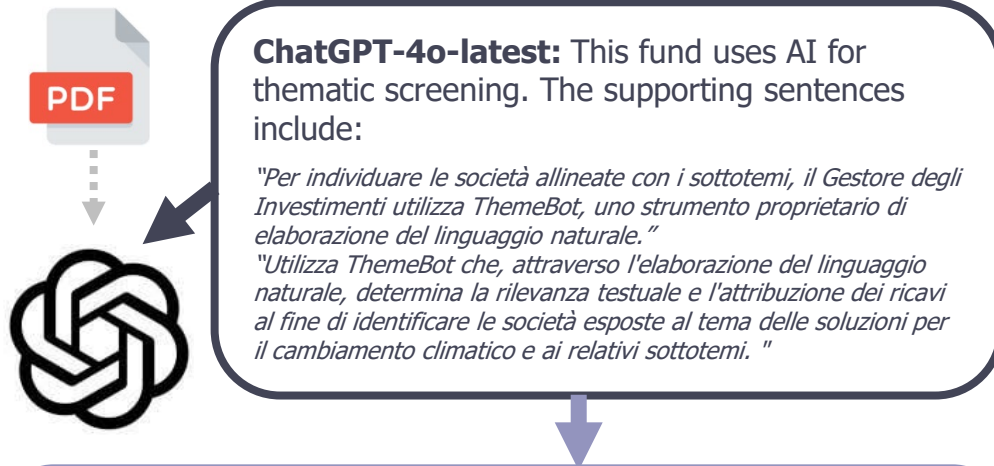
*"The Investment Manager utilizes a proprietary quantitative approach driven through artificial intelligence and high-frequency tracking of sustainability-related news as well as the market sentiment by using natural language processing to identify market sentiment towards a specific sustainability theme."*



# Appendix 9: Examples of ChatGPT identifying funds that use AI for thematic screening

- Some funds apply AI to thematic screening, identifying funds aligned with specific investment themes.

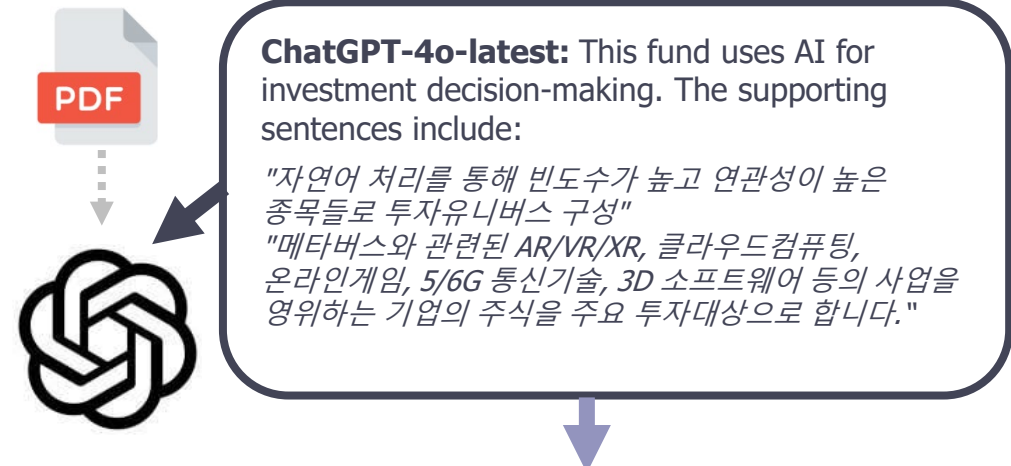
## Example 1:



**Google translate to English:** "To identify companies aligned with the sub-themes, the Investment Manager uses ThemeBot, a proprietary natural language processing tool."

"ThemeBot, which uses natural language processing to determine text relevance and revenue attribution to identify companies exposed to the Climate Change Solutions theme and its sub-themes."

## Example 2:



**Google translate to English:** "We compose the investment universe with stocks with high frequency and high relevance through natural language processing."

"We mainly invest in stocks of companies that engage in businesses related to the metaverse, such as AR/VR/XR, cloud computing, online games, 5/6G communication technology, and 3D software."



# Appendix 10: Examples of ChatGPT identifying funds that use AI for ESG risk assessment

- Some funds apply AI to ESG risks assessment, evaluating the ESG performance of assets.

## Example 1:



**ChatGPT-4o-latest:** This fund uses AI for assessing the ESG risks of assets. The supporting sentences include:

*"The systematic integration of ESG characteristics and the level of sophistication supported by artificial intelligence is considered fundamental to the Investment Manager's investment process. Another aspect of the Investment Manager's quantitative research is the identification of sustainability risk and the monitoring of news and media thoroughly both in-person and through the application of algorithms.*

*The Investment Manager utilizes a proprietary quantitative approach driven through artificial intelligence and high-frequency tracking of sustainability-related news as well as the market sentiment by using natural language processing to identify market sentiment towards a specific sustainability theme.*"

## Example 2:



**ChatGPT-4o-latest:** This fund uses AI for assessing the ESG risks of assets. The supporting sentences include:

*"The Manager will use proprietary technology that combines big data research and artificial intelligence to identify and determine the relevance of key words and concepts related to the sub-themes, and evaluate public documentation (e.g. companies' or organisations' regulatory filings, broker reports, news reports, company profiles, etc.) to assess and score each company's or organisation's textual relevance and revenue attribution to the sub-themes.*"

*"The theme of future transition, which is the thematic focus of the Fund, aligns with the pursuit of the key UN Sustainable Development Goals aiming to improve sustainable and socially responsible finance in relation to the promotion of smart city, digital education, autonomous vehicles, medical technology and social and environmental development (each a 'sub-theme', collectively the 'sub-themes').*"

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