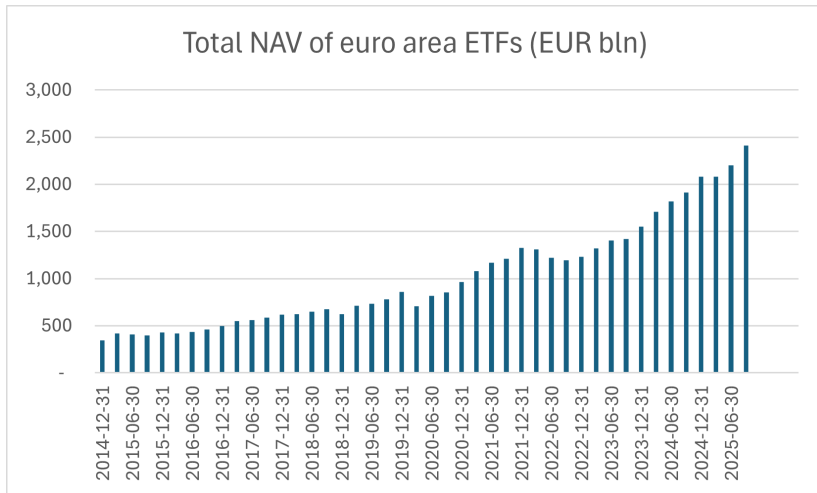


Managing Redemption Risk: The Use of ETFs by Open-Ended Funds

Lennart Dekker (DNB), Luis Molestina Vivar (ECB), Christian Weistroffer (ECB)

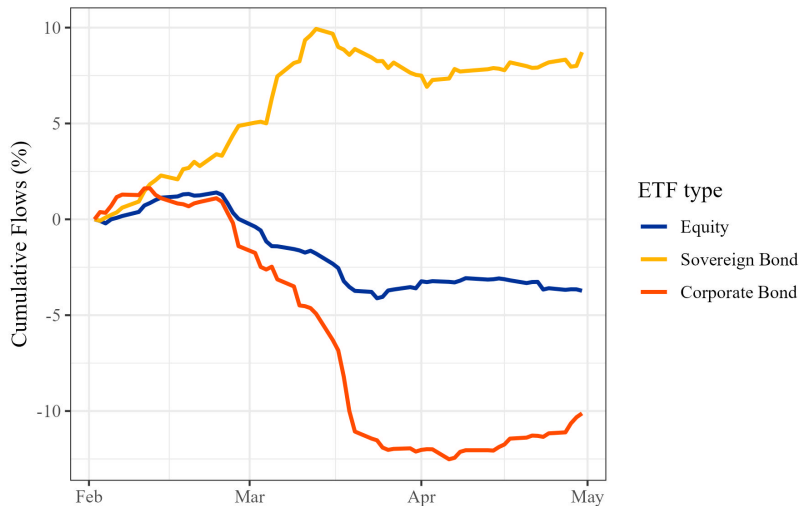
2025 ESMA Research Conference - Understanding investment funds:
Developments and risks in the EU fund industry

Motivating facts (1)



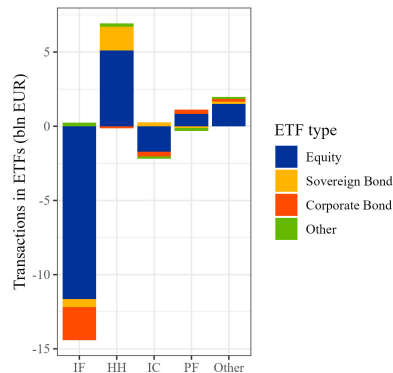
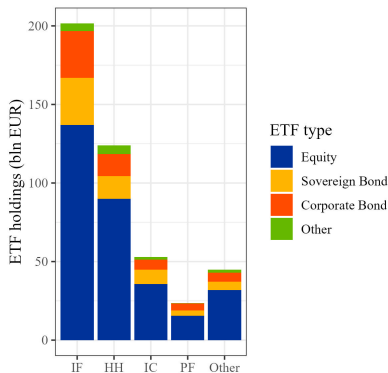
Motivating facts (2)

Figure: ETF primary market flows during 2020-Q1.



Motivating facts (3)

Figure: Ownership and transactions in ETFs during 2020-Q1.



(a) ETF ownership as of 2019-Q4.

(b) Transactions in ETFs during 2020-Q1.

Why would open-ended funds invest in ETFs?

- ▶ Low-cost opportunity to gain benchmark exposure and/or diversification (e.g. within a fund-of-funds structure)
- ▶ Liquidity management purposes:
 - ▶ Trading ETF shares can be more efficient than trading all the underlying securities
 - ▶ While the price of an ETF is not as stable as the value of cash-like instruments, ETFs have higher expected returns and allow for closer alignment with the fund's benchmark index
 - ▶ Hence, ETFs can be useful instruments to accommodate flows relatively efficiently without materially distorting the fund's portfolio composition

- ▶ When faced with sudden and large redemption requests, liquidity needs by open-ended funds may spill over to ETF markets:
 - ▶ A big ETF sell-off by investment funds may push the ETF's price below NAV
 - ▶ Authorized Participants (APs) buy the ETF share and redeem it with the ETF sponsor to pocket in the price/NAV difference
 - ▶ This way, secondary market ETF sales may lead to net ETF redemptions in the primary market

- ▶ We study how open-ended funds use ETFs to manage liquidity in periods of stress and how their trading affects ETF markets.

Related Literature

▶ **Cross-fund investments**

- ▶ Sherrill et al. (2020); Fricke et al. (2023); Fricke and Wilke (2023)

▶ **Liquidity management of open-ended funds**

- ▶ Coval and Stafford (2007); Lou (2012); Chernenko and Sunderam (2016); Choi et al. (2020); Jiang et al. (2021); Ma et al. (2022)

▶ **Impact of ETF creation/redemptions on underlying securities**

- ▶ Dannhauser and Hoseinzade (2022); Koont et al. (2025); Rhodes and Mason (2023); Shim and Todorov (2023); Brogaard et al. (2025); Holden and Nam (2024)

ETF Sample

- ▶ Refinitiv Lipper
 - ▶ We focus on equity and bond ETFs regulated under the Undertakings for Collective Investment in Transferable Securities (UCITS) Directive.
 - ▶ ETF characteristics + daily primary market flows and returns
- ▶ ECB Securities Holdings Statistics (SHS)
 - ▶ Information on the ownership composition of ETFs.
 - ▶ We only keep ETFs for which at least 75% is owned by euro area investors.

ETF Descriptives

Panel A. Asset Type

	Equity	Bond Corporate	Bond Sovereign	Bond Other	Total
# funds	404	57	116	17	594
TNA (€bln)	115	37	38	1	190

Panel B. Domicile

	France	Germany	Ireland	Luxembourg	Other	Total
# funds	50	78	136	327	3	594
TNA (€bln)	15	21	58	97	0	190

Panel C. Geographical Focus

	Europe	Global	Emerging Markets	US	Other	Total
# funds	225	87	37	95	150	594
TNA (€bln)	85	25	14	36	30	190

ETF Descriptives

Table: Ownership profile of ETFs as of December 2019.

ETF type:	Equity	Corporate Bond	Sovereign Bond
Banks	1.67	1.78	1.94
Government	1.77	2.53	2.47
Households	24.35	19.85	22.52
IC	10.08	9.09	11.38
IF	41.51	41.06	39.65
NFC	3.23	2.51	2.3
OFC	2	1.7	1.34
PF	3.7	5.24	4.53
Non-EA	11.67	16.23	13.86

Open-Ended Fund Descriptives

Panel A. Domicile

	FR	DE	IE	LU	UK	Other	Total
# funds	154	215	110	778	264	511	2030
TNA (€bln)	27	37	49	266	112	133	622

Panel B. Geographical Focus

	Europe	Global	Emerging Markets	UK	US	Other	Total
# funds	133	1739	45	31	21	62	2030
TNA (€bln)	34	525	22	16	6	19	622

Panel C. Portfolio composition

Asset Type	Mean	St. Dev.	5%	50%	95%
ETF	19.83	23.38	0.81	10.47	77.91
Mutual Funds	36.9	33.62	0	29.86	91.24
Equity	19.41	30.23	0	0.02	91.3
Sovereign Bond	7	14.55	0	0	38.41
Corporate Bond	8.54	17.71	0	0	48.2

Do fund flows drive ETF sales?

- ▶ Investment funds appeared to be the most run-prone investor type in ETFs during 2020-Q1.
- ▶ This is likely driven by the large outflows that open-ended investment funds faced themselves during 2020-Q1.
- ▶ We therefore relate ETF sales to OEF flows using the following regression:

$$Trade_{i,j,t} = \alpha_{j,t} + \beta Flow_{i,t} + \gamma' X_{i,t-1} + \varepsilon_{i,j,t}$$

- ▶ $Trade_{i,j,t}$ is the relative change in the number of shares of ETF j held by open-ended fund i during month t
- ▶ $Flow_{i,t}$ is the net flow for open-ended fund i during month t

Panel A: monthly ETF sales during 2019-2024

ETF Type Model:	All (1)	Equity (2)	Corp. Bond (3)	Sov. Bond (4)
Flow	1.25** (35.5)	1.24** (27.6)	1.42** (24.3)	1.35** (24.4)
ETF×Year-Month FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	707,087	453,615	86,140	93,869
Adjusted R ²	0.161	0.165	0.128	0.156

Panel B: monthly ETF sales during 2019-2024 - outflow sample

ETF Type Model:	All (1)	Equity (2)	Corp. Bond (3)	Sov. Bond (4)
Flow	1.26** (27.7)	1.27** (22.3)	1.49** (15.6)	1.41** (16.0)
ETF×Year-Month FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	385,702	240,421	50,424	52,871
Adjusted R ²	0.167	0.175	0.134	0.159

* p<0.05; ** p<0.01.

Fund's pecking order of liquidation

- ▶ We test whether fund managers rely relatively more on ETFs than holdings in other asset types to accommodate outflows.
- ▶ This would lend further support to the notion that fund managers use ETFs for liquidity management.
- ▶ We consider the following regression over 2019-2024, restricting attention to fund-months with negative net flows:

$$Trade_{i,j,t} = \alpha_{i,t} + \beta Flow_{i,t} + \gamma' (Flow_{i,t} \times Type_j) + \delta' Type_j + \varepsilon_{i,j,t}$$

- ▶ $Trade_{i,j,t}$ is the relative change in the number of shares of security j held by open-ended fund i during month t
- ▶ $Flow_{i,t}$ is the net flow for open-ended fund i during month t
- ▶ $Type_j$ is a categorical variable indicating the type of security j

Panel A. Mutual fund shares versus ETFs			
Obs:	All	All	$w > 0.5\%$
Model:	OLS	WLS	OLS
	(1)	(2)	(3)
$Type_j = \text{ETF}$	-1.63** (-12.0)	-1.39** (-11.2)	-1.60** (-12.2)
$\text{Flow} \times Type_j = \text{ETF}$	0.217** (4.53)	0.149** (3.21)	0.197** (4.17)
Fund $\times$ Year-Month FE	Yes	Yes	Yes
Observations	1,189,427	1,189,427	1,026,606
Adjusted R ²	0.086	0.132	0.087

* $p < 0.05$; ** $p < 0.01$.

Panel B. Equity versus Equity ETFs			
Obs:	All	All	$w > 0.5\%$
Model:	OLS	WLS	OLS
	(1)	(2)	(3)
$Type_j = \text{Eq. ETF}$	-0.391 (-1.35)	-1.19** (-3.96)	-1.81** (-6.01)
$\text{Flow} \times Type_j = \text{Eq. ETF}$	0.402** (3.64)	0.500** (4.19)	0.417** (3.66)
Fund $\times$ Year-Month FE	Yes	Yes	Yes
Observations	3,254,233	3,254,233	624,007
Adjusted R ²	0.108	0.164	0.143

* $p < 0.05$; ** $p < 0.01$.

Panel C. Corporate bonds versus Corporate Bond ETFs

Obs:	All	All	$w > 0.5\%$
Model:	OLS	WLS	OLS
	(1)	(2)	(3)
$Type_j = \text{CB ETF}$	0.322 (0.780)	0.216 (0.522)	0.405 (1.01)
$\text{Flow} \times Type_j = \text{CB ETF}$	1.09** (5.80)	1.07** (5.46)	1.07** (5.88)
Fund $\times$ Year-Month FE	Yes	Yes	Yes
Observations	1,026,243	1,026,243	153,180
Adjusted R^2	0.343	0.172	0.126

* $p < 0.05$; ** $p < 0.01$.

Panel D. Sovereign bonds versus Sovereign Bond ETFs			
Obs:	All	All	$w > 0.5\%$
Model:	OLS	WLS	OLS
	(1)	(2)	(3)
$Type_j = \text{SB ETF}$	2.28** (5.13)	2.16** (3.75)	2.13** (4.51)
$\text{Flow} \times Type_j = \text{SB ETF}$	0.864** (4.92)	0.704** (4.05)	0.636** (3.93)
Fund×Year-Month FE	Yes	Yes	Yes
Observations	249,140	249,140	99,374
Adjusted R ²	0.211	0.186	0.113

* $p < 0.05$; ** $p < 0.01$.

Investment fund ownership and primary ETF markets

- ▶ Outflows from OEFs were passed on to ETFs during 2020-Q1, which may have contributed to ETF net redemptions given the large ownership stake of investment funds in the ETF market.
- ▶ We test whether ETFs with higher ex-ante investment fund ownership faced larger primary market outflows (relative to ETFs with lower ex-ante investment fund ownership):

$$\begin{aligned} f_{i,q,t} = & \alpha_t + \delta_i + \gamma' (Crisis_t \times HighIF_{i,q-1}) \\ & + \delta HighIF_{i,q-1} + \lambda' Controls_{i,t-1} + \varepsilon_{i,q,t} \end{aligned}$$

- ▶ $f_{i,q,t}$ is the weekly primary market flow of ETF i during week t in quarter q
- ▶ $HighIF_{i,q-1}$ is a dummy equal to 1 if the fraction of ETF i held by EA investment funds in quarter $q - 1$ is above the median

ETF Type:	Equity (1)	Corp. Bond (2)	Sov. Bond (3)
HighIF × Week 1 [Feb 21 - Feb 28]	-1.34** (-13.0)	-0.961** (-3.72)	0.571 (1.76)
HighIF × Week 2 [Feb 28 - Mar 6]	0.134 (1.17)	-1.60** (-6.41)	1.68** (7.93)
HighIF × Week 3 [Mar 6 - Mar 13]	-1.43** (-11.9)	-0.339 (-1.35)	-2.61** (-7.62)
HighIF × Week 4 [Mar 13 - Mar 20]	-2.43** (-23.4)	-3.75** (-14.5)	-1.59** (-4.67)
HighIF × Week 5 [Mar 20 - Mar 27]	-0.714** (-6.17)	-2.60** (-9.64)	0.527** (2.76)
ETF FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	29,226	4,047	8,285
Adjusted R ²	0.047	0.062	0.061

* p<0.05; ** p<0.01.

Conclusion

- ▶ Investment funds were the main ETF sellers in the euro area during the COVID-19 crisis.
- ▶ Open-ended funds sold ETFs to meet redemptions, relying more on ETF sales than other assets.
- ▶ This behavior persisted beyond March 2020 (2019–2024), showing ETFs are used for liquidity management in both stressed and normal times.
- ▶ ETF selling preserved cash but shifted liquidity pressure onto ETF markets and underlying securities markets.
- ▶ Robust ETF market functioning is important for a resilient mutual fund sector.

Dilution and Strategic Complementarity in Fixed-Income Funds: Evidence from European UCITS

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Research Department

ESMA Research Conference November 2025



*The views expressed herein are those of the authors and do not necessarily reflect the views of the Investment Company Institute, its staff, or its member firms

- Investors redeem and purchase fund shares with intrinsic value (T) at the end-of-day NAV (N)
- A non-zero value differential, the difference between a fund's NAV and its intrinsic value, implies fund NAV staleness/latency
- Example
 - A: $N = 100, T = 90$
Dilution $90 - 100 = -10$ paid by remaining shareholders to redeeming shareholders per share
 - B: $N = 100, T = 110$
Subsidy $110 - 100 = +10$ paid by redeeming shareholders to remaining shareholders per share
- Reverse results when new shareholders purchase fund shares
- No asset sales and liquidity cost required
- Value differential and Dilution
 - Value differential can lead to dilution *if* investors redeem or purchase fund shares in the *direction* of the sign of the value differential

Investor Protection, Systemic Risk, and Regulatory Response

- What are the concerns with fund dilution?
- Investor protection concern
 - Redeeming investors can gain from value differentials and dilute value of fund shares
 - Dilution can negatively impact remaining (or current) shareholders
- Systemic risk concern
 - Strategic selling by some investors can incentivize others to also sell because of dilution concerns
 - Value differential can lead to a first-mover advantage and amplified outflows
 - Amplified outflows can lead to asset sales and a potential market impact can transmit to other asset holders

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- Domestic and International Regulatory Response
 - Mandate swing pricing to align NAV with intrinsic value

What do we know about Fund Dilution?

- Little is known about dilution in US funds
- Zitzewitz (2003), Choi, Kronlund, and Oh (2022), Investment Company Institute (2023)
 - Dilution in US bond and fixed-income mutual funds is small
 - Estimated to be less than 10 bps and small relative to investment risk
 - Fees in US fixed-income funds are $\approx 40(80)$ bps

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 - Estimated to be less than 10 bps and small relative to investment risk
 - Fees in US fixed-income funds are $\approx 40(80)$ bps
- Even less is known about dilution in European UCITS fixed-income funds despite being a significant portion of the global fund industry
 - Assets under management are more about 2/3 of the corresponding US fixed-income funds
 - Fees in UCITS fixed-income funds are $\approx 70(90)$ bps

- 1) Methodology: Developing a Robust Foundation to Measure Staleness and Dilution
 - Propose methodology to estimate staleness
 - Formalize mechanism how staleness affects flows
- 2) Empirical Evaluation: Measuring Realized Dilution and Strategic Trading Behavior of Investor in UCITS Funds
 - Investor Protection: How large is realized dilution in UCITS Funds?
 - Systemic Risk: Do value differentials lead to investors trade strategically?
- 3) Regulatory Assessment: Evaluating Swing Pricing as a Tool to Reduce Dilution and Strategic Trading
 - Swing Pricing: Do funds from countries without swing pricing exhibit higher realized dilution and strategic trading?

Measuring Dilution

- Relative loss for a non-redeeming shareholder can be written as

$$\text{Dilution} = f\left(1 - \frac{N}{T}(1 + \lambda)\right) = f(1 - (1 + \kappa)(1 + \lambda))$$

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 - $N^E/T^E = N^E/(P - QB)$
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- Realized Dilution Decomposition and Staleness δ

- Realized Dilution $\delta_{P_t} = f \frac{\delta_{P_t}}{1 + \delta_{P_t}} - f \frac{\lambda}{1 + \delta_{P_t}}$ and Staleness $\delta_{P_t} = \frac{T_t - N_t^E}{N_t^E} = \frac{P_t - Q_t B_t - N_t^E}{N_t^E}$
- Realized Dilution $\delta_{P_{t+1}} = f \frac{\delta_{P_{t+1}}}{1 + \delta_{P_{t+1}}} - f \frac{\lambda}{1 + \delta_{P_t}}$ and Staleness $\delta_{P_{t+1}} = \frac{P_{t+1} - Q_{t+1} B_{t+1} - N_t^E}{N_t^E}$

Validation of the Benchmark-Matching Algorithm

- ETF share-class matching
 - Use mutual funds that offer ETF share classes with identical portfolios to test whether the algorithm consistently selects the fund's own ETF share class as the best benchmark
 - Out of 11,055 daily matches, the algorithm failed only 157 times and matched perfectly on all 1,250 days during the stressed first half of 2020
- Future return-alignment
 - Compare next-day returns of each mutual fund and its assigned benchmark ETF to evaluate whether return differences remain close to zero, as required for a valid benchmark
 - Both equal-weighted and TNA-weighted return differences are statistically never different than zero
- Benchmark-persistence
 - Track whether the ETF chosen as the best benchmark on day t continues to be selected on subsequent days, thereby measuring the stability of benchmark assignments
 - Benchmark assignments are highly persistent and become more stable during the March 2020 stress period, demonstrating robustness under market dislocations

Sample of Fixed-Income Open-ended UCITS Funds

Daily OEF and ETF January 1, 2018 to December 31, 2022 from Morningstar and Refinitiv

	Number of Funds	Daily Observations	TNA December 2022
Domicile			
Ireland	395	261,559	166,813,818,273
Luxemburg	1,433	1,007,962	487,874,463,299
Other EU (17 Countries)	1,010	756,276	153,980,829,561
UK	132	98,608	31,350,827,172
Investment Objective			
Emerging Markets	444	343,537	133,640,921,699
Flexible Allocation	222	92,106	24,257,982,528
Government	252	204,195	87,455,332,484
High Yield Corporate	344	248,703	105,507,952,702
Investment Grade Corporate	748	584,144	254,458,589,917
Investment Grade General	916	618,254	222,420,326,646
Short Term	44	33,466	12,278,832,330
Full Sample	2,970	2,124,405	840,019,938,304

Investor Protection: Annualized and Risk-adjusted Realized Dilution

- Annualized Dilution is the average of the annual continuous compounded realized dilutions
- Risk-adjusted Dilution is the average of ratio of the absolute daily realized dilutions to rolling standard deviations of the fund's daily return

Investment Objective	Annualized Dilution		Risk-adjusted Dilution	
	δ_{P_t}	$\delta_{P_{t+1}}$	δ_{P_t}	$\delta_{P_{t+1}}$
Government	0.03249	0.43678	0.00190	0.00334
Short Term	-0.08033	-0.20755	0.00170	0.00264
Investment Grade General	-0.68334	-0.60433	0.00259	0.00355
Investment Grade Corporate	-2.31628	-2.94494	0.00664	0.00759
Emerging Markets	-3.09833	-4.36002	0.00239	0.00357
High Yield Corporate	-4.71326	-6.96255	0.00353	0.00482
Flexible Allocation	-5.43501	-6.38255	0.00405	0.00523
All	-2.11168	-2.73875	0.00386	0.00495

Annualized Realized Dilution in basis points (bps)

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All	-2.11168	-2.73875	0.00386	0.00495

Annualized Realized Dilution in basis points (bps)

- Average Realized Dilution is small compared to fund fees and investment risk across all investment objectives
- Dilution is also small compared to investment risk during stressed market conditions

Systemic Risk: Formalizing the Impact of Staleness on Flows

- Expand Chen, Goldstein, and Jiang's (2010) two period model
 - In equilibrium, redemptions increase in λ and κ after “bad” returns (Chen, Goldstein, and Jiang 2010)
- In reality κ , and δ , are unknown prior to close of trading, and fund investors need to forecast $\delta_{t+1|t}$ to decide whether or not to redeem at the end of day $t + 1$

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- Primary measure to proxy δ
 - $\delta_{t+1|t}^{(1)}$ computed from one-step ahead prediction of $\Delta\delta_{t+1}$ using fund-level partial adjustment models with rolling windows
- Alternative measures to proxy δ

Systemic Risk: Flow, Performance, Liquidity, and Staleness

- Expand baseline regression models by Goldstein, Jiang, and Ng (2017) and similarly restrict sample to fund-day observations $I_{\{\text{Return}_t < 0\}}$ to avoid multi-term interaction variables
- Subsample regressions for $\delta^L = I_{\{\delta < 0\}}$ and $\delta^H = I_{\{\delta \geq 0\}}$; pooled regressions for $\delta^L - \delta^H$

	Illiquid			Liquid		
	δ^L	δ^H	$\delta^L - \delta^H$	δ^L	δ^H	$\delta^L - \delta^H$
$\text{Return}_t \times I_{\{\text{Return}_t < 0\}}$	0.0790*** (0.0087)	0.1046*** (0.0100)	-0.0256*** (0.0095)	0.0166* (0.0087)	0.0252*** (0.0078)	-0.0086 (0.0094)
flow_t	0.1074*** (0.0105)	0.0977*** (0.0080)	0.0097 (0.0096)	0.1086*** (0.0072)	0.0987*** (0.0073)	0.0099 (0.0073)
$\ln \text{TNA}_t$	-0.0000*** (0.0000)	0.0000 (0.0000)	-0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000 (0.0000)
$\ln \text{Age}_t$	-0.0003*** (0.0000)	-0.0002*** (0.0000)	-0.0000 (0.0000)	-0.0002*** (0.0000)	-0.0002*** (0.0000)	0.0000 (0.0000)
Definition of δ	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$
Objective and Date FE	YES	YES	YES	YES	YES	YES
Fund Cluster	YES	YES	YES	YES	YES	YES
Num. obs.	122,115	151,536	273,651	136,176	136,038	272,214
Adj. R ²	0.0424	0.0269	0.0346	0.0192	0.0178	0.0185

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Systemic Risk: Flow, Performance, Liquidity, and Staleness

- Expand baseline regression models by Goldstein, Jiang, and Ng (2017) and similarly restrict sample to fund-day observations $I_{\{\text{Return}_t < 0\}}$ to avoid multi-term interaction variables
- Subsample regressions for $\delta^L = I_{\{\delta < 0\}}$ and $\delta^H = I_{\{\delta \geq 0\}}$; pooled regressions for $\delta^L - \delta^H$

	Illiquid			Liquid		
	δ^L	δ^H	$\delta^L - \delta^H$	δ^L	δ^H	$\delta^L - \delta^H$
$\text{Return}_t \times I_{\{\text{Return}_t < 0\}}$	0.0790*** (0.0087)	0.1046*** (0.0100)	-0.0256*** (0.0095)	0.0166* (0.0087)	0.0252*** (0.0078)	-0.0086 (0.0094)
flow_t	0.1074*** (0.0105)	0.0977*** (0.0080)	0.0097 (0.0096)	0.1086*** (0.0072)	0.0987*** (0.0073)	0.0099 (0.0073)
$\ln \text{TNA}_t$	-0.0000*** (0.0000)	0.0000 (0.0000)	-0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000*** (0.0000)	0.0000 (0.0000)
$\ln \text{Age}_t$	-0.0003*** (0.0000)	-0.0002*** (0.0000)	-0.0000 (0.0000)	-0.0002*** (0.0000)	-0.0002*** (0.0000)	0.0000 (0.0000)
Definition of δ	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$
Objective and Date FE	YES	YES	YES	YES	YES	YES
Fund Cluster	YES	YES	YES	YES	YES	YES
Num. obs.	122,115	151,536	273,651	136,176	136,038	272,214
Adj. R ²	0.0424	0.0269	0.0346	0.0192	0.0178	0.0185

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

- Results are robust to alternative measures of $\delta_{t+1|t}$ and alternative specifications
- Results hold or are not significant for stressed market conditions when VIX is above its mean or during March 2020

Swing Pricing as a Liquidity Management Tool

- If Swing Pricing is a successful LMT, then for funds in jurisdictions without swing pricing
 - 1) realized dilution must be larger
 - 2) investor flows must react more strongly to fund staleness

Swing Pricing as a Liquidity Management Tool

- If Swing Pricing is a successful LMT, then for funds in jurisdictions without swing pricing
 - 1) realized dilution must be larger
 - 2) investor flows must react more strongly to fund staleness

	Swing Pricing	Number of Funds	Daily Observations	TNA December 2022
Domicile				
Other EU (8 Countries)	Yes	634	465,388	102,010,404,597
Luxemburg	Yes	1,433	1,007,962	487,874,463,299
UK	Yes	132	98,608	31,350,827,172
Ireland	Yes	395	261,559	166,813,818,273
Other EU (9 Countries)	No	376	290,888	51,970,424,963
Final Sample		2,970	2,124,405	840,019,938,304
Investment Objective				
Short Term	Yes	37	28,483	10,700,177,935
Short Term	No	7	4,983	1,578,654,395
Government	Yes	210	167,796	83,748,580,182
Government	No	42	36,399	3,706,752,301
Investment Grade Corporate	Yes	669	521,356	244,035,354,955
Investment Grade Corporate	No	79	62,788	10,423,234,962
Investment Grade General	Yes	771	516,865	202,628,499,851
Investment Grade General	No	145	101,389	19,791,826,794
Flexible Allocation	Yes	205	84,540	22,316,548,123
Flexible Allocation	No	17	7,566	1,941,434,405
High Yield Corporate	Yes	318	227,624	101,548,884,823
High Yield Corporate	No	26	21,079	3,959,067,879
Emerging Markets	Yes	384	286,853	123,071,467,471
Emerging Markets	No	60	56,684	10,569,454,228
Final Sample		2,970	2,124,405	840,019,938,304

Investor Protection: Swing Pricing and Realized Dilution and Returns

$$\text{Excess Dilution}_{i,t,o,d} = \text{Dilution}_{i,t,o,d} - \text{Dilution}_{i,t}^{BM}$$

$$\text{Excess Return}_{i,t,o,d} = \text{Return}_{i,t,o,d} - \text{Return}_{i,t}^{BM}$$

	Full Sample		High VIX		March 2020	
	Excess Dilution _δ	Excess Return _τ	Excess Dilution _δ	Excess Return _τ	Excess Dilution _δ	Excess Return _τ
Emerging Markets	0.0006	−0.0491	0.0012	−0.0487	0.0102	−0.3803
Flexible Allocation	0.0001	−0.0160	0.0004	−0.0077	0.0196	0.0636
Government	−0.0002	0.0145	0.0004	0.0254	0.0013	0.1133
High Yield Corporate	0.0004	−0.0325	0.0006	−0.0043	0.0148	−0.2651
Investment Grade Corporate	−0.0010*	−0.0177	−0.0007	0.0031	−0.0038	0.0105
Investment Grade General	−0.0003	−0.0661	−0.0003	−0.0672	0.0053	0.3369
Short Term	0.0002	0.0350	0.0001	0.0377	0.0006	−0.6674

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Investor Protection: Swing Pricing and Realized Dilution and Returns

$$\text{Excess Dilution}_{i,t,o,d} = \text{Dilution}_{i,t,o,d} - \text{Dilution}_{i,t}^{BM}$$

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Short Term	0.0002	0.0350	0.0001	0.0377	0.0006	-0.6674

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

- Realized excess dilutions are not statistically different from zero, except marginally for Investment Grade Corporate funds, and excess returns are not statistically different from zero
- Realized excess dilutions and excess returns are not statistically different from zero for neither the high VIX sample nor for March 2020

Systemic Risk: Swing Pricing and Flow Sensitivity and Staleness

- “No Swing” sample of illiquid funds for which swing price was not available, and “Swing” sample of illiquid funds for which swing price was available, and “Swing – No Swing” contains the differences of the coefficients “Swing” and “No Swing”

	δ^L			δ^H		
	No Swing	Swing	Swing – No Swing	No Swing	Swing	Swing – No Swing
$\text{Return}_t \times I_{\{\text{Return}_t < 0\}}$	0.0333 (0.0231)	0.0862*** (0.0094)	0.0530** (0.0243)	0.0745*** (0.0224)	0.1118*** (0.0110)	0.0373 (0.0245)
flow_t	0.0081 (0.0291)	0.1187*** (0.0111)	0.1106*** (0.0303)	-0.0054 (0.0253)	0.1106*** (0.0080)	0.1160*** (0.0260)
$\ln \text{TNA}_t$	0.0000 (0.0000)	-0.0000*** (0.0000)	-0.0001 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	-0.0000 (0.0000)
$\ln \text{Age}_t$	-0.0003*** (0.0001)	-0.0003*** (0.0000)	0.0000 (0.0001)	-0.0002*** (0.0001)	-0.0003*** (0.0000)	-0.0000 (0.0001)
Definition of δ	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$
Objective and Date FE	YES	YES	YES	YES	YES	YES
Fund Cluster	YES	YES	YES	YES	YES	YES
Num. obs.	14,438	107,677	122,115	20,368	131,168	151,536
Adj. R ²	0.0430	0.0446	0.0436	0.0263	0.0317	0.0305

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

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$\ln \text{TNA}_t$	0.0000 (0.0000)	-0.0000*** (0.0000)	-0.0001 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	-0.0000 (0.0000)
$\ln \text{Age}_t$	-0.0003*** (0.0001)	-0.0003*** (0.0000)	0.0000 (0.0001)	-0.0002*** (0.0001)	-0.0003*** (0.0000)	-0.0000 (0.0001)
Definition of δ	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$	$\delta_{t+1 t}^{(1)}$
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*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

- Results hold or are not significant for stressed market conditions when VIX is above its mean or during March 2020

- Realized dilution in UCITS fixed-income funds too small to raise investor protection concerns
 - Annualized realized dilution across all UCITS fixed-income funds is -2.1 basis points and -4.7 basis points among High Yield Corporate bond UCITS, a small fraction of fund fees
 - Dilution is small in comparison to the investment risk even during stressed markets
- No evidence of strategic trading that would suggest systemic risk concerns
 - Investors do not trade strategically when the incentive to trade seems large
 - NAV staleness does not amplify the flow-performance relationship also for stressed markets
- The absence of swing pricing does not result in higher dilution and strategic trading
 - Funds without swing pricing do not exhibit worse realized dilution or returns than their peers in jurisdictions where swing price is available
 - Flows sensitives to past performance conditional on large expected value differentials of funds without swing pricing are not more pronounced than for those with swing pricing

Thank you!



Implications of AI Usage for Financial Stability: Evidence from AI-driven Investment Funds identified by Generative AI

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Research Department, Market Research Division**

Victor Pak-Ho LEUNG, Joe Ho-Yeung WONG, and Siru LU

25th Nov 2025

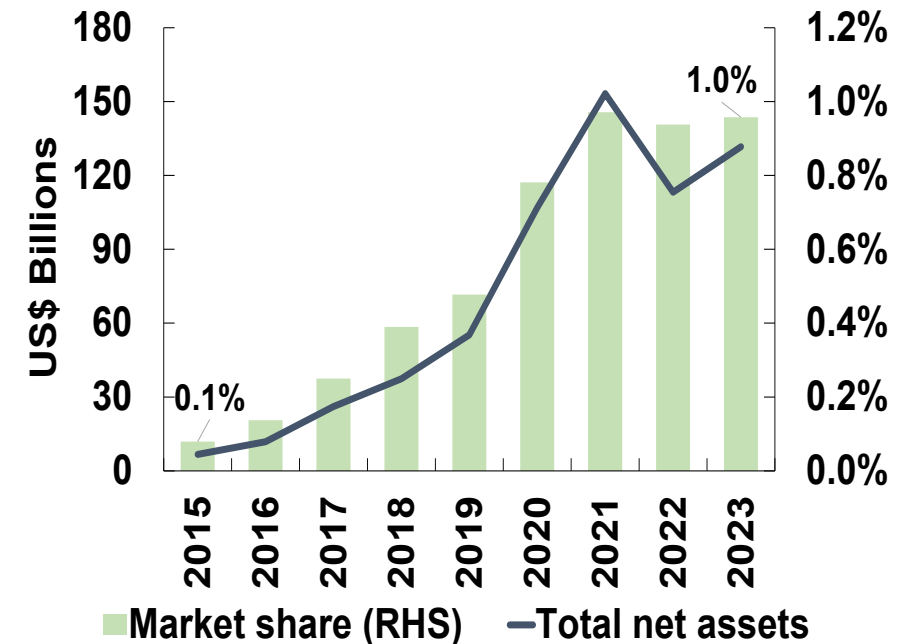
Disclaimer: The authors would like to thank Eric Tak-Chuen Wong for his helpful comments and suggestions. This study represents the views of the authors, which are not necessarily the views of the Hong Kong Monetary Authority, Hong Kong Academy of Finance Limited, or Hong Kong Institute for Monetary and Financial Research. The above-mentioned entities except the authors take no responsibility for any inaccuracies or omissions contained in the study.

Background



- Growing adoptions of artificial intelligence (AI) have been observed in the sector of investment funds, which include major applications in:
 - **investment decision-making (AI-driven)**
 - trade execution
 - monitoring process
 - daily operation
- Investment funds have been using **AI to guide investment decisions** by:
 - Using machine learning (ML) to generate trade signals and financial forecasts
 - Using natural language processing (NLP) to analyse text to track investor sentiment
- **A comparable trend is evident in EU funds**, as more than 58% of the open-ended funds within our sample are EU funds.

Growing trends of AI-driven equity OEFs

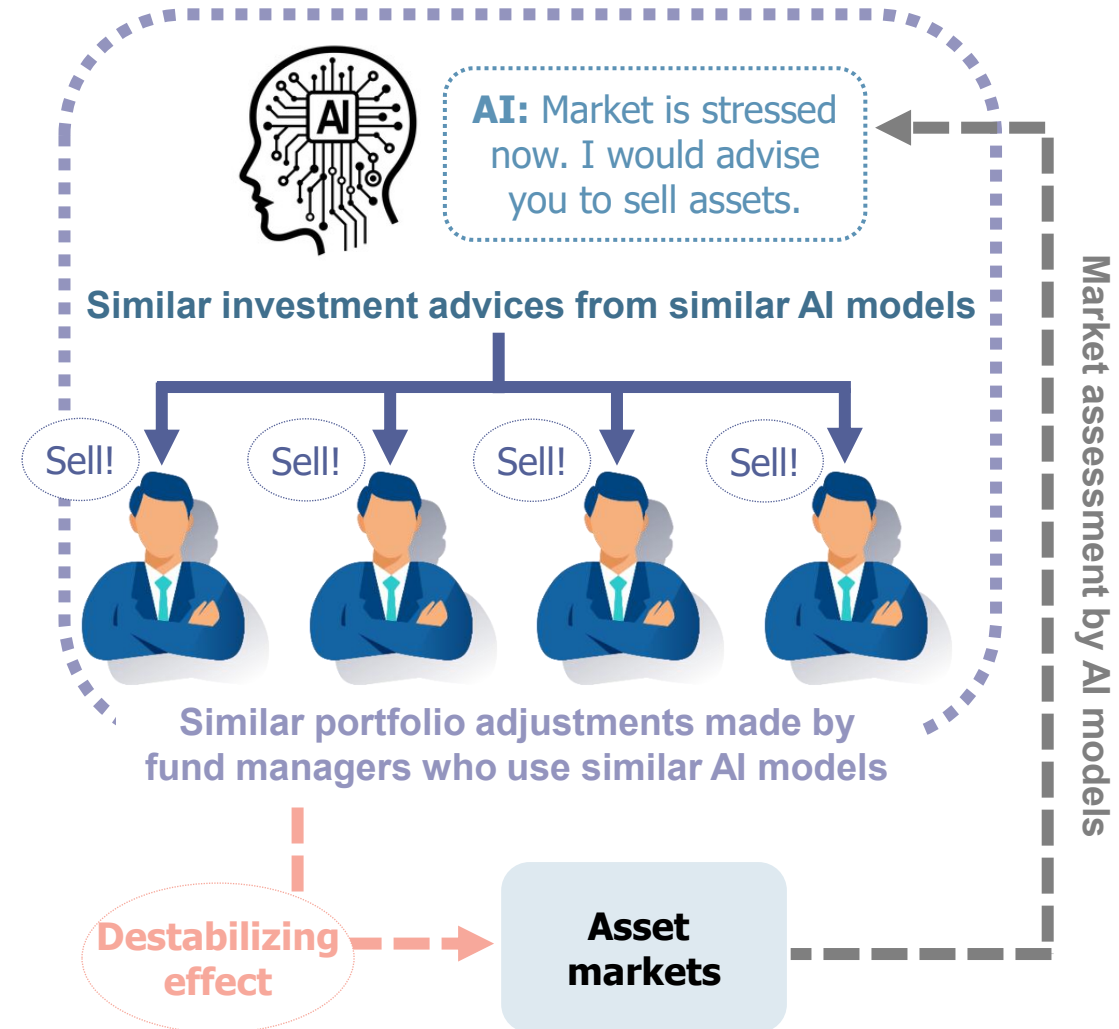


Sources: Morningstar Direct, EPFR and authors' estimation.

Motivation



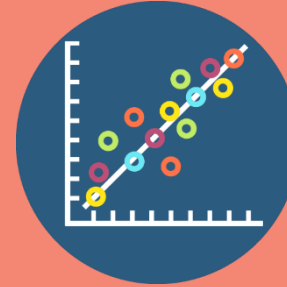
- While the use of AI can improve operational efficiency and data analytics, it also raises **financial stability concerns** – “herding behaviour” ([Financial Stability Board](#), 2024)
- For example, fund managers may get similar investment advices from similar AI models:
 - Possibly lead to **more similar trades** and higher market volatilities
 - In stressed times, AI could advise fund managers to **sell assets simultaneously**, possibly deepening the market downturn



Research Questions



- Against this background, this study aims to answer **three questions with empirical evidence** for the first time
 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 **same use of AI** by investment funds, such as applying AI to same investment strategy?
 3. Does the use of AI by investment funds lead to **collective asset sales** among them in periods of market stress?



Higher trading correlation?



Same AI uses by fund managers?



Collective asset sales under stress?

Data Collection: AI Applications of Funds



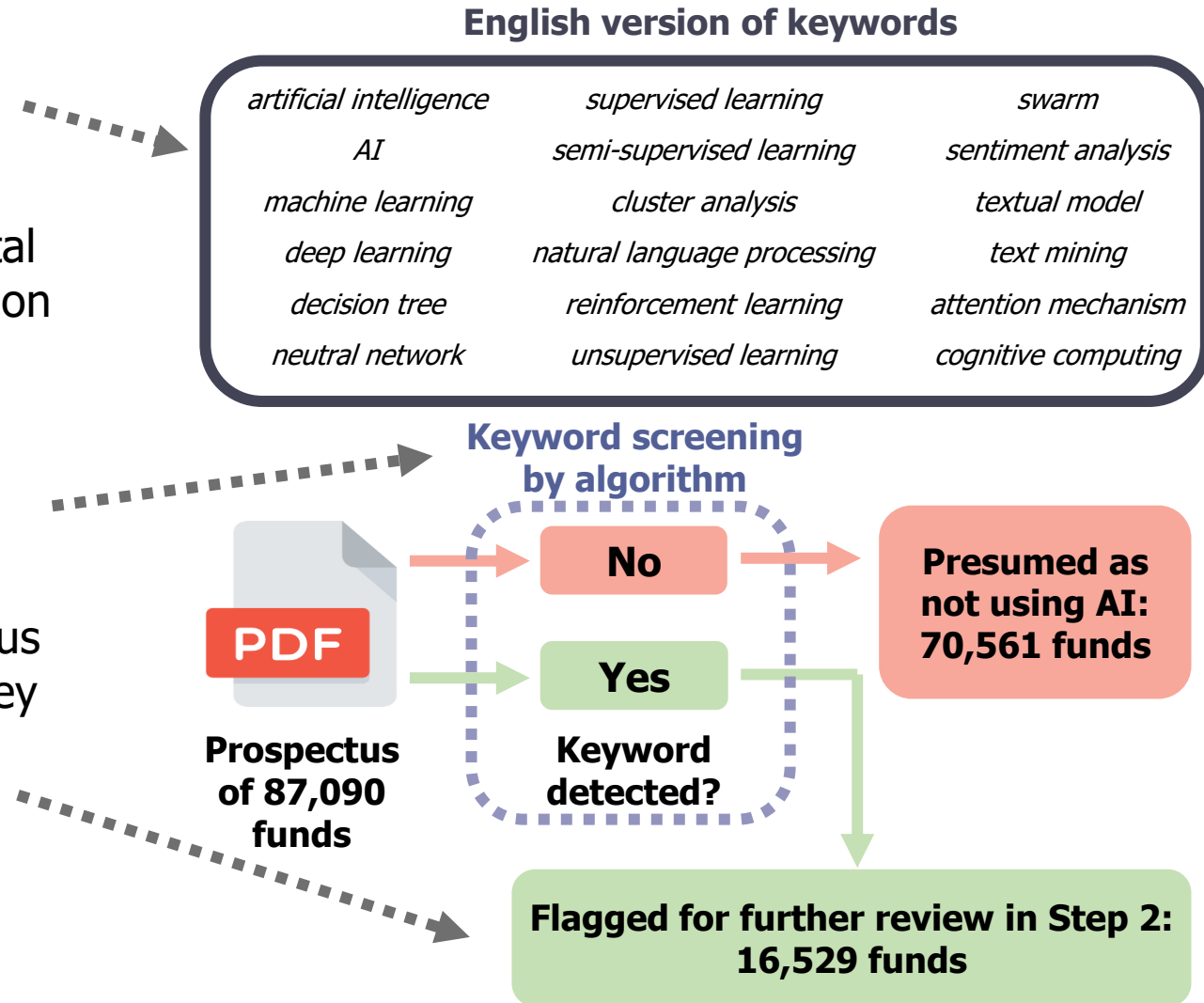
- To answer **these questions**, we first needed to identify which funds are using AI to guide their investment decisions.
 - **Created a sample of all equity open-ended funds** that have prospectus in Morningstar (87,090 funds, representing 70% of total assets of the fund type in 2023)
 - **Downloaded their prospectuses** from the Morningstar Document Library.
 - **Analyzed these prospectuses** to identify investment funds' use of AI in three steps.



Step 1: Keyword Screening on Fund Prospectuses



- We first established a bank of **keywords** related to AI subfields
 - The prospectuses were written in a total of 28 languages. We used the translation of the keywords for screening
- We then used an algorithm to **scan the prospectus** for the keywords
- We found **16,529 funds** whose prospectus contains at least one of the keywords. They are flagged for further review in **Step 2**.
- Other funds that do not contain such keywords are presumed as not using AI



Step 2: Analysis of Fund Prospectuses

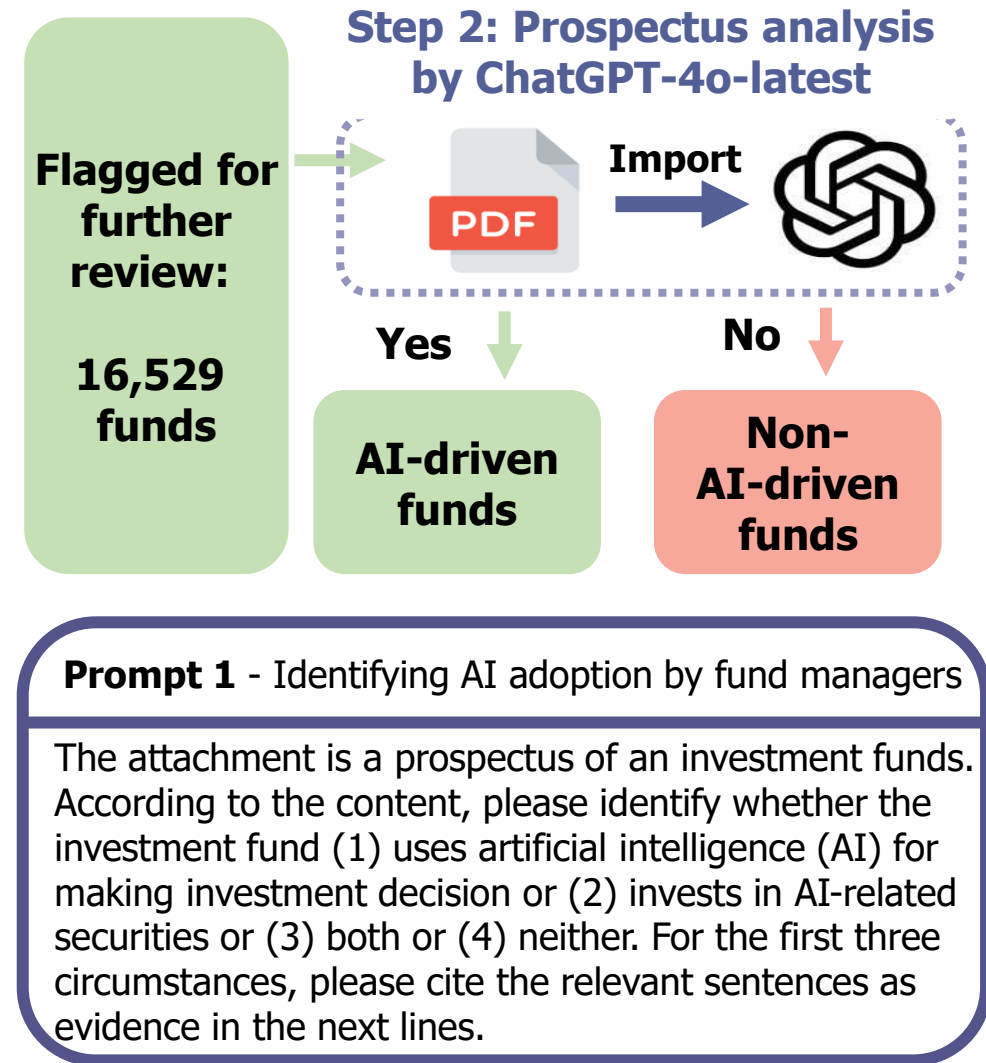


- The reason for further review:
having these keywords ≠ use AI to make investment decisions
- We reviewed a sample of prospectuses and found that some keywords were mentioned only for describing issues **irrelevant to AI applications**, including:
 - Background information, e.g. trends of the growing AI applications
 - Profile of fund managers, e.g. their AI-related experience or education
 - Fund portfolios, e.g. investment in AI companies
- Therefore, we needed to **analyze each prospectus** to ensure more accurate identification of their AI applications

Step 2: Analysis of Fund Prospectuses (cont.)



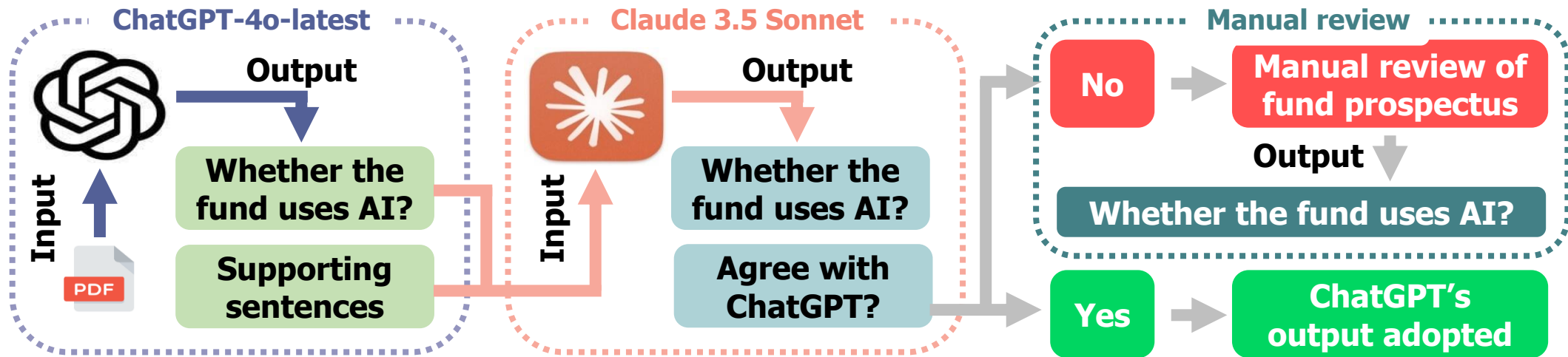
- **Technical challenges:**
 - a) **Large volume:** 16,529 prospectuses containing keywords were pending for review
 - b) **Multiple languages:** Many different languages were used across prospectuses
- To address these issues, we used **ChatGPT** to analyse these prospectuses. We prompted it to:
 - a) Determine whether the fund uses AI to make investment decision; and
 - b) Extract sentences from the prospectus to support its identification
- To make sure ChatGPT was not making things up, we conducted validation tests in **Step 3**



Step 3: Validation of ChatGPT's Outputs



- We **double checked** all ChatGPT's output **with another Gen AI model - Claude**:
 - a) If Claude agreed with ChatGPT, we adopted ChatGPT's judgement;
 - b) If not, we manually reviewed the prospectus;
 - c) The validation results revealed that the error rate of ChatGPT was about 1%

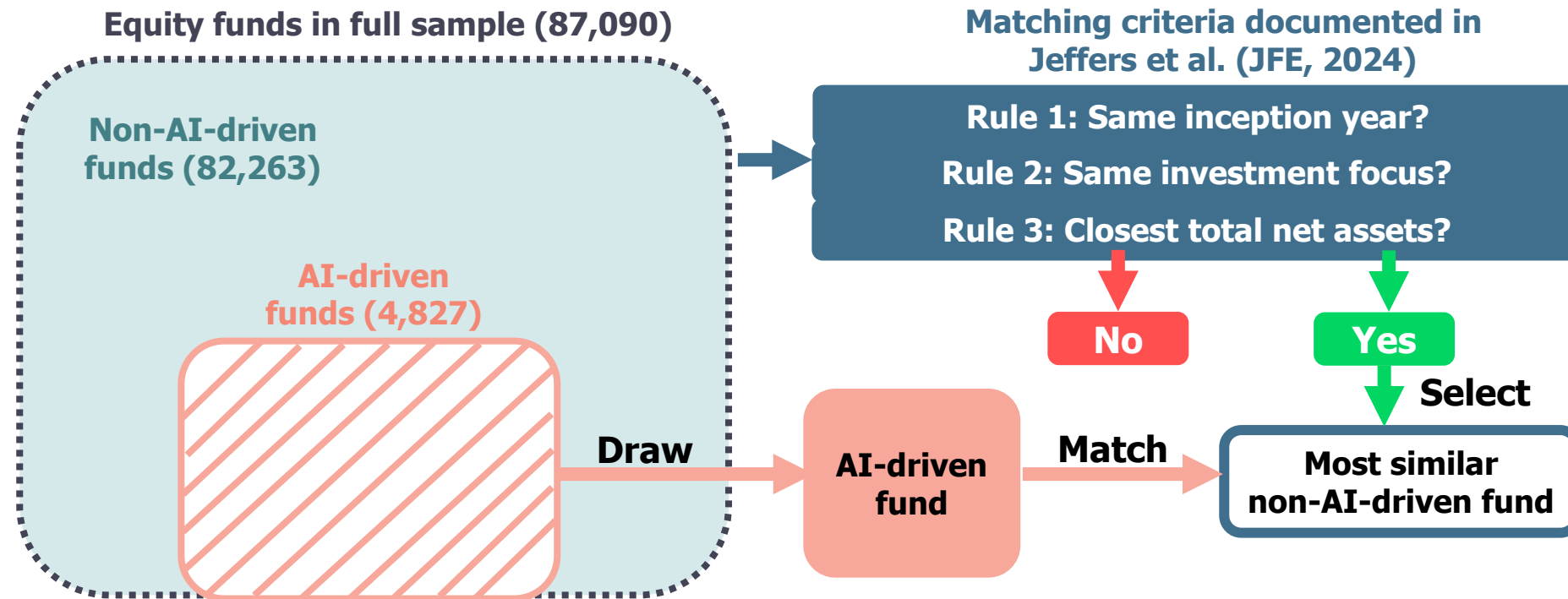


- We also randomly drew **10% of the funds'** prospectuses for **manual checking**.
- For all errors spotted in the above processes, we would **manually re-classify** the funds.
- Finally, **we identified 4,827 AI-driven funds** (about 1% of global AUM)

Construction of the Matched Sample



- Then, we followed the methods in Jeffers et al. (JFE, 2024) to **match** AI-driven funds with non-AI-driven funds with similar characteristics



- We successfully matched 2,698 AI-driven funds with 2,374 non-AI-driven funds with replacement.**

Overview of the Panel Dataset

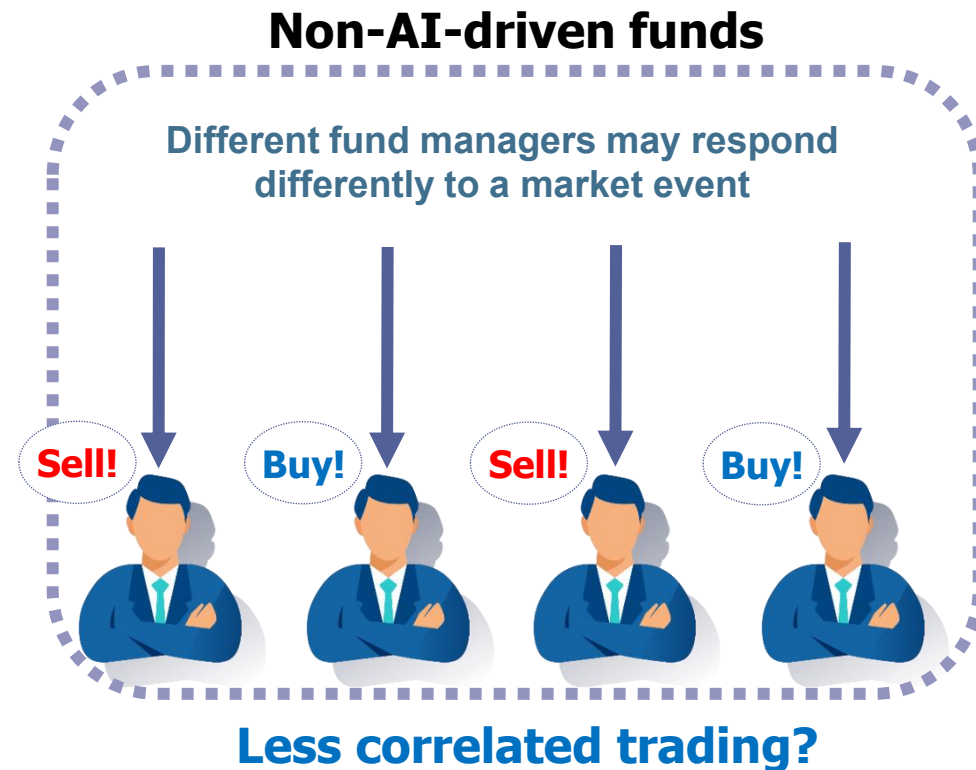
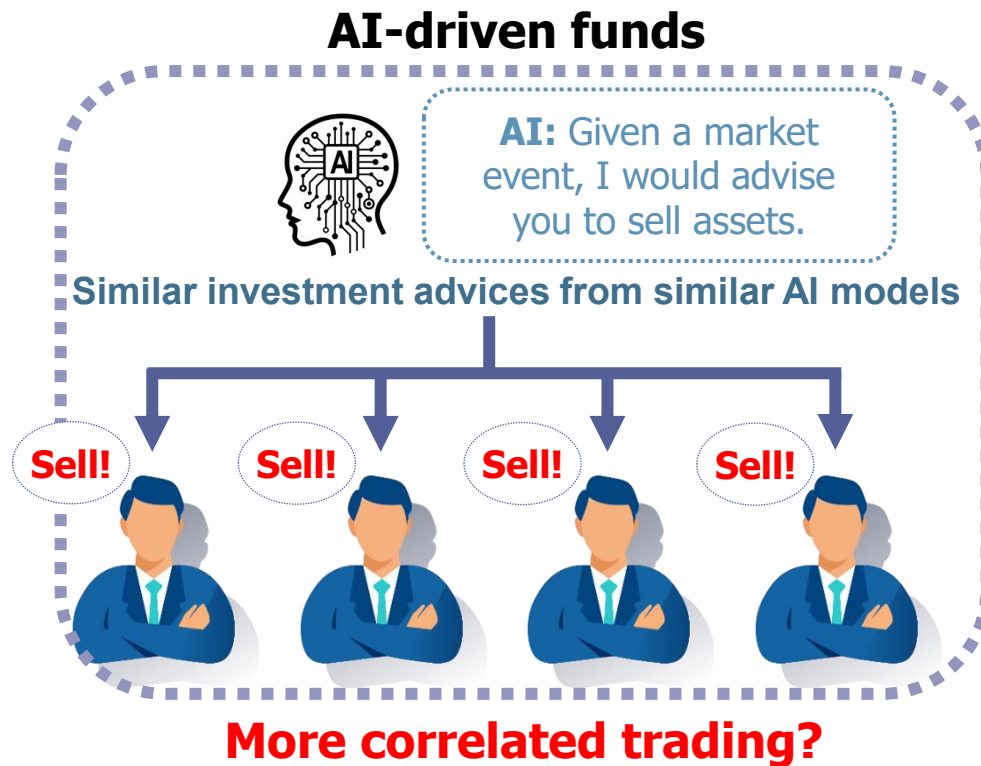


- **Panel Data (Fund-Time-Asset Level):**
 - 1) Source: Morningstar Direct and Morningstar Document Library
 - 2) Fund: 2,698 AI-driven funds and 2,374 non-AI-driven funds
 - 3) Time: Monthly frequency; January 2022 to June 2024
 - 4) Asset: 35,806 assets held by funds (incl. cash-like assets, risky 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: Does the use of AI by investment funds increase the trading correlation among them?



- The first question examines whether the **use of AI will increase the trading correlations** among investment funds
- Our approach is to compare whether AI-driven funds would **adjust their portfolio holdings more similarly among themselves**, as compared to non-AI-driven funds



Question 1: Estimation 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 $AI_i = AI_j$

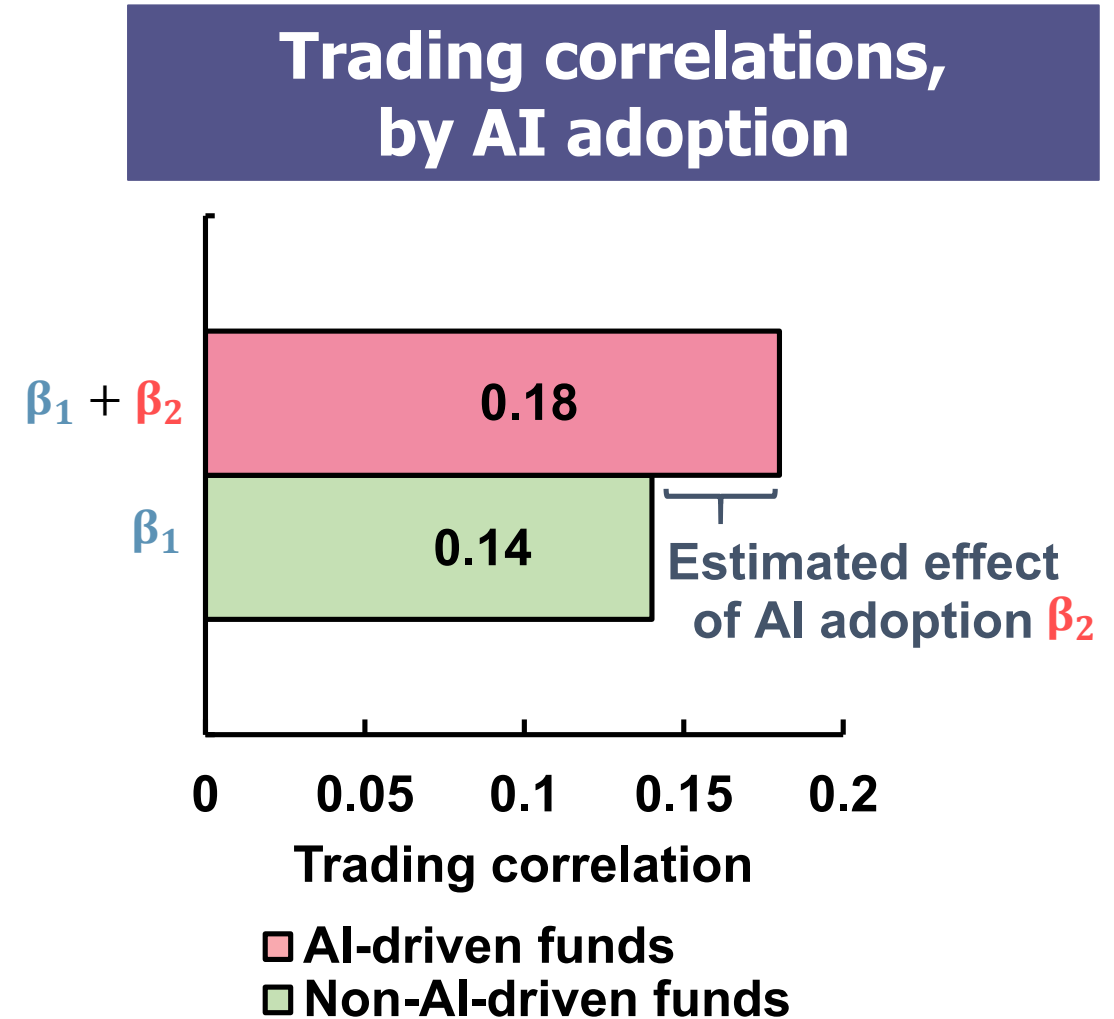
= 1 if fund i is AI-driven; or 0 otherwise

- β_1 indicates the trading correlation within **non-AI-driven funds**
- $\beta_1 + \beta_2$ indicates the trading correlation within **AI-driven funds**
- Hypothesis:** $\beta_1 + \beta_2 > \beta_1$ if the use of AI can increase their trading correlation

Result 1: More positive trading correlation among AI-driven funds



- Our results support the hypothesis:
 - **Trading correlation among AI-driven funds ($\beta_1 + \beta_2$) is 0.18, almost one-third higher than non-AI-driven funds (β_1)**
 - The difference is also statistically significant
 - This indicates that AI adoption generally contributes to more similar investment decisions



Note: Each unit of trading correlation is equal to a 1 percentage change in a fund's asset holdings in response to a 1 percentage change in the holdings of the same asset by other funds in the respective group.

Question 2: Does the increased trading correlation result from the same use of AI by investment funds



- The second question examines whether the **increased trading correlation come from the same use of AI**
- We prompted ChatGPT to analyze fund prospectuses to identify their AI uses:
 - a) Asset value prediction (*AVP*)
 - b) Market sentiment analysis (*MSA*)
 - c) Thematic screening (*TS*)
 - d) ESG risk analysis (*ERA*)

Prompt 2 - Identifying different AI uses by fund managers

The attachment is a prospectus of an investment funds. According to the content, please identify the use case(s) of AI by this fund. The use case(s) can be (1) using AI techniques to predict asset values to inform investment decisions; (2) using AI techniques to measure market sentiment to inform investment decisions; (3) using AI techniques to identify assets aligning with specific investment themes; (4) using AI techniques to measure ESG risks of assets.

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

Note: The sum of these percentages is larger than 100%, as some funds implemented multiple “AI-driven investment strategies”.

Question 2: Estimation Methodology



- Our approach is to compare **whether AI-driven funds adjust their portfolio holdings more similarly with funds that have the same AI use**
- We considered **Equation (2)** to estimate the trading correlations for different **groups of AI-driven funds**

Expected: $\pi_1 > \pi_2$; $\pi_3 > \pi_4$; and $\pi_5 > \pi_6$

- 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_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 (thematic screening and ESG risk analysis)**

Result 2: Higher trading correlation only among some funds with the same AI use



- **Trading correlations for funds using AI for AVP and MSA:**
 - **Positive** with funds that have same AI use (*green box and red box*)
 - **Negative** with funds that have different AI uses (*grey boxes*)
- Trading correlations are **insignificant for OTH** (*blue box and grey box at the bottom*)
- In summary,
 - a) Higher trading correlations only occurs to some funds with the same AI use (AVP, MSA)
 - b) Funds with different AI uses may trade differently.

Trading correlations, by different AI strategies

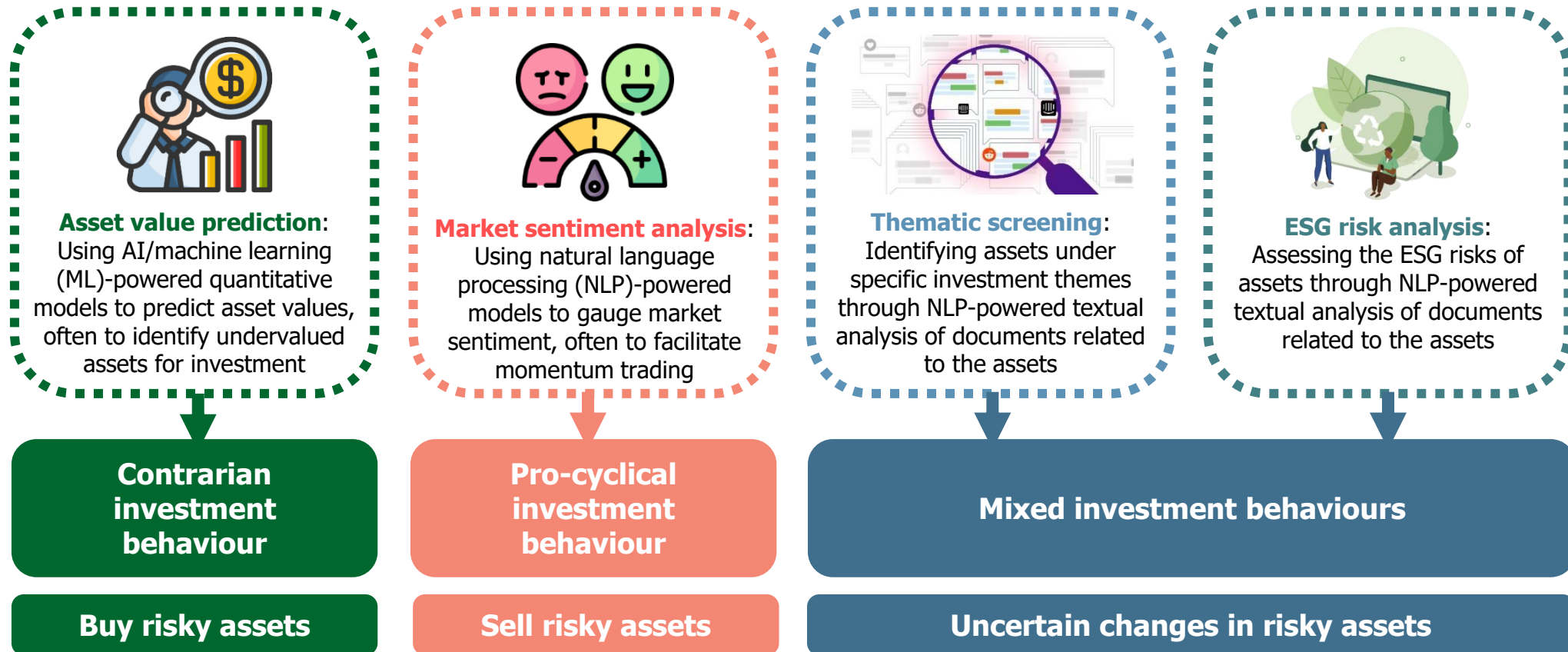
	Same use	Different use
Asset value prediction (AVP)	0.20 (π_1)	-0.03 (π_2)
Market sentiment analysis (MSA)	0.13 (π_3)	-0.11 (π_4)
Other strategies (OTH)	Not significant (π_5)	Not significant (π_6)

Note: Each unit of trading correlation is equal to a 1 percentage change in a fund's asset holdings in response to a 1 percentage change in the holdings of the same asset by other funds in the respective group.

Question 3: Does the use of AI by funds lead to collective asset sales in periods of market stress?



- The third question examines how **AI-driven funds respond to market stress**. We hypothesize that their responses may vary with **investment strategies**



Question 3: Estimation Methodology



- We considered **Equation (3)** to estimate the portfolio adjustments of funds in response to market stress, by different AI use
- For asset k held by fund i in month t :

$$\begin{aligned}\Delta \log(1 + \text{Share}_{i,k,t}) = & \beta_1 \times \text{Stress}_t \times (1 - \text{AI}_i) \times \text{Cash}_k + \beta_2 \times \text{Stress}_t \times (1 - \text{AI}_i) \times \text{Risky}_k + \\ & \pi_1 \times \text{Stress}_t \times \text{AVP}_i \times \text{Cash}_k + \pi_2 \times \text{Stress}_t \times \text{AVP}_i \times \text{Risky}_k + \\ & \pi_3 \times \text{Stress}_t \times \text{MSA}_i \times \text{Cash}_k + \pi_4 \times \text{Stress}_t \times \text{MSA}_i \times \text{Risky}_k + \\ & \pi_5 \times \text{Stress}_t \times \text{OTH}_i \times \text{Cash}_k + \pi_6 \times \text{Stress}_t \times \text{OTH}_i \times \text{Risky}_k + \\ & \text{Size}_{i,t-1} + \text{Age}_{i,t-1} + \text{Return}_{i,t-1} + \theta_i + \theta_k + \varepsilon_{i,k,t}\end{aligned}\tag{3}$$

- β_1 and β_2 indicate the % change in the number of shares 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 π_6 indicate the same changes for funds that use AI for **asset value prediction**, **market sentiment analysis**, and **other strategies**

Question 3: Estimation Methodology (cont.)



- We considered Equation (3) to estimate the **portfolio adjustments of funds in response to market stress, by different AI use**

- 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)

Expected:

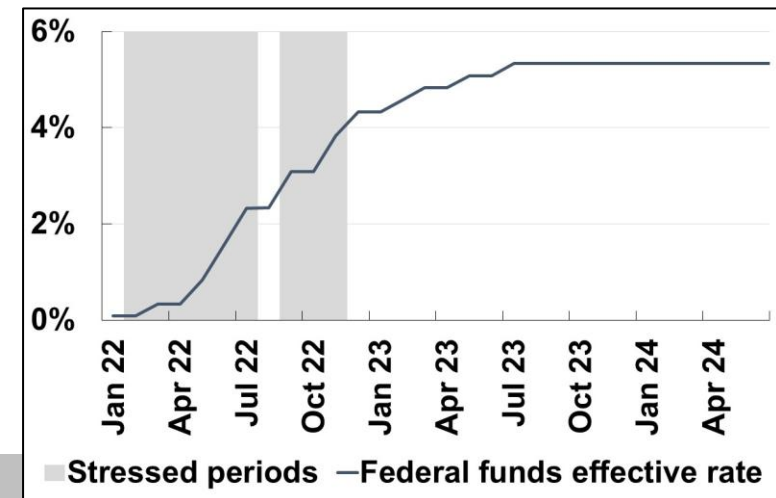
$\pi_1 < 0, \pi_2 > 0$ (counter-cyclical);

$\pi_3 > 0, \pi_4 < 0$ (pro-cyclical);

$\pi_5 = 0, \pi_6 = 0$ (mixed)

=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.

- 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.



Result 3: The responses of AI-driven funds to market stress vary, depending on their AI use



- **Our estimation results showed that:**

- **Funds that use AI for AVP:**

- ❑ sell 3% cash-like assets
- ❑ buy 2% risky assets

- **Funds that use AI for MSA:**

- ❑ buy 4% cash-like assets
- ❑ sell 11% risky assets; the sale is 5 times greater than non-AI-driven funds

- **Funds that use AI for OTH:**

- ❑ No statistically significant changes

- These imply **AI adoption does not necessarily lead to collective asset sales**

Percent change in holdings by funds in market stress

	Cash-like assets	Risky assets
Asset value prediction (AVP)	-3% ($\pi_1 < 0$)	2% ($\pi_2 > 0$)
Market sentiment analysis (MSA)	4% ($\pi_3 > 0$)	-11% ($\pi_4 < 0$)
Other strategies (OTH)	Not significant	Not significant

Conclusion and policy implications



- **This study empirically shows that:**
 - Funds using AI for investment decision making may increase trading correlation among them, but only when they are applied in the same way
 - Also, the use of AI does not necessarily lead to collective asset sales during market stress
 - Some AI applications could act as market stabilizers, while some of others may act as market destabilizers
- **These findings carry two policy implications for financial stability:**
 - Policymakers should consider a more nuanced approach when assessing risks associated with AI adoption. Instead of treating all AI uses as the same, they should recognise the diversity of AI applications and their different impacts
 - They should closely monitor the AI applications that could potentially destabilise the market, including those identified in this study



- **Our results should be interpreted with caution for reasons below:**
 - a) **We only focus on equity open-ended funds**, which are relatively transparent and subject to more regulatory oversight. However, the use of AI could be more prevalent in other opaque financial segments (e.g. hedge funds), with possibly different financial stability implications
 - b) **The identification of AI adoption for each fund was solely based on its prospectus**, with no guarantee that the disclosure was accurate and complete
 - c) **Funds' investment processes might still involve a certain degree of human judgement**. Our estimations only reflect the "partial" AI adoption by fund managers, rather than the "full" adoption



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
$\Delta \log\left(1 + \sum_{j \neq i, AI_j = AI_i} \text{Share}_{j,k,t}\right)$	-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
$\Delta \log\left(1 + \sum_{j \neq i, AVP_j = 1} \text{Share}_{j,k,t}\right)$	-0.09	3.36	-0.53	0.00	0.37	21,819,354
$\Delta \log\left(1 + \sum_{j \neq i, AVP_j = 0} \text{Share}_{j,k,t}\right)$	-0.04	4.06	-0.19	0.00	0.20	21,819,354
$\Delta \log\left(1 + \sum_{j \neq i, MSA_j = 1} \text{Share}_{j,k,t}\right)$	-0.06	3.45	-0.38	0.00	0.30	21,819,354
$\Delta \log\left(1 + \sum_{j \neq i, MSA_j = 0} \text{Share}_{j,k,t}\right)$	-0.06	3.27	-0.50	0.00	0.38	21,819,354
$\Delta \log\left(1 + \sum_{j \neq i, OTH_j = 1} \text{Share}_{j,k,t}\right)$	-0.04	3.67	-0.37	0.00	0.31	21,819,354
$\Delta \log\left(1 + \sum_{j \neq i, OTH_j = 0} \text{Share}_{j,k,t}\right)$	-0.12	3.48	-0.56	0.00	0.37	21,819,354
Stress_t	0.25	0.43	0.00	0.00	1.00	29,829,902
Cash_k	0.28	0.45	0.00	0.00	1.00	29,829,902
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)	(2)	(3)	(4)
	Full matched sample	Of which: Cash-like assets	Of which: Risky assets	Of which: Derivatives
$\Delta \log(1 + \sum_{j \neq i, AI_j = AI_i} \text{Share}_{j,k,t})$	0.14***	0.09***	0.23***	0.12***
$\Delta \log(1 + \sum_{j \neq i, AI_j = AI_i} \text{Share}_{j,k,t}) \times AI_i$	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

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 classes**, including:

Cash-like assets: Currencies, MMFs, US Treasuries

Risky assets: Stocks, corporate bonds, non-MMF mutual funds,

Derivatives: Forwards, futures, swaps, warrants

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
$\Delta \log(1 + \sum_{j \neq i, AVP_j=1} \text{Share}_{j,k,t}) \times AVP_i$	0.20***	0.08***	0.19***	0.25***
$\Delta \log(1 + \sum_{j \neq i, AVP_j=0} \text{Share}_{j,k,t}) \times AVP_i$	-0.03***	-0.02***	0.01***	-0.04***
$\Delta \log(1 + \sum_{j \neq i, MSA_j=1} \text{Share}_{j,k,t}) \times MSA_i$	0.13***	0.09***	0.18***	0.14***
$\Delta \log(1 + \sum_{j \neq i, MSA_j=0} \text{Share}_{j,k,t}) \times MSA_i$	-0.11***	-0.04***	-0.14***	-0.15***
$\Delta \log(1 + \sum_{j \neq i, OTH_j=1} \text{Share}_{j,k,t}) \times OTH_i$	0.02	0.01	0.03	0.02
$\Delta \log(1 + \sum_{j \neq i, OTH_j=0} \text{Share}_{j,k,t}) \times OTH_i$	-0.01	-0.01	-0.04	-0.01
$\text{Size}_{i,t-1}$	0.00	0.00**	0.00***	-0.01***
$\text{Age}_{i,t-1}$	-0.07***	-0.05***	0.01*	-0.26***
$\text{Return}_{i,t-1}$	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

Trading correlations among funds that use AI for the same strategies are largely positive: Asset value prediction ($\pi_1 > 0$) Market sentiment analysis ($\pi_3 > 0$)

However, trading correlations among funds that use AI for other strategies are insignificant ($\pi_5 = 0$)

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 _t defined by	VIX	SLFFSI	OFRFSI
Stress _t × Cash _k × (1 − AI _i)	-0.06***	0.04***	-0.07***
Stress _t × Risky _k × (1 − AI _i)	-0.02***	0.08***	0.01***
Stress _t × Cash _k × AVP _i	-0.03***	-0.02***	-0.09***
Stress _t × Risky _k × AVP _i	0.02***	0.09***	0.06***
Stress _t × Cash _k × MSA _i	0.04***	0.00	0.00
Stress _t × Risky _k × MSA _i	-0.11***	-0.11***	-0.11***
Stress _t × Cash _k × OTH _i	-0.01	0.01	-0.01
Stress _t × Risky _k × OTH _i	-0.01	-0.01	-0.01
Size _{i,t-1}	0.00***	0.00***	0.00***
Age _{i,t-1}	-0.36***	-0.26***	-0.34***
Return _{i,t-1}	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

Asset value prediction:
Counter-cyclical investment behaviour ($\pi_1 < 0$; $\pi_2 > 0$)

Market sentiment analysis:
Pro-cyclical investment behaviour ($\pi_3 > 0$; $\pi_4 < 0$)

Other strategies:
Mixed investment behaviours ($\pi_5 = 0$; $\pi_6 = 0$)

Market sentiment analysis:
More pro-cyclical than non-AI-driven funds ($\pi_4 - \beta_2 < 0$)

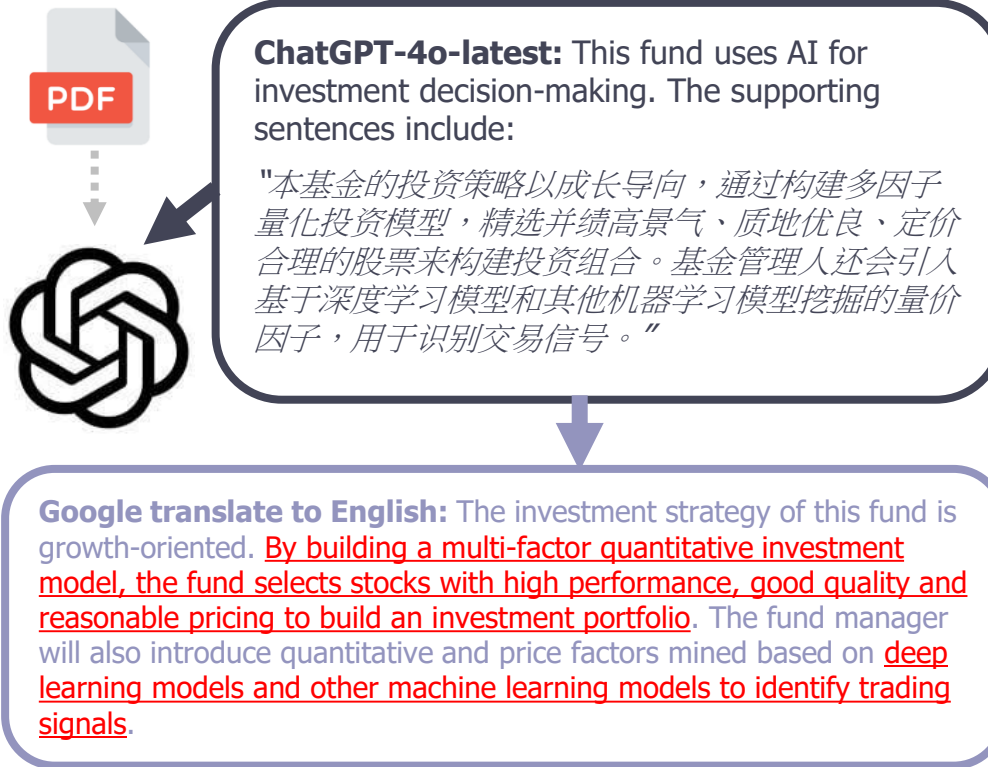
Note: ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively

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

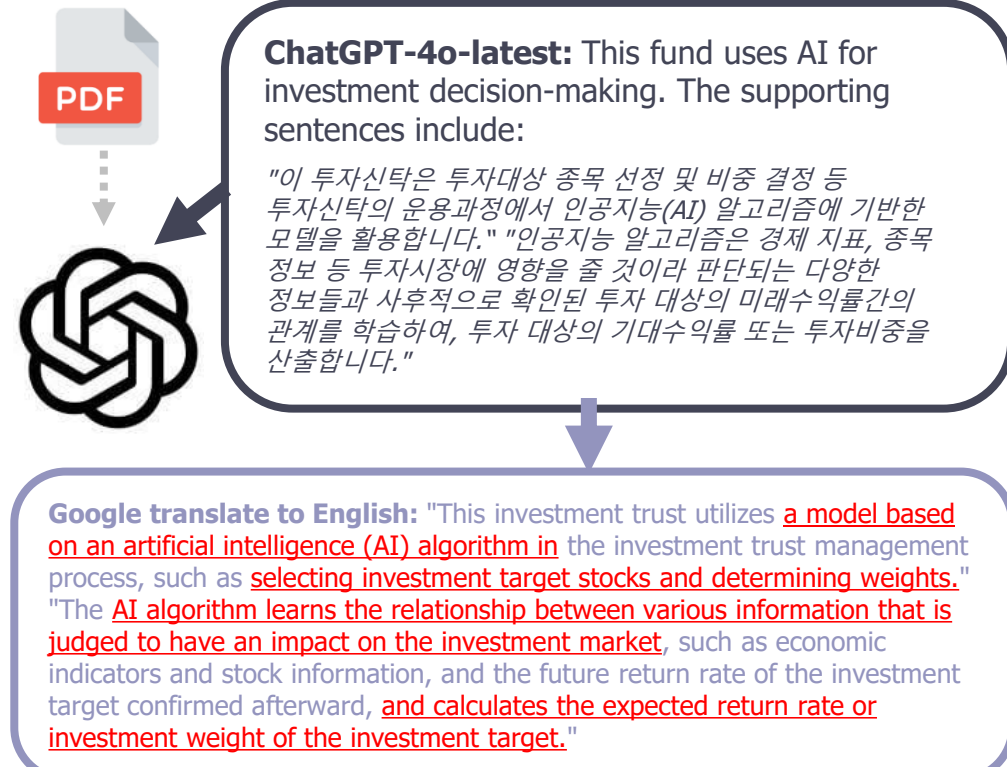


- ChatGPT-4o-latest was excellent in comprehending content in a variety of languages

Example 1: Simplified Chinese prospectus



Example 2: Korean prospectus

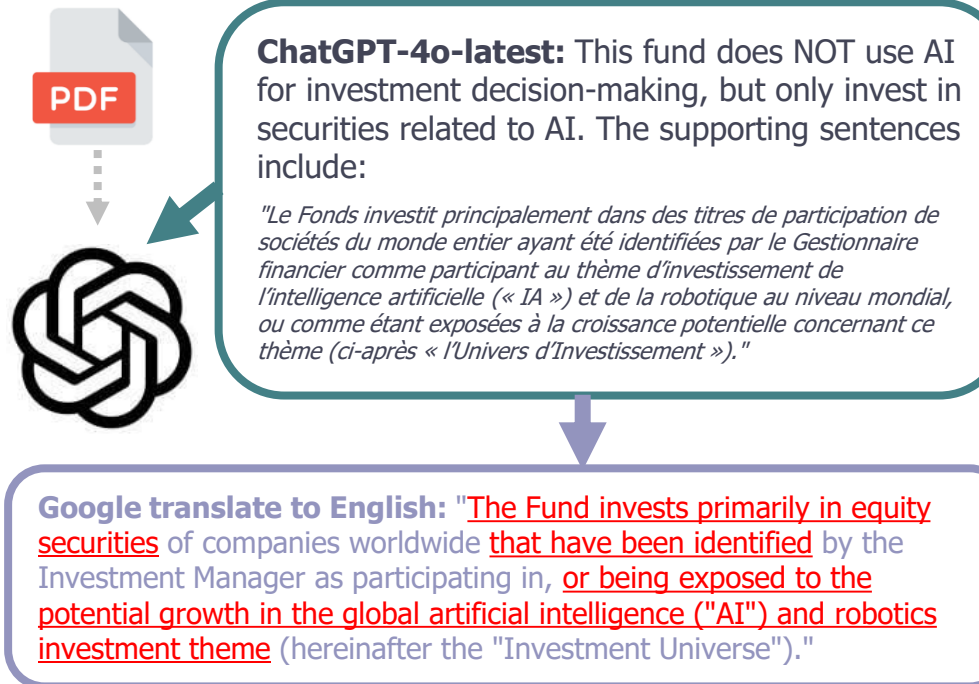


Appendix 6: Examples of ChatGPT's analysis on prospectuses without mentions of funds' AI use

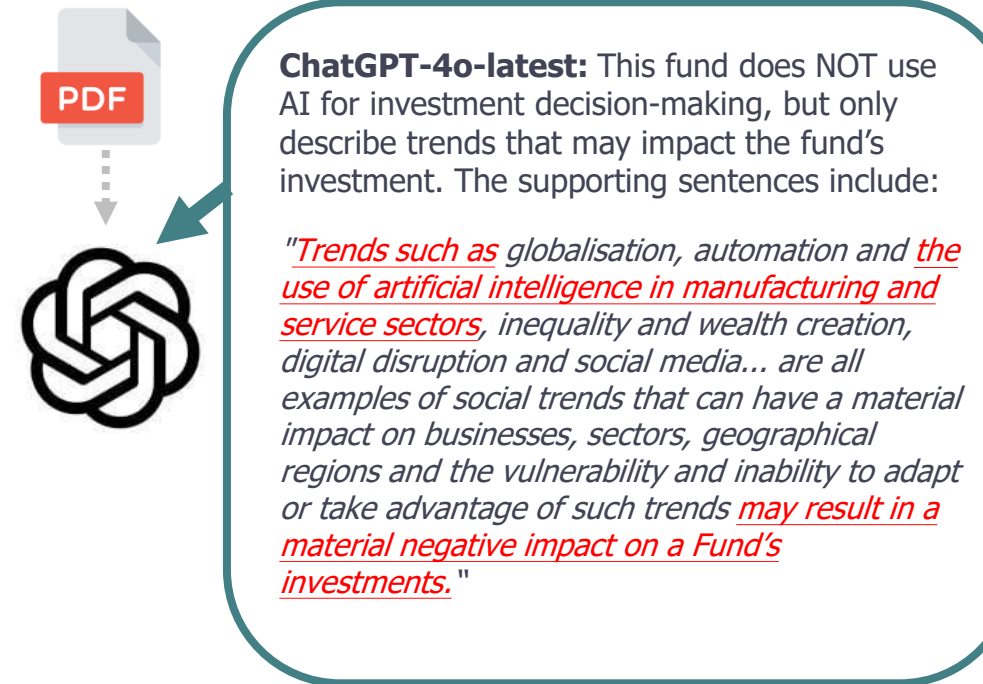


- ChatGPT-4o-latest demonstrates a understanding of prospectus content, capably making well-informed judgement on each fund's application of AI

Example 1: Fund's investment focus



Example 2: AI-related market trends

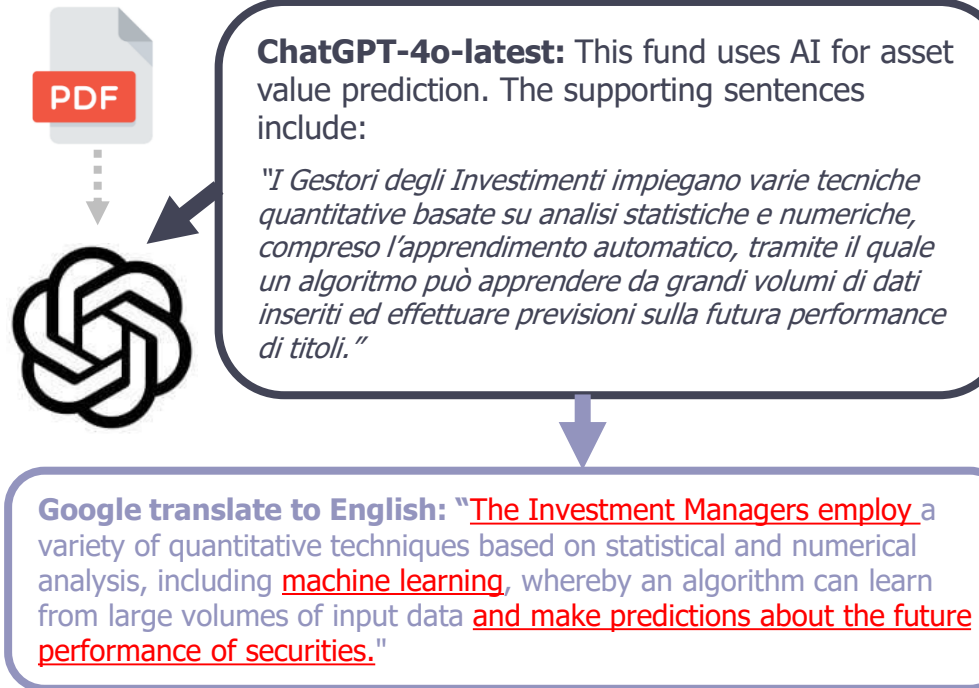


Appendix 7: Examples of ChatGPT identifying funds that use AI for asset value prediction

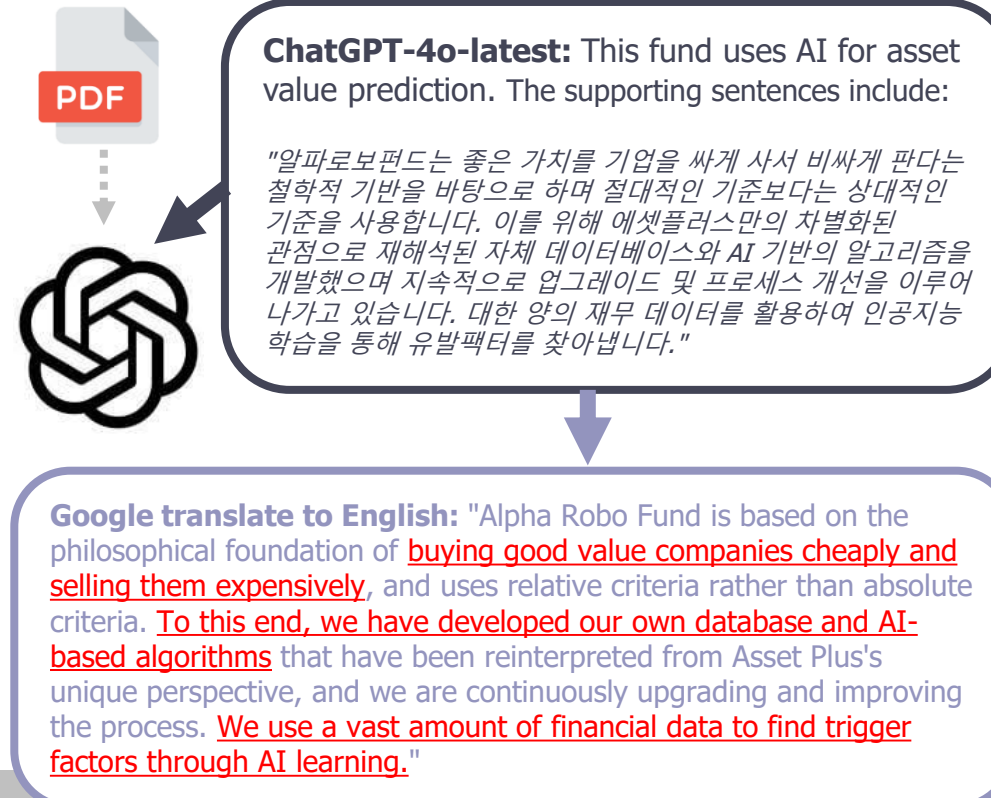


- Some funds apply AI to asset value prediction, often to identify undervalued assets for investment

Example 1:



Example 2:



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:

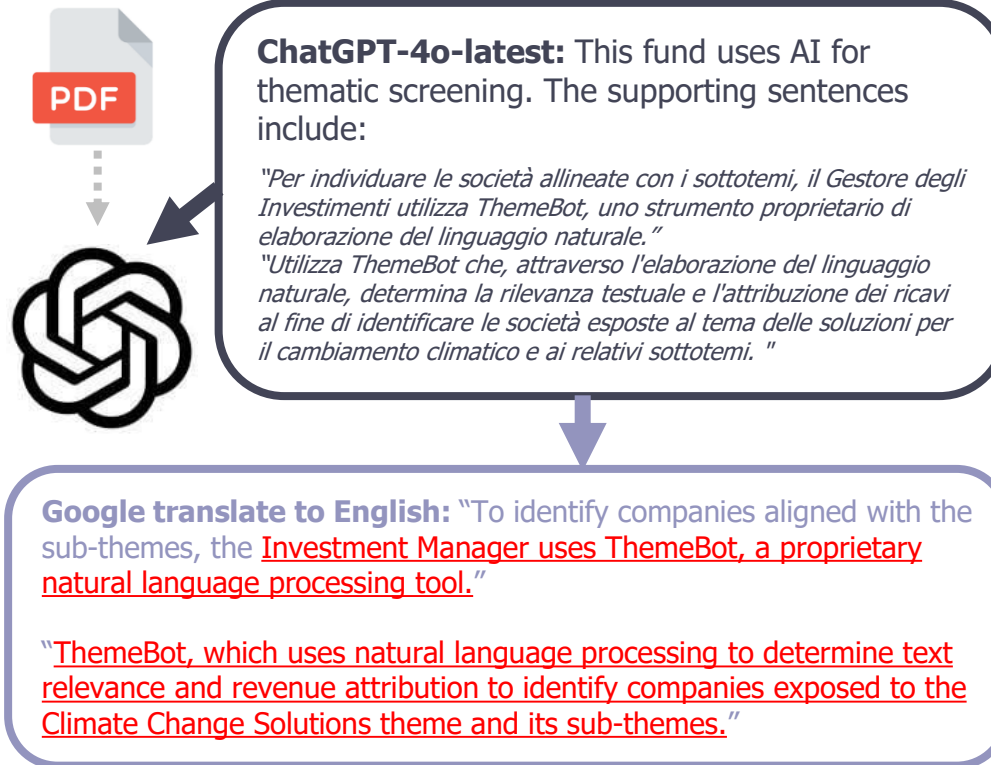
"The Investment Manager utilizes a proprietary quantitative approach driven through artificial intelligence and high-frequency tracking of sustainability-related news as well as the market sentiment by using natural language processing to identify market sentiment towards a specific sustainability theme."

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

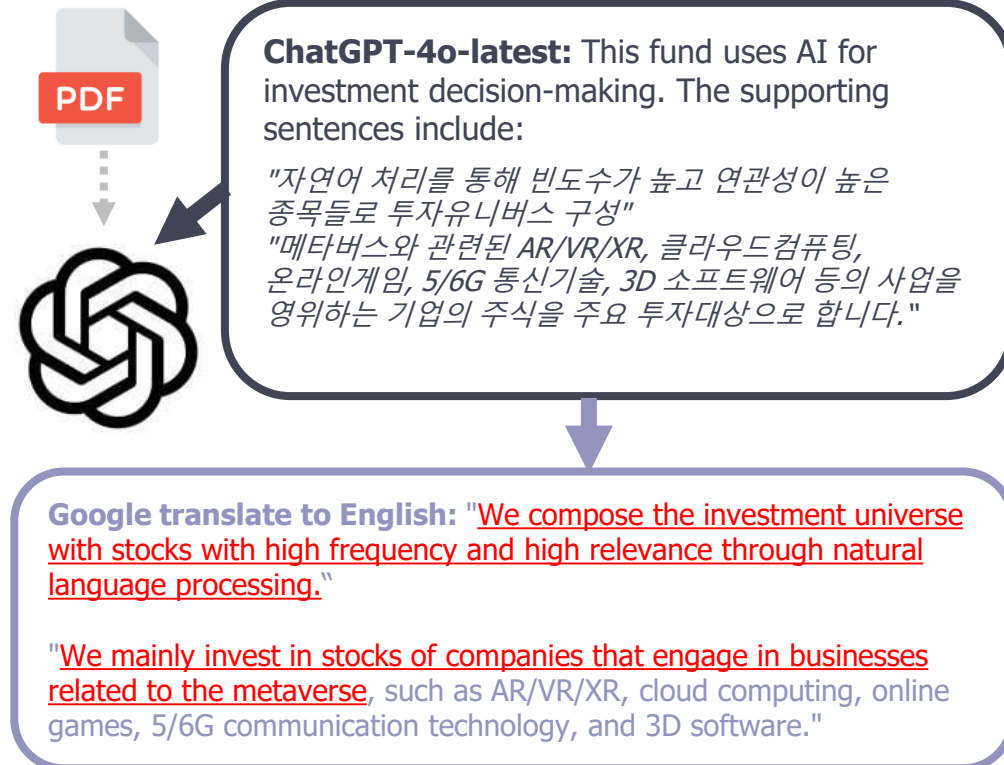


- Some funds apply AI to thematic screening, identifying funds aligned with specific investment themes

Example 1:



Example 2:



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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ETFs as a Disciplinary Device

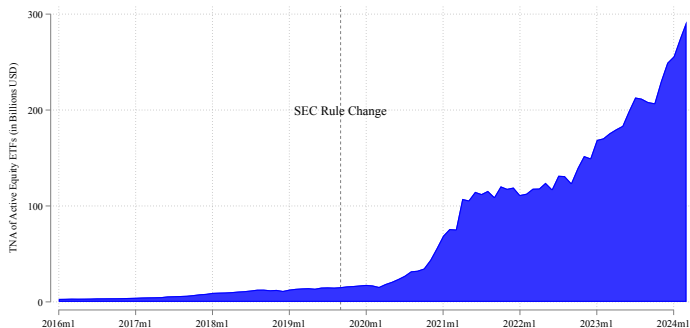
Yuet Chau (HKUST), **Karamfil Todorov (BIS)**, Eyub Yegen
(HKUST)

ESMA, Paris, November 2025

The views are those of the authors and do not necessarily reflect the views of the BIS

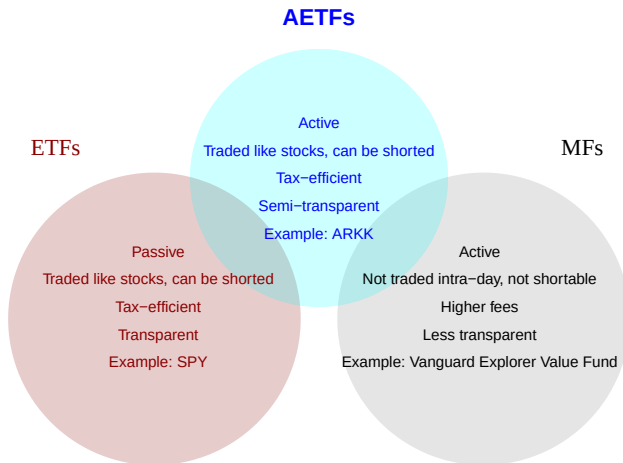
Rapid growth of Active ETFs

- Active ETFs (AETFs) grew **15 times** (\$20 bn to \$300 bn) over the past 4 years.
- BlackRock projects AETFs to reach \$4 tn by 2030

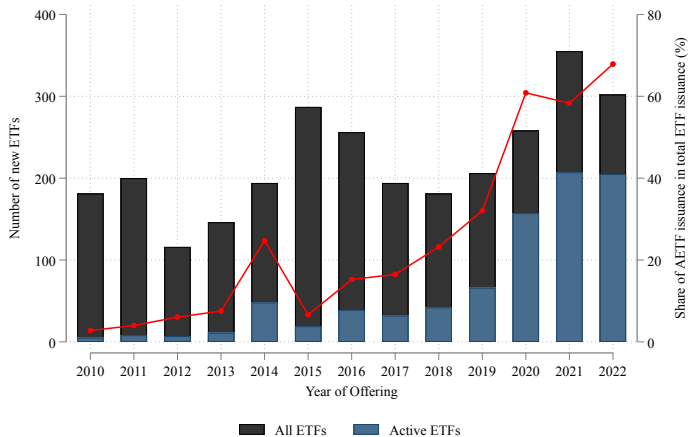


Institutional background on AETFs

- AETFs are ETFs that do not track a specific index
- **New investment vehicle** that combines active management with the structural benefits of ETFs

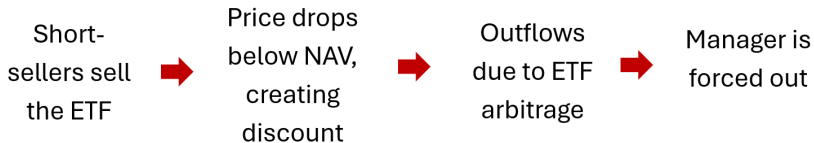


AETFs dominate new ETF issuance



- AETFs exhibit more than **5 times larger flow-performance sensitivity** compared to MFs
 - Means AETFs get punished more for poor performance than MFs
 - When investors can short-sell a fund, its flows become more sensitive to performance
 - AETFs load more on momentum stocks and on stocks with higher idiosyncratic component
- We **document a novel role of ETFs: short-selling AETFs acts as a disciplinary tool** for poor-performing managers
 - Investors ramp up short sales when bad (good) manager joins (leaves) a fund
 - Highly shorted managers are more likely to quit the industry
 - AETFs improve overall efficiency by driving out bad managers
- **Sorting of managers based on their quality:** best-performing ones manage AETF, worst-performing ones manage only MF

The Key Mechanism in a Nutshell



Data

- ETF Global: ETF characteristics such as flows, returns, assets, holdings
- Compustat and CRSP: Mutual fund characteristics
- IHS Markit: Equity borrowing market data for securities lending and borrowing, covering over 90% of transactions: "covered shorts"
- Period: 2016 – 2023, >6K equity funds

Summary stats

Compared to MFs, AETFs are smaller and younger, have lower expense ratios with higher turnover and alphas

	(1) MFs			(2) AETFs			Mean (1) - mean (2)
	Mean	SD	Median	Mean	SD	Median	
TNA (\$mn)	1979	8148	287	275	1323	42	1703.23***
ExpRatio (%)	0.92	0.49	0.94	0.71	0.28	0.75	0.20***
TurnRatio	0.71	1.7	0.44	1.5	4.5	0.41	-0.81***
Age (Year)	16	12	14	2.7	3.1	1.8	13.17***
Flow (% TNA)	-0.021	4.5	-0.5	6.1	28	0.1	-6.10***
Excess Return (%)	0.71	4.5	0.93	0.38	5.4	0.62	0.33***
CAPM Alpha (%)	-0.23	2.1	-0.14	-0.24	2.9	-0.11	0.01
FF3 Alpha (%)	-0.26	1.8	-0.19	-0.22	2.6	-0.13	-0.04*
FF4 Alpha (%)	-0.29	2	-0.2	-0.26	2.8	-0.15	-0.03*
FF5 Alpha (%)	-0.17	2	-0.15	-0.1	2.9	-0.067	-0.07***
InstOwn (%)	0.15	2.8	0	45	31	45	-44.70***
Discount/Premium (%)	0	0	0	0.12	2.9	0.0095	-0.12***
CoveredShort (%)	0	0	0	0.11	0.67	0	-0.42***
Number of funds	5468			627			

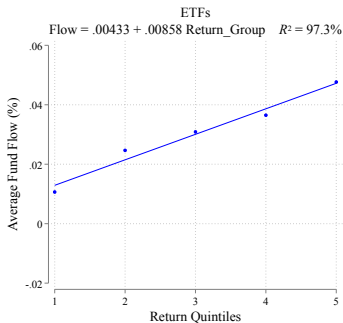
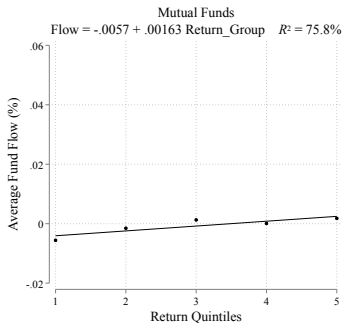
Evident benefits of AETFs: lower fees

- AETFs use in-kind creations and redemptions, **avoiding taxable events**
- Reduces need for trading underlying securities leads to lower expense ratios for AETFs vs MFs (0.71% vs. 0.92%) and no tax expenses (0% vs. 0.34%)
- Total **cost savings of AETFs** relative to MFs: **0.55% p.a.**
- Generates significant potential for reducing investor costs by **\$60.5 billion** p.a. if all MFs are converted to AETFs

ETFs as a disciplinary device

AETFs have higher flow-performance sensitivity

- AETFs exhibit more than **5 times larger** flow-performance sensitivity vs MFs, meaning they are more sensitive to performance changes
- The relation is also **more concave for AETFs**: negative performance (bottom quintile) impacts AETF flows more severely than positive performance



Converted AETFs have higher flow-performance sensitivity

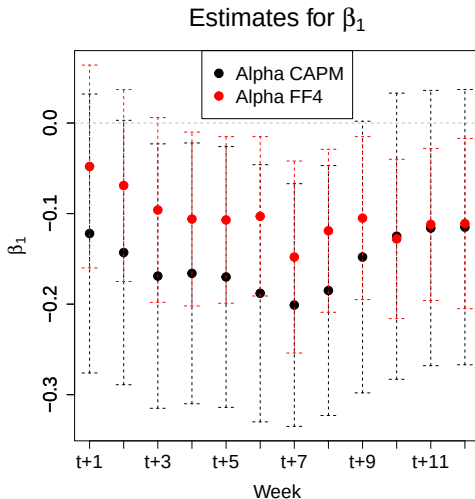
- More formal test: AETFs that were converted from MFs have higher flow-performance sensitivity vs similar MFs
- When investors can short-sell a fund, its flows become more sensitive to performance

	Dependent variable: Fund flows			
	(1) CAPM	(2) Alpha FF3	(3) Alpha FF4	(4) Alpha FF5
Alpha $\times$ ShortInt	0.027** (0.012)	0.031*** (0.008)	0.026** (0.012)	0.029** (0.014)
Alpha	0.051** (0.022)	0.041* (0.021)	0.027 (0.019)	0.035* (0.019)
ShortInt	-0.001** (0.000)	-0.000 (0.000)	-0.001** (0.001)	-0.000 (0.001)
Observations	34,135	34,088	34,098	34,074
R-squared	0.234	0.232	0.228	0.230
Controls	Yes	Yes	Yes	Yes
Stack FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes

Investors are correct in their short-sale bets against AETFs

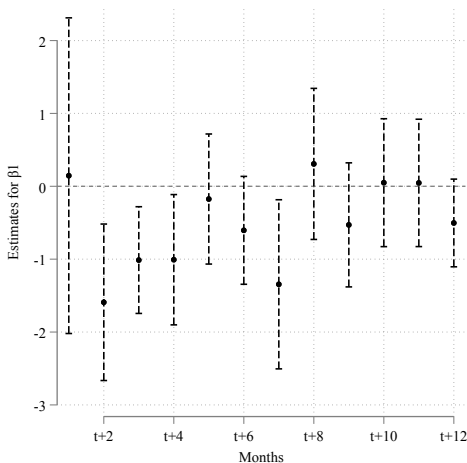
- AETFs with **higher short interest perform worse** in the future

- $$\text{Alpha}_{i,t+n} = \beta_1 \text{ShortInt}_{i,t} + \beta_2 \text{Alpha}_{i,t+n-1} + \beta_3 \text{ExpRatio}_{i,t+n-1} + \beta_4 \ln(\text{TNA}_{i,t+n-1}) + \beta_5 \ln(\text{FAMTNA}_{i,t+n-1}) + \beta_6 \ln(\text{Discount Premium}_{i,t+n-1}) + \sum_{s=t+n-4}^t \beta_s \text{Flow}_{i,s} + \gamma_i + \epsilon_{i,t+n}.$$



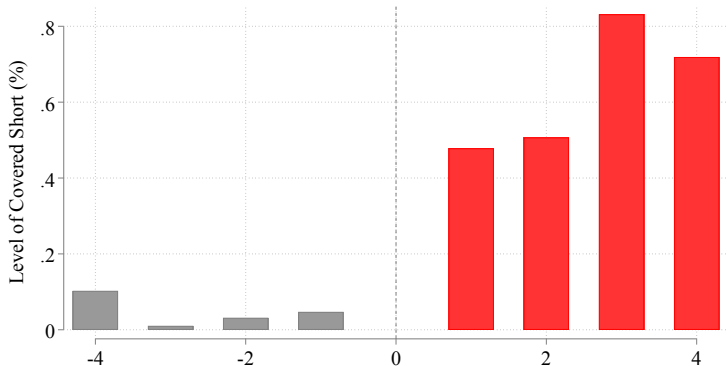
Higher short interest predicts fund outflows

- 1st increase in SI predicts 1.5% outflows in 2 months
- $Flow_{i,t+n} = \beta_1 ShortInt_{i,t} + \beta_2 Alpha_{i,t+n-1} + \beta_3 ExpRatio_{i,t+n-1} + \beta_4 \ln(TNA_{i,t+n-1}) + \beta_5 \ln(FAMTNA_{i,t+n-1}) + \beta_6 \ln(Discount\ Premium_{i,t+n-1}) + \sum_{s=t+n-4}^t \beta_s Flow_{i,s} + \gamma_i + \epsilon_{i,t+n}$



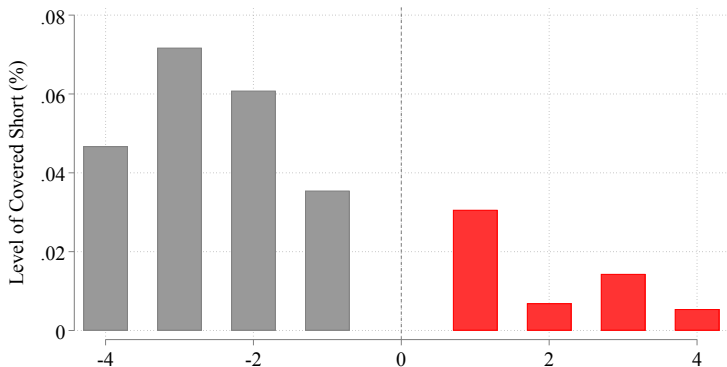
Investors ramp up short sales when bad manager joins

- Split managers into poorly performing ("bad") and well-performing ("good") based on the past 3m cumulative raw excess return
- A good (bad) manager is a manager that performs above (below) the median manager before the turnover
- **Investors bet against a fund when a bad manager joins**



Investors ramp up short sales before bad manager leaves

- Investors ramp up short sales before bad manager leaves



Investors bet against bad managers by shorting fund shares

$$\begin{aligned} Short_{i,t} = & \beta_{DID} 1(Turnover_i) \times 1(Post_t) + \beta_2 \ln(TNA_{i,t-1}) \\ & + \beta_3 \ln(Age_{i,t-1}) + \beta_4 Alpha_{i,t-1} + \beta_5 Flow_{i,t-1} + \lambda_t + \gamma_i + \epsilon_{i,t} \end{aligned}$$

	Bad Join (1)	Good Join (2)	Bad Leave (3)	Good Leave (4)	Bad Leave Good Join (5)
β_{DID}	0.848*** (0.205)	-0.112* (0.060)	0.004 (0.036)	0.054 (0.047)	-0.200** (0.100)
Observations	483	15,454	7,482	12,845	1,005
R-squared	0.720	0.494	0.624	0.450	0.657
Controls	Yes	Yes	Yes	Yes	Yes
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes

Highly shorted managers are more likely to quit

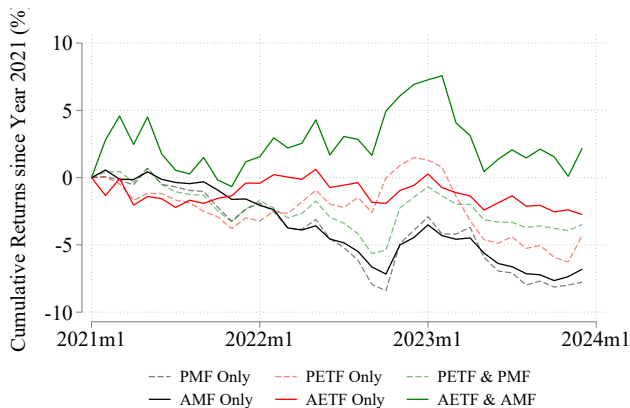
Highly shorted managers (columns 1–2, 5–6) and worse performing managers (3–4, 7–8) are more likely to quit the industry

$$1_{Quit_{m,t}} = \beta_1 ShortInt_{m,t} + \beta_2 NumFunds_{m,t} + \beta_3 Tenure_{m,t} + \lambda_t + \epsilon_{m,t}$$

1_{Quit}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Fund Universe: AETFs				Fund Universe: AETFs & MFs			
ShortInt	0.103*** (0.015)	0.072*** (0.021)			0.080*** (0.017)	0.050*** (0.018)		
Return quintile			-0.098*** (0.010)	-0.108*** (0.015)			-0.038*** (0.009)	-0.035*** (0.008)
NumFunds	-0.009*** (0.002)	0.012*** (0.003)	-0.142*** (0.009)	-0.111*** (0.006)	0.080*** (0.010)	0.090*** (0.009)	-0.012*** (0.004)	-0.013*** (0.003)
Tenure	-0.101*** (0.004)	-0.076*** (0.003)	-0.051*** (0.003)	-0.044*** (0.002)	-0.022*** (0.002)	-0.012*** (0.002)	-0.027*** (0.002)	-0.024*** (0.001)
Observations	30,113	29,925	54,732	45,464	26,995	26,994	48,956	48,956
Week FE	No	Yes	No	Yes	No	Yes	No	Yes

Average quality of managers

- Best managers (in terms of CAPM α) clone MF into AETF
- Middle quality ones convert MF to AETF
- Worst managers stay in MF
- Active-only managers outperform passive-only ones



Implications for AETFs' portfolio choice and stocks

Implications for AETFs' portfolio choice

- AETFs **load less on the market** compared to MFs but **more on growth stocks and momentum** stocks
- Only the momentum result survives in a DiD setting of MFs that are converted into AETFs

	Excess Return (Baseline)	Excess Return (Matched DiD)
$1_{ActiveETF} \times MKTRF$	-0.05** (0.02)	
$1_{ActiveETF} \times SMB$	0.02 (0.03)	
$1_{ActiveETF} \times HML$	-0.07*** (0.02)	
$1_{ActiveETF} \times MOM$	0.05*** (0.01)	
$1_{Post} \times 1_{Converted} \times MKTRF$		0.02 (0.03)
$1_{Post} \times 1_{Converted} \times SMB$		0.08 (0.07)
$1_{Post} \times 1_{Converted} \times HML$		0.06 (0.04)
$1_{Post} \times 1_{Converted} \times MOM$		0.10**
Observations	387,810	63,741
R-squared	0.74	0.66
Controls, Fund FE, Year×Month FE	Yes	Yes

- Long-short strategy based on AETF's short selling is **profitable**, generating 76 bps p.m. Also profitable after fees

Portfolios sorted on one-month lagged short interest			
Portfolio	Return (%)	Std. Dev. (%)	T-Stat
1 (Low)	0.018	6.00	0.104
5 (High)	-0.740	9.40	-2.580
Low minus High (1 - 5)	0.758		2.283

ETF Hub Exchange traded funds Added

Bets against Cathie Wood's flagship ETF hit record high

Investors are beginning to lose faith, analysts say, after stellar run in 2020



The rising scepticism reflects doubts in the tech-heavy strategy that worked so well for Cathie Wood © Alex Flynn/Bloomberg

Emma Boyde and Michael Mackenzie

Published AUG 6 2021

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FT (2021): *“Short sellers have ramped up bets against Cathie Wood’s flagship Ark innovation fund as belief in its **[active]** strategy shows signs of faltering. A record 12 per cent of the ARKK ETF’s shares are being **shorted by investors betting on a decline** – a bet worth more than **US\$2.7 billion** on August 3 [2021]”*

*FT reported on **Cathie Wood** who later **resigned** from two ARK funds as portfolio manager*

- **Active ETFs:**

- Du et al. (2023): AETFs impact fund flow competition
- Our paper shows short-selling as a discipline mechanism, primarily for newly established and converted AETFs

- **Short-selling of ETFs:**

- Li and Zhu (2022), Karmaziene and Sokolovski (2022): Short-selling passive ETFs to bypass constraints
- Our paper extends by showing short-selling AETFs targets managers, not just underlying stocks

- **Short-selling and stock performance:**

- Asquith et al. (2005), Diether et al. (2009): Short-selling predicts negative stock performance
- Our paper shows short-selling AETFs also disciplines managers, improving the quality of the active asset management industry

- **Market efficiency:**

- Boehmer and Wu (2013), Huang et al. (2021): ETFs impact market efficiency
- Our paper shows that AETFs ownership is correlated with higher price informativeness

- AETFs exhibit more than **5 times larger flow-performance sensitivity** compared to MFs
 - Means AETFs get punished more for poor performance than MFs
 - When investors can short-sell a fund, its flows become more sensitive to performance
 - AETFs load more on momentum stocks and on stocks with higher idiosyncratic component
- We **document a novel role of ETFs: short-selling AETFs acts as a disciplinary tool** for poor-performing managers
 - Investors ramp up short sales when bad (good) manager joins (leaves) a fund
 - Highly shorted managers are more likely to quit the industry
 - AETFs improve overall efficiency by driving out bad managers
- **Sorting of managers based on their quality:** best-performing ones manage AETF, worst-performing ones manage only MF

Thank you for your attention!

Appendix

- **Short-selling AETFs** vs. taking positions in **individual stocks**
 - **Cost efficiency:** Short-selling AETFs is cheaper than mimicking their portfolios or shorting individual stocks
 - **Bet on manager's choices:** Short-selling AETFs targets the manager's investment decisions, while passive ETFs are better suited for betting against a fixed portfolio due to lower fees
 - **High turnover:** AETFs have a much higher turnover (150% vs. 68% for passive ETFs), making them less suitable for taking positions against static portfolios
- Disciplinary tool **less pronounced in cloned MFs** as those are typically managed by better-performing managers

- Managers who perform worse and are more heavily shorted get **lower compensation**: a \$1,000 increase in short positions predicts a \$21-\$25 drop in compensation
- **Main results are robust** to using other measures of **manager quality** (Morningstar ratings)
- **Main results robust** with 6m or 12m instead of 3m window
 - **Validation with longer horizons**: The main results hold for longer horizons of 6 and 12 months
 - **Performance persistence**: Manager performance is persistent, with bad managers staying bad (75%) and good managers staying good (74%) in the next 3-month period

What if bitcoin is a risk-free asset in the end?

Giulio Anselmi*

(*) This presentation summarizes a research paper co-authored with Giorgio Alessandro Motta (CETIF, Università Cattolica, Milan).

Current Environment

- Quantitative easing measures and prolonged inflation debase the store of value for fiat money
- US debt-to-GDP ratio is posited to reach 156 percent by 2055, with a deficit spending above 7 percent (Congressional Budget Office, 2025) and recurring US debt-ceiling reminds that even sovereign governments with a lender of last resort face political default risk
- Strategic Bitcoin Reserve (SBR) Executive Order approved in March 2025
- Bitcoin (BTC) expanded the feasible investment universe and a small allocations to BTC pushes the efficient frontier outward (Bouri et al., 2017; Coinshares, 2024; McGee, 2024; O'Shea, 2025)
 - BTC remains a high-risk/high-reward asset, its correlation with equities spikes during systemic stress, and its safe-haven credentials are episodic (Bouri et al., 2017)
 - The role of safe haven remains in the hands of gold and Treasuries, with the yield of latter serving as benchmark for the risk-free rate
- What qualifies as “risk-free” in twenty-first-second-century finance?

What this paper is about (and not)

- A risk-free Bitcoin is just a hypothetical scenario and with limitation
 - Drawdowns in Bitcoin price are avoided only for long-term holding period, because the financial institution manages short-term volatility
 - A risk-free asset has (almost) zero transaction costs
- The topic is worth exploring to understand the future development of financial markets given the affirmation of BTC as the main digital asset

In short: if Bitcoin follows a power-law behavior in price and volatility how the future of the efficient frontier would reshape?

- A future, e.g., 10%-yield, low-risk Bitcoin is a fanciful extrapolation or the next step in the long search for a politically independent risk-free asset?
- This paper is not about
 - finding a risk-free rate for Bitcoin, nor comparing Bitcoin with Treasuries
 - forecasting future Bitcoin price and volatility

Previous Literature – Power law models

- Bitcoin obeys **power-law scaling** regularities characteristic of complex adaptive systems, such as social networks (Begusic et al., 2018; da Cunha & da Silva, 2020; Takaishi, 2020; Sornette & Zhang, 2024)
 - Gabaix (2009) for a review on power-law regularities in economics and finance
- In brief, Bitcoin's long-run price path follows a power-law scaling relation of the form (Santostasi, 2018; Santostasi, 2024)

$$P(t) = A (t - t_0)^\gamma, \quad \gamma > 0$$

where t_0 is BTC genesis block (9 Jan 2009) and γ is a stable exponent across a decade long sample. We also define $d_t = t - t_0$ in our time series regression

Previous Literature – Power law models

- The variance of long-horizon returns falls as an inverse power of time (Sornette & Zhang, 2024), Begušić et al. (2018) find a slowly decaying tails in returns that corresponds to a power-law behaviour in Bitcoin returns, and similarly conclude Larralde & Navarro (2025)
- Bariviera (2017) links heavy tails to long-memory processes in both price and realised volatility, suggesting that time-scaling properties are fundamental to Bitcoin's dynamics, and detecting a Hurst exponent that changes significantly during the first years of existence of Bitcoin but tends to stabilize in recent times
- Under such frameworks, the variance shrinks over time and if BTC network adoption increases fast enough, the power-law exponent delivers equity-like return with bond-like volatility

Theoretical framework

- Power-law regularity in price levels and return gives an internally consistent framework: price-level scaling gives a positive drift; when transferred into returns generates a declining-variance trajectory whose ultimate limit is explored in this paper
- A quasi-risk-free Bitcoin is relevant for capital-market equilibrium
 - Governments and firms would confront a structurally higher financing rate
 - Investors get an attractive low volatility payoff holding BTC-related products
 - In portfolio space, we have a temporary rotation of the efficient frontier as optimal weights migrate towards Bitcoin
- However, power-law trajectory is self-attenuating, the drift shrinks over time, and the distortion is temporary
 - Our hypothesis suggest a window of roughly ten years from today in which BTC's risk-adjusted dominance is most acute
- As expected return decreases in the long run, the classical CAPM geometry re-emerges and Bitcoin will cover a role as a deflationary and decentralized risk-free assets
- But transient does not mean trivial: the scenario would still ripple through fiscal sustainability, corporate funding, and real-economy investment

Why it is relevant for investors

- Long-horizon investors can treat Bitcoin as a long-duration asset
 - pays no dividend yield but experiences an increase in price that beats inflation
- Retail-oriented structures can exploit this decline in volatility to harvest the expected drift while capping draw-downs over a multi-year holding periods
 - e.g. buffered notes, target-volatility funds, or option-overlay products
- Transform Bitcoin's raw return into a smoother income-like instrument, with hedge on political risk and inflation
- Development of hybrid financial instruments such as the Bitcoin-enhanced US Treasury Bonds proposed by Hohns & Pines (2025)

Contribution

This paper asks whether the scenario is empirically plausible and, if so, how affects the efficient frontier. We make three contributions:

1. **Price and tail-risk dynamics**. We estimate time-varying power-law exponents for BTC daily returns and test whether the downward trend in volatility is statistically significant
 - power-law regularities for Bitcoin emerges since 2018 with an upward trending goodness-of-fit
 - a thick-to-thin tail transition—especially on the left tail—consistent with faster decay of volatility and extreme negative return reduction that follows a power-law
2. We (partially) corroborate our analysis with **option implied volatilities**
3. **Efficient-frontier rotation** and asset pricing implication. We embed a declining-volatility Bitcoin into a tri-asset (stocks-bonds-BTC) deriving a long-term hypothetical scenario of asset allocation.
 - Where the optimal allocation to Bitcoin rises materially in 10 years and become dominant afterwards only in the scenario with minimum volatility

Methodology

1. We provide an analysis on price and tail risk dynamics to verify if Bitcoin price is rising and if volatility is shrinking under a power-law
 - addressing also for asymmetric reductions in positive and negative volatility
2. We corroborate our analysis with time series and a panel regression analysis on BTC options implied volatility and verify if the forward-looking volatility follows the same power-law dynamic
3. We estimate a trajectory for BTC volatility based on our findings: the rapidity at which it will reduce is directly related to the rise in expected price increases due to power-law dynamics
 - If the volatility reduces at a faster rate than the expected return, then the efficient frontier presents a significant allocation on Bitcoin
 - If not, the current efficient frontier remains unaltered

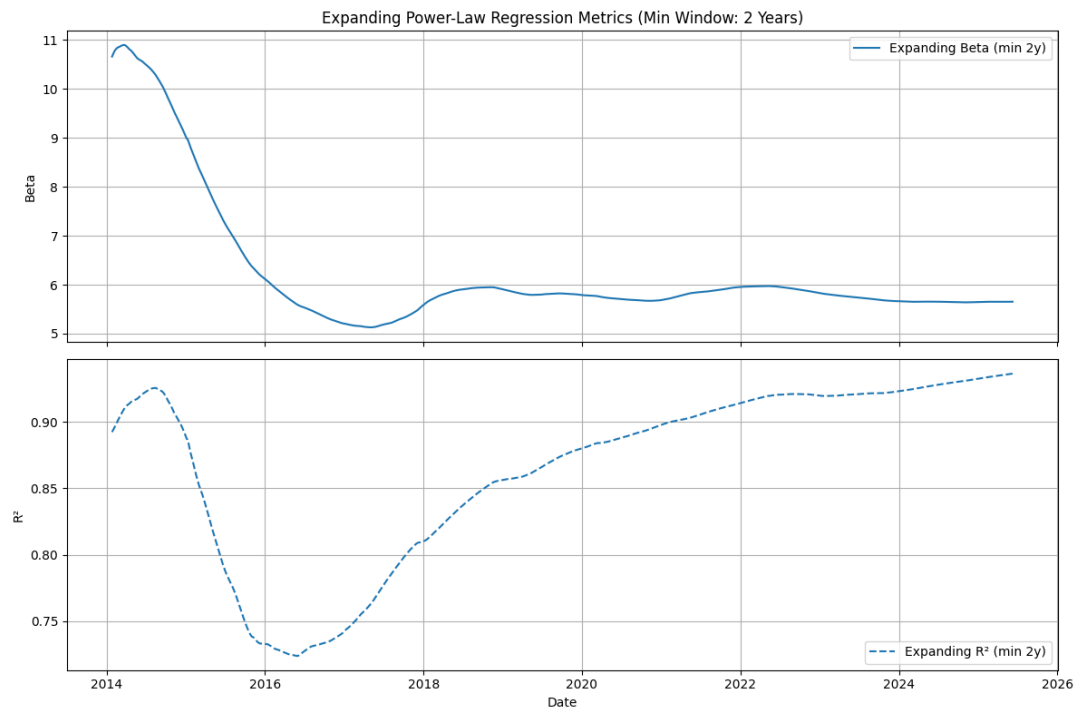
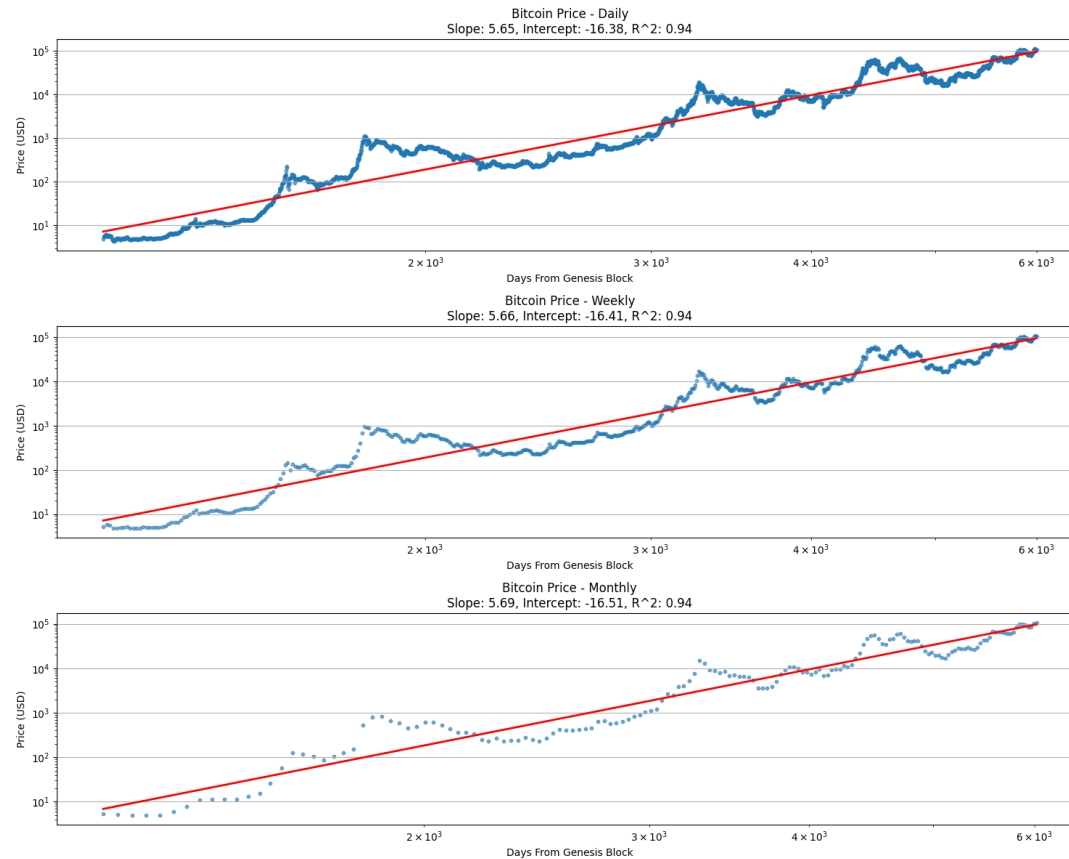
Data

- BTC prices sample is based on daily close-to-close prices for BTC/USD between **August 2011 through the first half of 2025** ($\approx 3,600$ observations) downloaded from LSEG
- Option data is based on daily implied volatility prices traded between **January 2022 and the first half of 2025** for calls and puts downloaded from Deribit
 - The time series sample pertains Deribit's DVOL implied volatility index that averages volatilities for at-the-money (ATM) option with approximately 1-month maturity (1,000 observations)
 - The panel sample spans from call and put options with maturity between 1 week and 1 year, and delta between 2% and 65% for calls and -7% and -49% for puts ($\approx 32,200$ observations)

Power-law dynamics for Bitcoin price

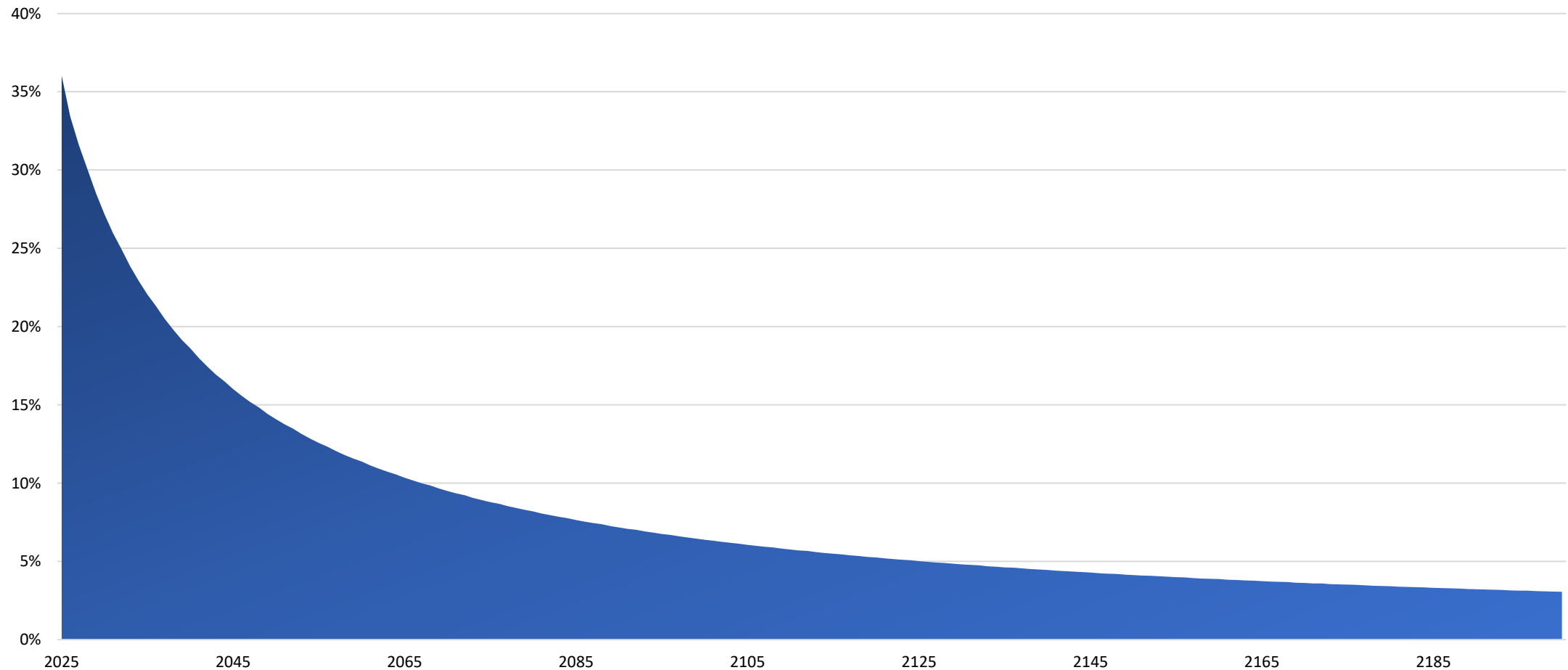
$$\log_{10} P_t = \alpha + \beta \log_{10} d_t + \varepsilon_t$$

Where $d_t = t - t_0$ and t_0 is BTC genesis block



What if bitcoin is a risk-free asset in the end?

Power-law dynamics for Bitcoin returns



What if bitcoin is a risk-free asset in the end?

Assessing tail-risk dynamics

- Local tail index ($\hat{\mu}_t$) using a Hill (1975) estimator to keep the variance-bias trade-off optimal, k_t is chosen following Boucheron & Thomas (2015)
- Positive and negative tails, yielding $\hat{\mu}_t^{(+)}$ and $\hat{\mu}_t^{(-)}$ to track asymmetry, as deterioration concentrates in the left tail, where portfolio risk is mostly defined
- We map the volatility-decay parameter over horizon h as

$$Var(R_{t+h}) \propto h^{2/\hat{\mu}_t-1}$$

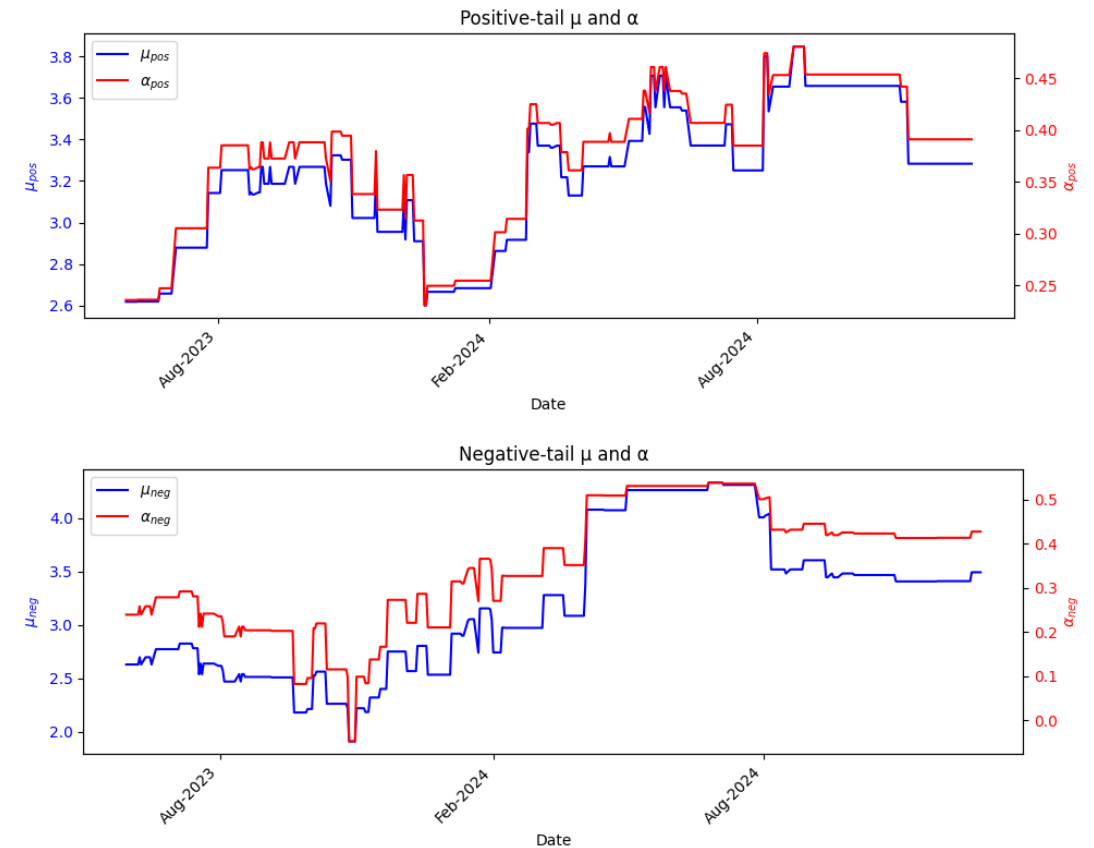
- An increasing $\hat{\mu}_t$ therefore implies a larger $\hat{\alpha}_t$ and faster variance decay toward zero as $h \rightarrow \infty$
- With this, the expected volatility in n year is presented as

$$\sigma_{t+n} = \sigma_d h^{1/\hat{\mu}_t-1/2}$$

Expected volatility from tail-risk dynamics

$$\sigma_{t+n} = \sigma_d h^{1/\hat{\mu}_t - 1/2}$$

Period	$\bar{\sigma}_d$	Mean $\mu^{(-)}$	Last $\mu^{(-)}$	Mean σ_y	Last σ_y
<i>in 10 years</i>					
Full	5.27%	2.586	3.492	39.73%	17.44%
From 2014	4.38%	2.675	3.492	29.69%	14.49%
From 2020	4.17%	2.717	3.492	26.96%	13.79%
From 2022	3.52%	3.034	3.492	16.63%	11.66%
<i>in 20 years</i>					
Full	5.27%	2.586	3.492	36.73%	15.04%
From 2014	4.38%	2.675	3.492	27.20%	12.50%
From 2020	4.17%	2.717	3.492	24.60%	11.89%
From 2022	3.52%	3.034	3.492	14.78%	10.05%
<i>in 30 years</i>					
Full	5.27%	2.586	3.492	35.08%	13.79%
From 2014	4.38%	2.675	3.492	25.85%	11.46%
From 2020	4.17%	2.717	3.492	23.32%	10.91%
From 2022	3.52%	3.034	3.492	13.79%	9.22%



Option implied volatility regression

Sample	N	Mean	SD	p5	p25	Median	p75	p95
Full sample	32,239	.663	0.221	.45	.56	.63	.73	.94
2021	291	.928	0.447	.7	.77	.82	.93	1.34
2022	8,697	.764	0.268	.59	.67	.72	.79	1.06
2023	10,110	.579	0.166	.4	.49	.56	.63	.8
2024	10,498	.661	0.161	.51	.57	.63	.71	.89
2025	2,643	.636	0.243	.49	.55	.6	.66	.89

	(1) <i>log(iv)</i>	(2) <i>log(iv)</i>
<i>logblock</i>	-0.433*** (-3.840)	-0.426*** (-3.806)
<i>r_{btc}</i>		0.003** (2.165)
Constant	3.343*** (7.906)	3.318*** (7.898)
Observations	1000	999
R-squared	0.015	0.029
Std. Errors	Robust	Robust

t-values are in parentheses

*** $p < .01$, ** $p < .05$, * $p < .1$

maturity is the time to maturity of the option,

delta is the delta of the option,

call is a dummy variable that identifies call options

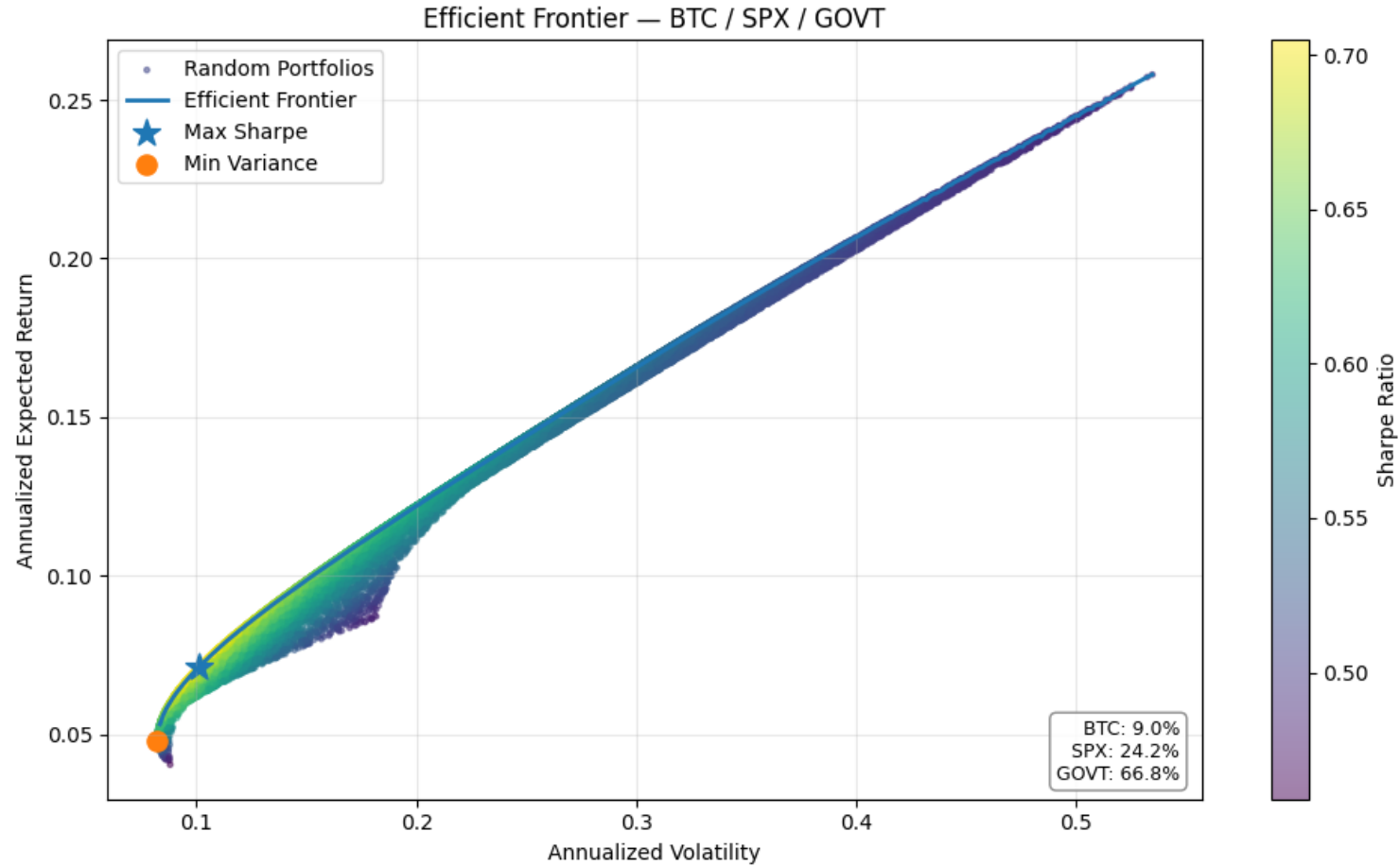
otm and *dotm* are dummy variables that identify out-of-the-money options (with delta lower than 40% in absolute value), and deep-out-of-the-money options (with delta lower than 20% in absolute value).

	(1) <i>log(iv)</i>	(2) <i>log(iv)</i>	(3) <i>log(iv)</i>	(4) <i>log(iv)</i>	(5) <i>log(iv)</i>
<i>logblock</i>	-10.107*** (-12.541)	-10.100*** (-12.550)	-10.133*** (-12.597)	-9.906*** (-12.880)	-9.959*** (-12.553)
<i>maturity</i>	-0.049*** (-5.668)	-0.049*** (-5.664)	-0.049*** (-5.656)	-0.061*** (-7.129)	-0.046*** (-5.297)
<i>delta</i>	0.044** (2.391)	0.044** (2.393)	0.044** (2.406)		
<i>call</i>	-0.050*** (-3.414)	-0.050*** (-3.413)	-0.050*** (-3.433)	-0.009* (-1.793)	-0.015*** (-2.852)
<i>r_{btc}</i>		-0.005 (-0.468)	-0.001 (-0.121)	0.003 (0.239)	0.003 (0.216)
<i>r_{spx}</i>			-0.076** (-2.013)	-0.075** (-1.978)	-0.071* (-1.874)
<i>r_{xau}</i>			0.159*** (3.945)	0.160*** (3.967)	0.158*** (3.921)
<i>otm</i>				0.014*** (4.689)	
<i>dotm</i>					-0.014*** (-2.770)
Constant	46.904*** (12.496)	46.871*** (12.505)	47.026*** (12.553)	45.950*** (12.831)	46.201*** (12.506)
Observations	32239	32239	32239	32239	32239
R ²	0.149	0.149	0.150	0.189	0.139
Std. Errors	Robust	Robust	Robust	Robust	Robust

t-values are in parentheses

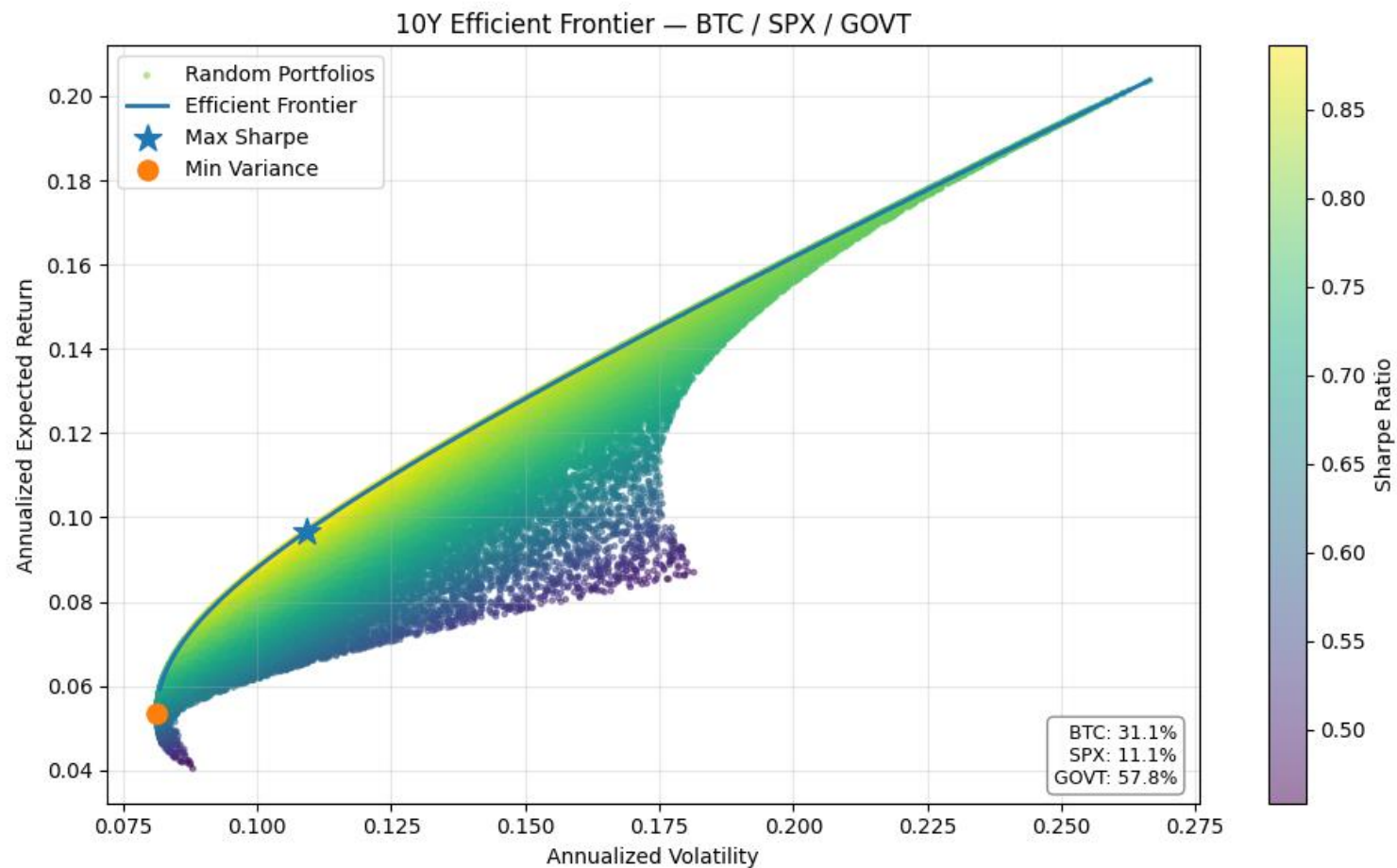
*** $p < .01$, ** $p < .05$, * $p < .1$

Current Efficient Frontier



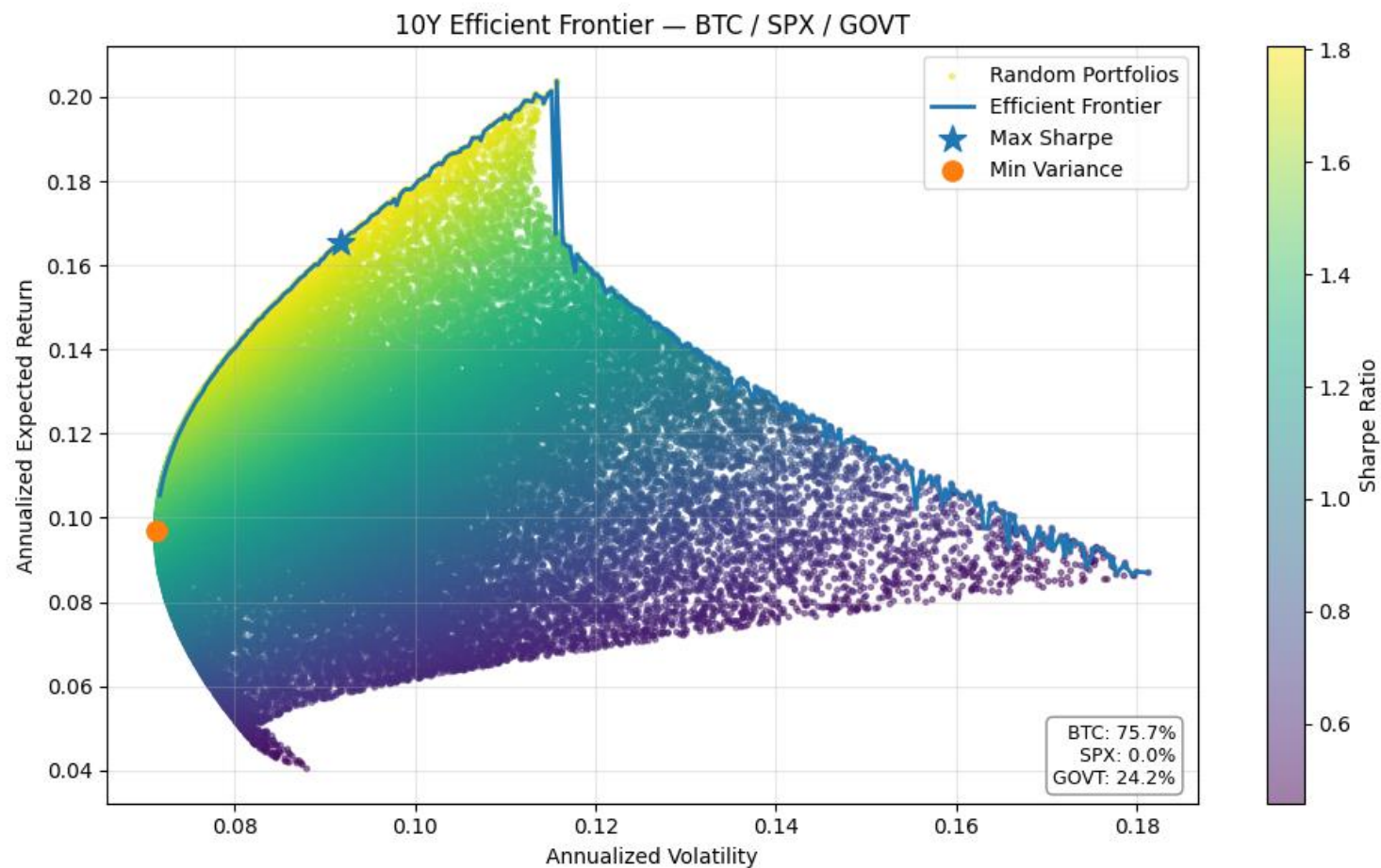
What if bitcoin is a risk-free asset in the end?

New efficient frontier (max volatility)



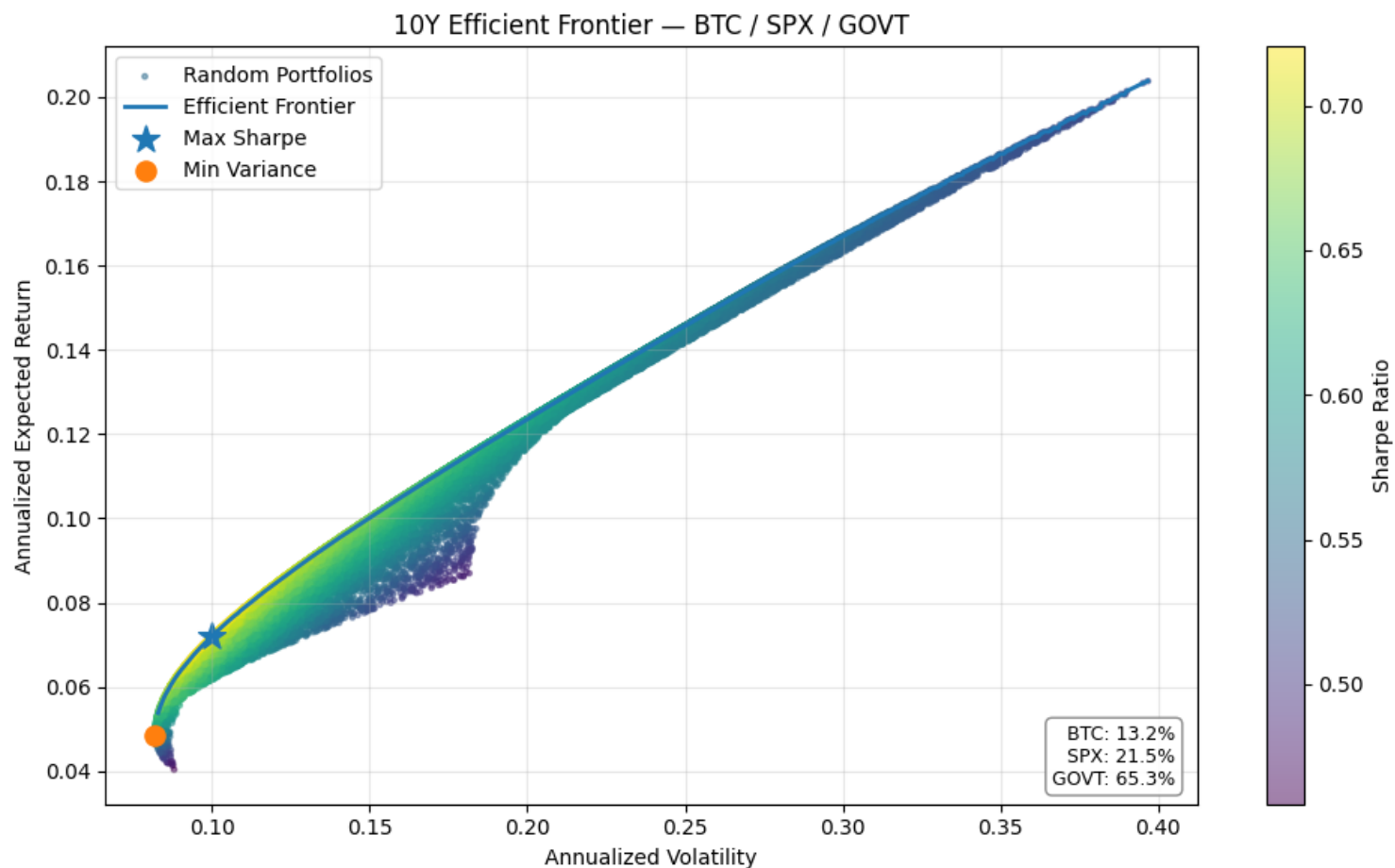
What if bitcoin is a risk-free asset in the end?

New efficient frontier (min volatility)



What if bitcoin is a risk-free asset in the end?

New efficient frontier (implied volatility)



What if bitcoin is a risk-free asset in the end?

Concluding remarks (1)

- If – like in our scenario – Bitcoin’s variance declines while returns maintain a positive drift implied by the power-law, the asset assumes both store-of-value and return-generation roles
- Holding correlations fixed at their 2022–2025 estimates, **Bitcoin’s weight peaks near one-third at a 10-year horizon** under our maximum-volatility tail-risk path
- Using fitted implied-volatility dynamics, the allocation stays consistent with the current one (13% vs 9%)
 - These alternative findings might be influenced by the reduced availability of data for option implied volatility, where power-law works at its best for long time series
- These gains come at the expense of equities, but different results are expected with a lower interest rate regime
 - Although levels are sensitive to estimated mean returns (8% for equities, 4% for bonds), the qualitative result is robust: longer horizons and thinner left tails shift the efficient set toward Bitcoin
- We have a reallocation toward a higher Sharpe-ratio as BTC compresses the compensation required for traditional risky claims
- The mechanism is self-attenuating, so dominance is best viewed as a transitional regime rather than a permanent new order

Concluding remarks (2)

- **Market completion.** The secular stabilization we measure coincides with the evolution of Bitcoin's market structure
 - From near-zero transactions and unreliable price discovery process
 - To deep, multi-venue spot intermediation (e.g., large brokerages/exchanges), fully developed derivatives markets (e.g., listed and crypto-native venues), and ETF/ETC wrappers
- Policy discussions about public-sector balance-sheet engagement (e.g., proposals for SBR) signal a maturing demand base
- **We read these developments as causes, not consequences,** of declining volatility
 - Each step enlarges market depth, and strengthens the price discovery process for an asset whose fundamental valuation (and methodology) remains contested
- Any continuation of the upward-drift/volatility-decay path likely depends on further institutional steps. Absent such progress, the de-risking process could stall or reverse, with sharp drawdowns and volatility spikes.

Concluding remarks (3)

- Institutionalization of Bitcoin is a cumulative social choice process—reflecting sequential decisions by legislators, financial authorities, intermediaries, and households
- Illustrative waypoints
 - Supervisory proposals to recognize crypto exposures for mortgage-credit models
 - Inclusion of Bitcoin allocations in retirement plans
 - Engineering of Bitcoin-enhanced sovereign instruments
- With this broader adoption we see key implications for product design
 - The scenario we outline motivates intermediation structures to warehouse medium-term volatility and pass through the long-term return to investors
- A financial institution could engineer term-transformation products that
 - i. cap medium-term mark-to-market swings via listed options
 - ii. harvest the premium in long-dated options
 - iii. offers to investors the participation in the multi-year buy-and-hold appreciation implied by the power-law.

Limitations

1. Correlations are held constant across 10–30-year projections; secular correlation declines as adoption broadens would strengthen our portfolio results, whereas crisis-period spikes would dampen them
2. Tail inference depends on threshold choice and finite-sample Hill estimates; structural breaks or liquidity droughts can interrupt the thinning-tail trajectory.
3. Implied-volatility panel is short and coincides with market-structure innovations (ETF launches, options depth) whose permanence is uncertain. As a result, our implied-volatility estimates may overstate/understate longer-run variance dynamics
4. Our “risk-free Bitcoin” is horizon-conditioned: it speaks to multi-year buy-and-hold variance, not to short-horizon mark-to-market, funding, custody, or policy risks
5. Our analysis is explicitly scenario-based and does not provide a formal out-of-sample forecasting evaluation. We do not quantify forecast errors, compare alternative predictive models, or implement real-time recursive tests that would assess stability and incremental predictive content relative to benchmarks

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Appendix

Previous Literature – Valuation models

- Models that focus on supply-side fundamentals and treat Bitcoin like a commodity, with equilibrium prices anchored to its marginal cost
- Stock-to-Flow (S2F) model, where Bitcoin's price is driven by its scarcity, as the ratio between circulating supply and new issuance.
 - Halving events reduce new supply and are predicted to increase the price (Morillon & Chacon, 2022)
 - Bitcoin affirms as the sole deflationary asset
- Hash Rate and Mining Cost models where BTC price reflects the higher cost of production of the digital asset
 - As mining becomes more energy-intensive and expensive, the BTC price rises to ensure mining profitability (Hayes, 2017).
 - Proof-of-Work is an upside rather than a downside
 - What about Miners lending computing power to AI when the BTC price is down?

Previous Literature – Valuation models

- Metcalfe's Law, the Network Value to Transactions (NVT) ratio, and sentiment-based predictors—add network utility and behavioural components to the pricing framework,
 - but misses to address BTC statistical return structure or long-run risk profile (Peterson, 2018) and often fail short in providing out-of-sample forecasting (Shelton, 2024).
- Although these frameworks highlight important economic mechanisms, they fall short in accounting for the empirical stylized facts of Bitcoin.
- As Bitcoin's monetary base strengthens and its adoption grows, a deeper question arises: could its risk profile ever evolve to something less risky? Will its volatility shrink over time and land the asset to safer havens? Here is where a more recent development comes to help.

Power law models – pros and cons

- Although this approach does not represent a complete stranger in the study of financial assets (Sornette, 2017) its main field of application is physics rather than finance and this peculiarity stimulated a back-and-forth discussion whether it is a valuable one to value long-term Bitcoin pricing or not.
- Stolte (2022) considers the model severely flawed and criticizes its statistical soundness, arguing that the log-time transformation is not meaningful and that the relationship is spurious without cointegration.
- Burger (2019) presents the model as empirically well-fit and as a surprisingly predictive framework, and although it is purely time-based, also Bitcoin's programmed scarcity (e.g., halvings) is itself time-driven, and this make plausible that such a model remains valid in the long run,
- Burger and Santostasi (2024) furtherly preserve the validity of power-law thesis defending the idea that a time-based power-law corridor is not spurious, but instead shows stationary residuals and cointegration, which makes the model statistically meaningful
 - The model is accurate in describing average long-term Bitcoin prices in the past, hence we consider it as a part of our scenario to investigate what pertain the allocation of financial resources by investors and the estimation of a more efficient portfolio frontier

Structural breaks in volatility

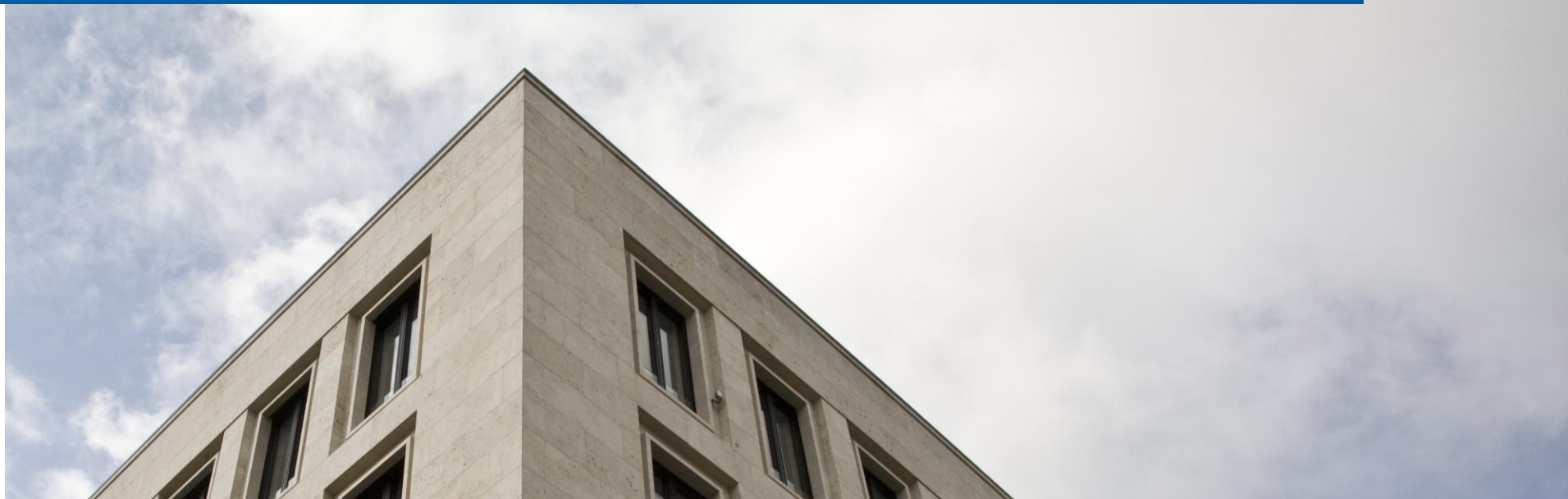
- Mid-2014, exchange defaults (see Bariviera, 2017; Thies and Molnar, 2018)
- Late-2020, institutional adoption (see Tekin, 2024)
- Late-2021, introduction of the first U.S. futures-based ETF (BITO) (Chen et al., 2025) changed the composition of participants in the derivatives market and improved liquidity in Bitcoin derivative contracts.
- Oct-2023, first U.S. spot-ETF approval (Li & Patel, 2025)
 - Not enough data to work with
- The analysis distinguishes between these different regime shifts to better calibrate our findings and provide
 - on the one hand, an analysis wide enough to comprehend any fall back in the process of reducing volatility endured by Bitcoin
 - on the other hand, a good proxy of the rate of reduction according to current market condition.

Kurtosis and KPSS tests

Sample	Statistics	coeff	p-value	dw
Full	Kurtosis	-0.0034	6.09E-18	0.0078
	KPSS (pos)	5.111	0.01	
	KPSS (neg)	3.948	0.01	
From 2014	Kurtosis	-0.0001	0.69	0.0056
	KPSS (pos)	3.0991	0.01	
	KPSS (neg)	0.7228	0.011	
From 2020	Kurtosis	0.0034	0.00014	0.0086
	KPSS (pos)	1.757	0.01	
	KPSS (neg)	1.1944	0.01	
From 2022	Kurtosis	-0.02231	6.58E-44	0.059
	KPSS (pos)	1.6514	0.01	
	KPSS (neg)	2.2358	0.01	

Between Compliance and Strategy: Determinants of voluntary PAI Disclosure Decisions under the SFDR

F. Fiore, A. Knetsch, L. Carmelo, L. Pelizzon, P. Rajan, K. Vozian



Introduction

- **The EU has advanced an ambitious sustainability agenda:** The SFDR is a key instrument to enhance transparency and reorient capital flows.
- **Main Objectives of the SFDR:** Support investor decision making by:
 - Enhancing transparency with regard to ***sustainability risks*** and ***adverse impacts***
 - Establishing standardized market requirements and
 - Ensuring comparability across financial products
- **Principal Adverse Impact (PAI) indicators:** Standardized non-commercial measures quantifying **negative environmental and social effects** of investments
- ***Disclosure is only mandatory at the entity level***



Motivation

- **SFDR June 2023: Mandatory PAI disclosure at entity level (>500 employees)**
- The SFDR provides asset managers with the unique opportunity to *disseminate standardized adverse impact metrics* with their product offerings.
- **Product-level disclosure remains discretionary**
- We focus on the **14 mandatory PAI indicators** that pertain to corporate assets and are part of the entity-level PAI disclosures (Annex I of the Commission Delegated Regulation (EU) 2022/1288)



Our current work – Central Research Question

FOCUS on product-level disclosure

- **How product-, market-, and firm-level characteristics** determine Funds Asset Managers' disclosure decisions.
- How have asset managers responded to SFDR's disclosure?
- which factors determine their product-level disclosure decisions?

FOCUS on Principal Adverse Impacts (PAIs)?

Our Current Work - Related Literature

Studies on SFDR mainly focus on Article Classification

- ESG ratings for EU-based funds rose after the announcement of the SFDR (Becker et al., 2022), reflecting a positive *ESG-information market* response to the anticipated broader regulatory transparency effects.
- However, rating improvements are not directly attributable to specific article classifications (Martinez-Meyers et al., 2024) and article classifications remain less influential than external ESG ratings (Ferriani, 2024).
- Article classifications affect fund flows and investors value in particular the Article 9 label despite their comparable financial underperformance (Becker et al., 2022; Scherer et al., 2023; Bosio et al., 2025; Ferriani, 2024).
- Article 9 funds show greater sectoral concentration and varying levels of impact ambition (Bosio et al., 2025; Scheitza et al., 2024).
- Self-selected article classifications suffer from category fuzziness and ambiguity (Cremasco et al., 2022; Bodellini, 2023). Regional and global Article 9 funds differ in sectoral exposure, resembling carbon home-bias patterns (Lambillon et al., 2023; Bolton et al., 2024; Boermans et al., 2025).

Despite crucial relevance and rising market adoption, evidence on SFDR PAIs remains scarce

- AMs product level PAI *consideration* and *disclosure* rose compared to last year (89.2% of Art. 8 and 97.2% and of Art.9 Funds consider PAIs as of Jan. 2025). Data coverage improved significantly for corporate PAI indicators (ESA, 2025).
- Traditional ESG ratings suffer from ambiguity and offer limited impact related insights (Berg et al. 2022, Popescu et al., 2021). Despite reflecting a valuable first step, current SFDR PAI indicators lack granularity and suffer from methodological ambiguities, prompting calls for more rigorous, measures that closing the gaps between SFDR, EU Taxonomy, and CSRD (Popescu et al., 2024)

We offer the first EU-wide evidence on voluntary fund-level PAI disclosures, uncover its institutional, regulatory, and strategic drivers, and introduce a Misalignment Index to reveal potential strategic reporting.

Conceptual Framework – PAI Disclosure ≠ PAI Consideration

PAI Entity-Level
Disclosure

Mandatory for Asset Managers that have more than 500 Employees

*Cheaper
Disclosure
(size channel)*

MIFID II – Art. 7 (c): PAIs may be used to substantiate sustainability preferences (All Funds)

PAI
Consideration

**All Funds
(incl. Art. 6)**

Funds need to account for sustainability risks and publish a statement on the same

Article 8 Funds

Promotion of sustainable investments (e.g. ESG filters, tilts, or screens)

Article 8+ Funds

Funds which have a sustainable investment target i.e. include sustainable investments

Article 9 Funds

Funds that invest exclusively or predominantly in holdings that qualify as sustainable investments

*More Costly
Disclosure
(consideration channel)*

PAI
Utilization

Example: Fund may exclude any company flagged under PAI 10 (UNGC Violations) to ensure alignment with its promoted social or environmental characteristics.

Do no significant harm (DNSH): PAIs are used to confirm that sustainable investments do no significant harm

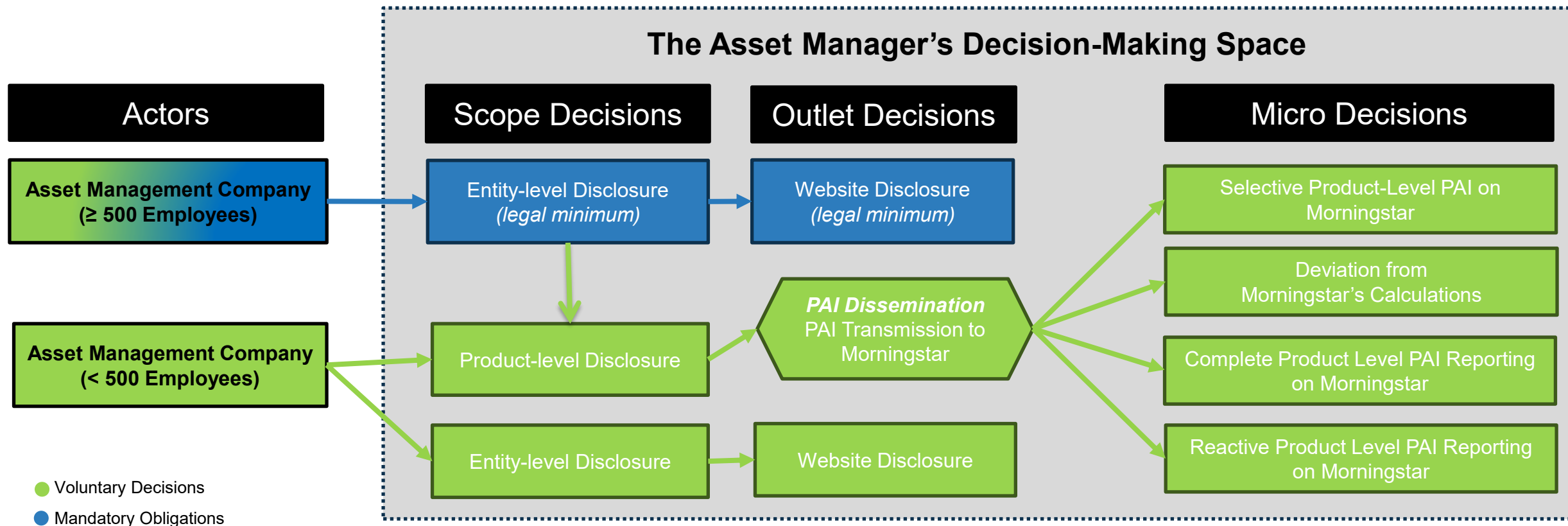
PAI Fund-Level
Disclosure

?

Conceptual Framework –The Asset Manager’s Decision-Making Space

The SFDR entails varying regulatory obligations, implying different product-level disclosure costs

- Large entities (>500 employees) already have PAI infrastructure in place, lowering product-level disclosure costs.
- Small entities voluntarily disclosing product-level PAIs must perceive comparably greater benefits from doing so.



Institutional Factors

- H1: Funds belonging to entities with more than 500 employees are more likely to disclose PAIs.
- H2A: Article 8 and 9 funds are more likely to disclose PAIs than Article 6 funds.
- H2B: Article 8 and 9 funds belonging to large asset managers (≥ 500 employees) are more likely to disclose PAIs than Article 6 funds managed by similarly large entities.

Supervisory Factors:

- H3: Product-level PAI disclosure patterns do not vary systematically by the fund's country of registration.

Strategic Factors:

As the SFDR increases transparency, Asset Managers product-level PAI dissemination decisions are not primarily driven by strategic misrepresentation considerations, thus...

- H4A: ...entity-level SFDR disclosure obligations do not lead to higher product-level reporting quality.
- H4B: ... fund-level PAI indicators disseminated by Asset Managers to the broader public do not systematically deviate from PAI indicators provided by Morningstar.

Data – Sample

Source: from Morningstar.

- AM report product-level PAIs to Morningstar voluntarily via the EET (Self-reported fund-level PAIs)
- Morningstar independently computes product-level PAIs (Morningstar fund-level PAIs)

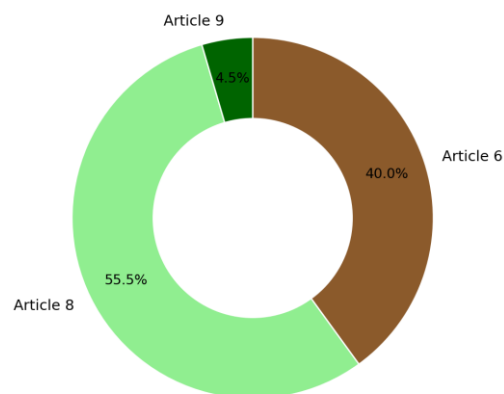
Selection: Funds within SFDR scope and $\geq$ EUR 10m AUM.

Final Sample: 16,908 funds (monthly, Jun 2023–Mar 2025).

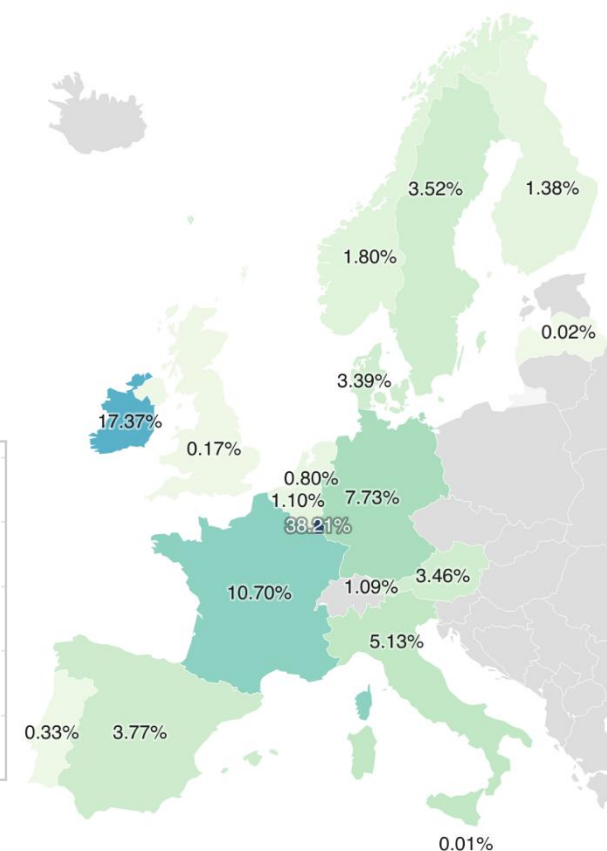
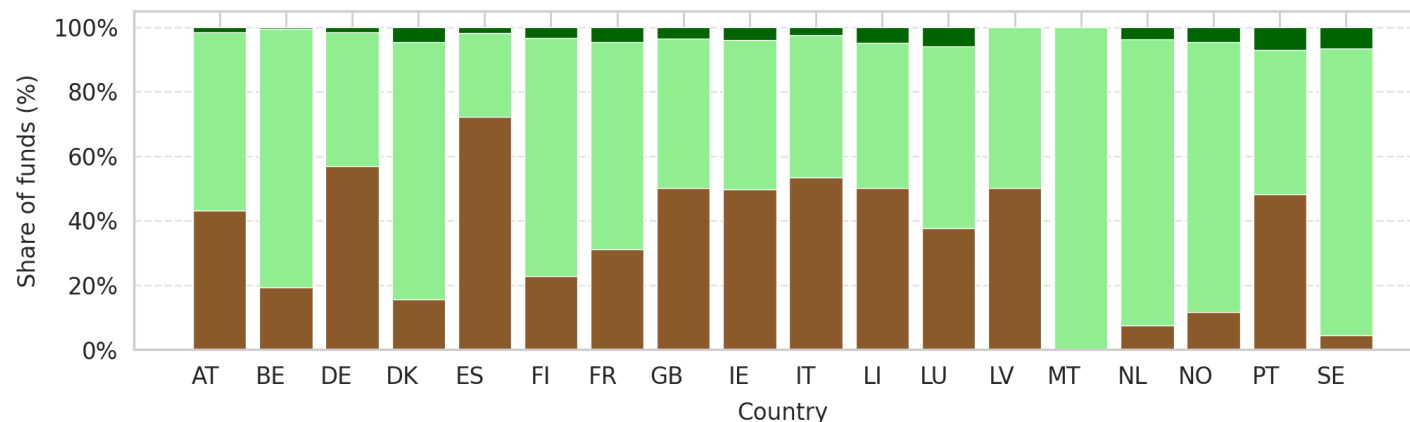
Fund Registration by Country (%)



SFDR Article Distribution (Fund-Level)



SFDR Article Distribution per Country (%)



Data – Fund-level PAI Dissemination

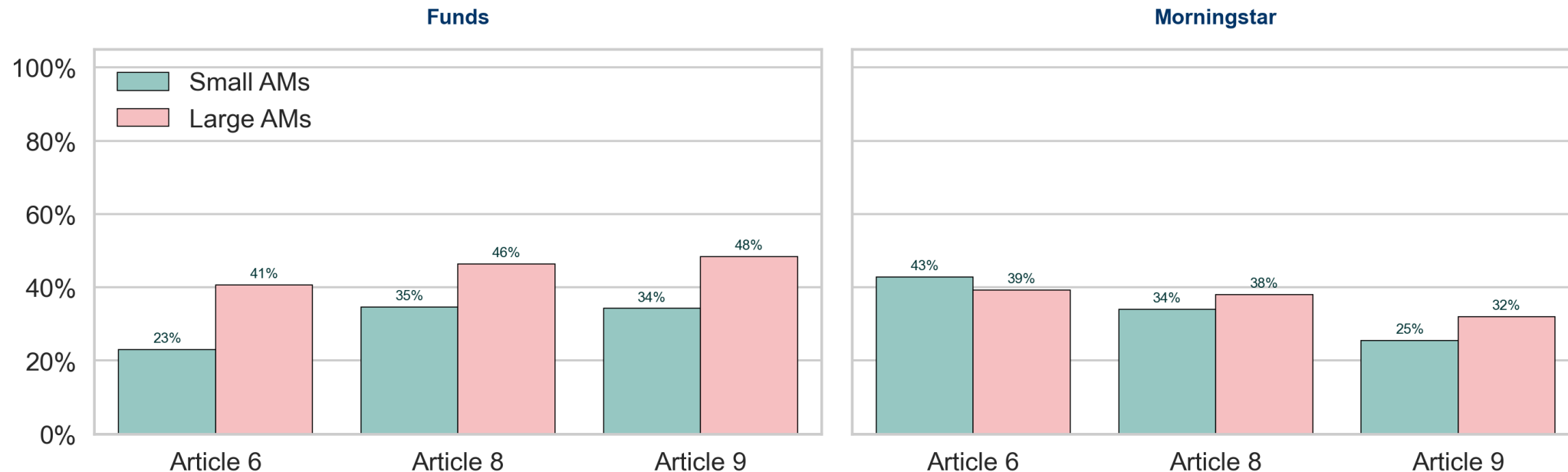
Fund-Level PAI Disclosure — Large vs Small AMs



- **Large AMs clearly disclose more often PAIs at fund level:** This could reflect the *lower cost of reporting* at fund level.
 - **Despite higher product-level disclosure costs:** Small AMs report PAIs more frequently for Article 8 and 9 funds than for Article 6 funds
- Together with Morningstar's fund-level PAI provision, this points to a strong demand for product-level adverse impact information, particularly from investors in Article 8 and 9 funds.

Data – Fund-level PAI Dissemination

Provided all mandatory PAIs (%) — Funds vs Morningstar



- **Funds disseminate all mandatory PAIs more often than Morningstar:** Irrespective of AM size, AMs offering Article 8 and 9 products report all mandatory PAIs more often than Morningstar indicates, highlighting strong demand for product-level adverse impact information.
- **Could this reflect the SFDR’s “best effort obligation” Art. 7 (2) SFDR RTS?:** Accordingly, “FMPs are under a best-effort obligation to obtain PAI data through engagement, third parties or additional research where this is not available.” (Partiti 2024, p. 316)

Empirical Analysis – Drivers of PAI Disclosure

$$AOP_{ijt} = ENT_{\geq 500_i} + ARTICLE8_j + ARTICLE9_j + ENT_{\geq 500_i} \times ARTICLE_j + MSAOP_{jt} + CONTROLS_j + \varepsilon_{ijt}$$

- H1: Funds belonging to entities with more than 500 employees are NOT more likely to disclose PAIs. **NO!**
- H2A: Article 8 and 9 funds are NOT more likely to disclose PAIs than Article 6 funds. **NO!**
- H2B: Article 8 and 9 funds belonging to large asset managers (≥ 500 employees) are NOT more likely to disclose PAIs than Article 6 funds managed by similarly large entities. **Y/N**

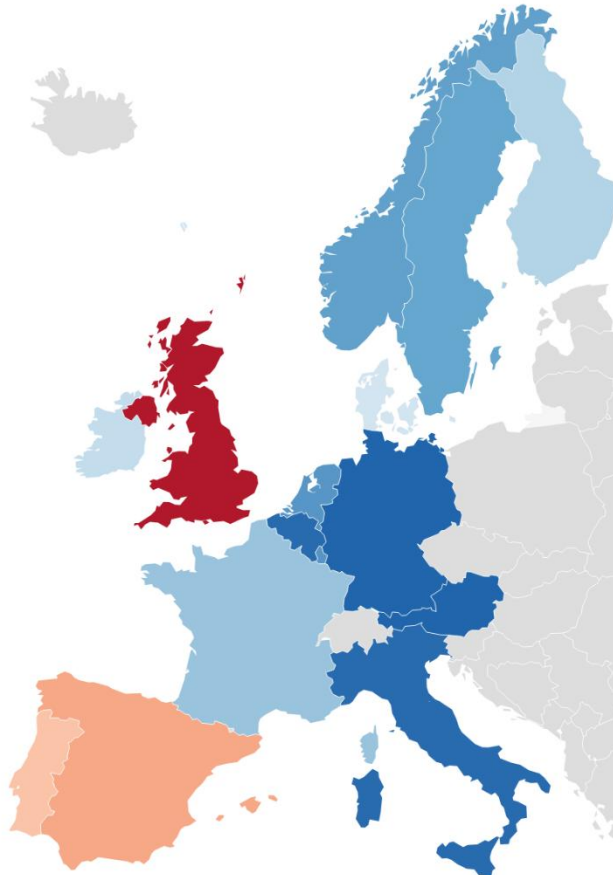
Table 1: Provision of at Least One Product-Level PAI Indicator

Dependent Variable: AOP	(1)	(2)	(3)
ENT ≥ 500	0.11*** (11.34)	0.12*** (12.68)	0.10*** (6.34)
ART8		0.23*** (24.46)	0.22*** (17.64)
ART9		0.27*** (13.17)	0.23*** (8.93)
ART8*ENT ≥ 500			0.02 (1.19)
ART9*ENT ≥ 500			0.11** (2.46)
MSAOP	0.21*** (4.97)	0.17*** (4.02)	0.17*** (4.08)
MSR	0.02*** (3.02)	0.01*** (2.79)	0.01*** (2.91)
MSESGR	0.03*** (6.48)	0.00 (0.95)	0.00 (1.02)
Observations	13,679	13,679	13,679
Pseudo R ²	0.0839	0.134	0.135

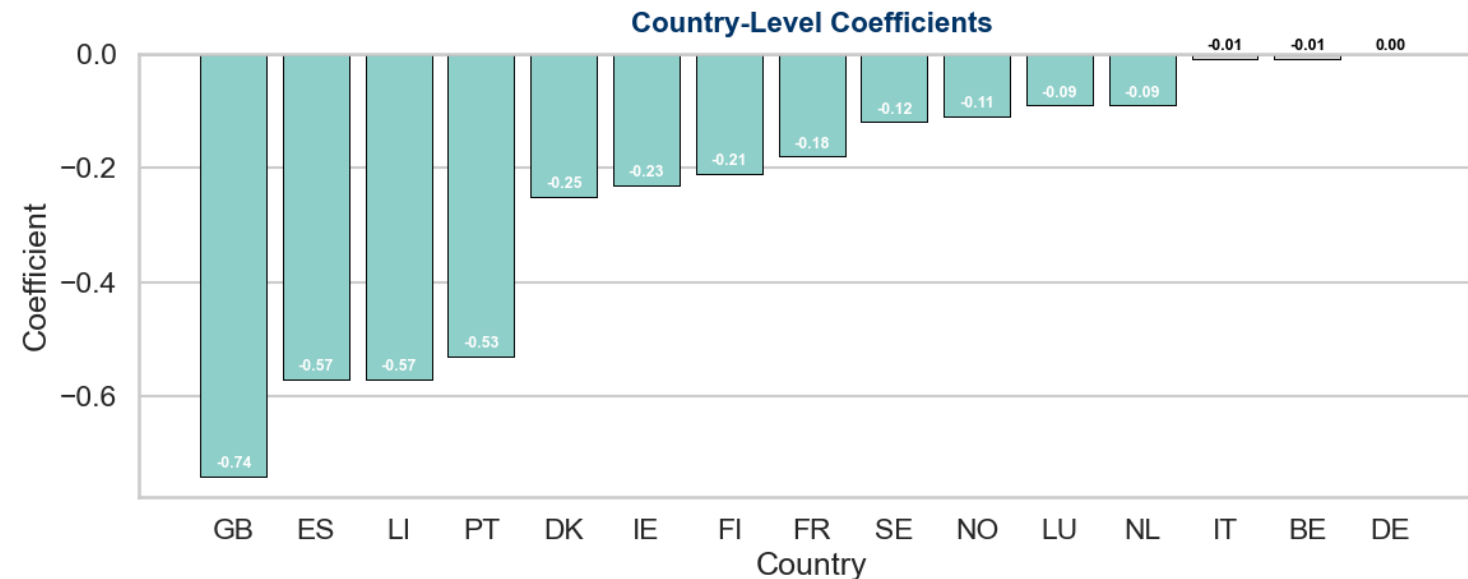
Note: All regressions include other controls, country FE, and year FE. Z-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Empirical Analysis – Drivers of PAI Disclosure: Country

Country Effects on Product-level PAI Disclosure



- H3: Product-level PAI disclosure patterns do NOT vary systematically by the fund's country of registration.



Empirical Analysis – Drivers of Reporting Quality

$$ARQ_{ijt} = ENT \geq 500_i + ARTICLE8_j + ARTICLE9_j + ENT \geq 500_i \times ARTICLE_j + MSARQ_{jt} + CONTROLS_j + \varepsilon_{ijt}$$

Table 3: Reporting Quality (Average Eligible Coverage)

Dependent Variable: ARQ	(1)	(2)	(3)
ENT $\geq$ 500	0.11*** (11.34)	0.12*** (12.68)	0.10*** (6.34)
ART8		0.23*** (24.46)	0.22*** (17.64)
ART9		0.27*** (13.17)	0.23*** (8.93)
ART8*ENT $\geq$ 500			0.02 (1.19)
ART9*ENT $\geq$ 500			0.11** (2.46)
AUM	0.03*** (9.34)	0.02*** (5.38)	0.02*** (5.47)
MSARQ	0.21*** (4.97)	0.17*** (4.02)	0.17*** (4.08)
MSR	0.02*** (3.02)	0.01*** (2.79)	0.01*** (2.91)
MSESGR	0.03*** (6.48)	0.00 (0.95)	0.00 (1.02)
Observations	13,679	13,679	13,679
Pseudo R ²	0.08	0.13	0.14

Note: All regressions include other controls, country FE, and year FE. Z-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

- H4A: ...entity-level SFDR disclosure obligations do NOT lead to higher product-level reporting quality. **NO!**

Empirical Analysis – Strategic Reporting

Table 3: Misalignment Index

Dependent Variable: MISALIGN	(1)	(2)	(3)	(4)
ENT $\geq$ 500	-10.92*** (-2.83)	-9.82*** (-2.99)	-9.86*** (-3.00)	-9.56 (-1.36)
ART8			-2.45 (-0.61)	-3.17 (-0.51)
ART9			-0.59 (-0.09)	10.15 (0.92)
ART8*ENT $\geq$ 500				1.62 (0.21)
ART9*ENT $\geq$ 500				-20.83* (-1.68)
ARQ		-0.26*** (-2.69)	-0.25*** (-2.67)	-0.26*** (-2.72)
MSARQ		-0.12 (-1.05)	-0.12 (-1.05)	-0.12 (-1.04)
RETURN	-8.31*** (-3.07)	-3.43* (-1.69)	-3.38 (-1.64)	-3.34 (-1.62)
FLOW	2.12*** (3.25)	1.77*** (3.33)	1.77*** (3.33)	1.75*** (3.31)
AUM	-1.49 (-1.15)	-0.82 (-0.77)	-0.73 (-0.68)	-0.72 (-0.67)
AGE	6.18*** (2.80)	3.77** (2.15)	3.69** (2.12)	3.70** (2.12)
MSR	0.67 (0.30)	-0.26 (-0.16)	-0.27 (-0.16)	-0.25 (-0.14)
MSESGR	-2.41 (-1.25)	-1.77 (-1.12)	-1.62 (-1.03)	-1.71 (-1.09)
Observations	8,600	8,330	8,330	8,330
R-squared	0.03	0.02	0.02	0.02

Note: All regressions include other controls, country FE, and year FE.
Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

$$\Delta_j = \frac{MSCalculated_j - Disseminated_j}{Disseminated_j}$$

$$MISALIGN_f = \frac{1}{N_f} \sum_{j=1}^{N_f} \Delta_{j,f}$$

- H4B: ... fund-level PAI indicators disseminated by Asset Managers to the broader public do NOT systematically deviate from PAI indicators provided by Morningstar.

- NO

Thank you for your attention



Smoke and Mirrors in ESG Reporting: Does Ownership Matter?

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2025 ESMA Research Conference

“Understanding investment funds: Developments and risks in the EU fund industry”

25.11.25

PRIN 2022: Tackling social-and green-washing: is the current EU regulatory framework enough?



Objective and motivation

The ESAs understand greenwashing as a practice where sustainability-related statements, declarations, actions, or communications do not clearly and fairly reflect the underlying sustainability profile of an entity, a financial product, or financial services. This practice may be misleading to consumers, investors, or other market participants.

ESMA (June 1, 2024)

- *Introduction of ESG washing Severity Index (ESGSI)*
- *Importance of accurate ESG assessment*
- *Increasing concerns of ESG washing in corporate disclosures*

Research Overview



Novel Text-Based Indicator

We introduce the ESG Severity Index (ESGSI) to capture inconsistencies between positive ESG narratives and actual ESG content density



Ownership Focus

Examining how ownership structures—especially family and institutional control—affect ESG reporting credibility



Advanced Analysis

Using topic modeling and explainable machine learning to decompose content of ESG reports



Investor Protection Implications

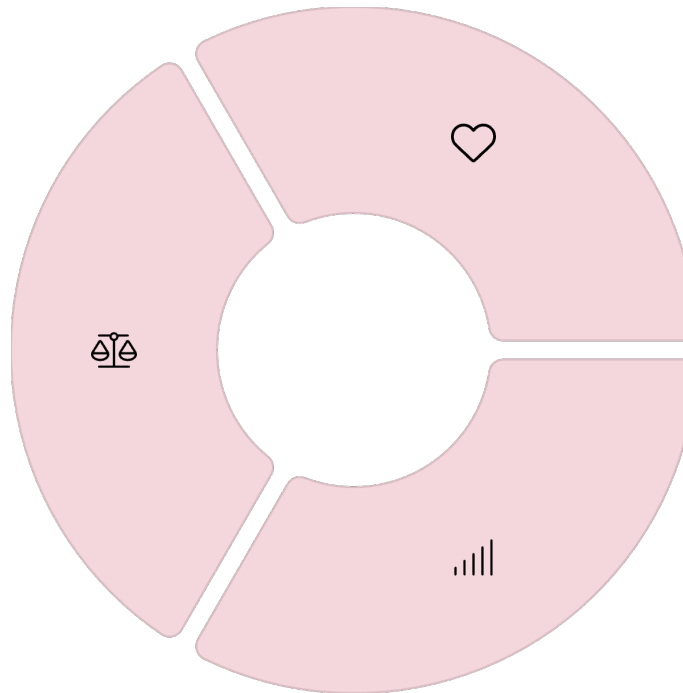
Findings suggest that relying solely on aggregate ESG scores may expose investors to misrepresented sustainability performance

Theoretical Framework

Agency Theory

ESG disclosure functions as both a governance device and a strategic instrument for managing stakeholder perceptions

Type II agency problems between controlling families and minority shareholders



Socioemotional Wealth

Non-financial goals of family firms including legacy, identity, and social capital can motivate authentic ESG engagement or encourage impression management

Signaling Theory

ESG disclosures as tools to convey unobservable firm quality

Cost asymmetry between symbolic and substantive ESG actions

Hypotheses Development

01

Family Ownership Effect

Family firms exhibit higher ESGSI values than non-family firms due to reputational sensitivity and identity preservation concerns.

02

Institutional Monitoring

Institutional ownership is negatively associated with ESGSI, as external monitors constrain symbolic disclosure behavior.

03

Market Discipline

Higher free float reduces ESGSI through increased market scrutiny and transparency pressure.

04

Performance Alignment

Among family firms, high ESGSI values are negatively associated with actual ESG performance—better performers engage in less rhetorical inflation.

05

Governance Moderation

Institutional ownership moderates the family control-ESGSI relationship, mitigating ESG-washing tendencies.

Data Collection

- 1,622 firms selected from top 10,000 publicly listed companies
- English-language sustainability reports (2018-2023)
- Ownership structure data from Refinitiv and Orbis
- ESG scores and controversy indicators from Refinitiv Eikon

Family Firm Identification

A firm is classified as family-controlled if:

- A founder/family member holds a board or executive role
- The family directly/indirectly owns $\geq 5\%$ of voting rights

ESGSI Formula

$$ESGSI_i = \text{Sentiment}_{i,norm} - \text{Sustainability}_{i,norm}$$

Positive values indicate excessive optimism relative to ESG content. The index captures **narrative decoupling**—when tone exceeds substance.

Sentiment measured via TextBlob polarity; sustainability content via TF-IDF weighting of curated ESG term dictionary (extracted from GRI, SASB frameworks, EU Taxonomy).

Variable	Definition	Source	Mean (SD)
<i>Textual Variables</i>			
<i>ESG Severity Index (ESGSI)</i>	Sentiment-content gap in ESG disclosure	NLP from ESG reports	-0.26 (0.15)
<i>Normalized Sentiment Score</i>	TextBlob polarity score normalized to [0,1]	NLP	0.3150 (0.0638)
<i>Normalized Sustainability Score</i>	TF-IDF-based ESG content score normalized to [0,1]	NLP	0.5737 (0.1342)
<i>Sentiment Polarity</i>	Polarity score [-1, 1]; > 0 = positive tone	NLP	0.0932 (0.0301)
<i>Sentiment Subjectivity</i>	Subjectivity score [0,1]; higher = more opinionated tone	NLP	0.3506 (0.0465)
<i>Ownership Variables</i>			
<i>Family Control Dummy</i>	1 if a founder/family member holds a board role and owns $\geq 5\%$ voting rights	Hand-collected;	0.25 (0.43)
<i>Fund Control Dummy</i>	1 if a mutual or investment fund is the largest blockholder	Refinitiv	0.07 (0.26)
<i>Institutional (%)</i>	Shareholding by institutional investors	Refinitiv	49.78 (23.41)
<i>Free Float (%)</i>	Percentage of publicly held shares	Refinitiv	62.31 (24.08)
<i>Performance and Size Controls</i>			
<i>ROA</i>	Return on Assets: Net Income / Total Assets	Refinitiv	–
<i>Refinitiv ESG Score</i>	Composite ESG rating (0–100)	Refinitiv	49.62 (22.83)
<i>Total Assets_{t-1}</i>	Natural log of total assets	Refinitiv	15.84 (2.12)
<i>Employees_{t-1}</i>	Natural log of total employees	Refinitiv	–
<i>Net Income_{t-1}</i>	Natural log of net income	Refinitiv	–
<i>Interaction Terms</i>			
<i>Family × ESG Score</i>	Interaction: family control and ESG score	Constructed	–
<i>Fund × ESG Score</i>	Interaction: fund control and ESG score	Constructed	–
<i>Institutional Ownership × ESG</i>	Interaction term	Constructed	–
<i>Family × Free Float</i>	Interaction term	Constructed	–
<i>Fund × Free Float</i>	Interaction term	Constructed	–
<i>Institutional Ownership × Free Float</i>	Interaction term	Constructed	–
<i>Fixed Effects / Controls</i>			
<i>Sector Fixed Effects</i>	Dummies for TRBC industry sectors	Refinitiv	–
<i>Continent Fixed Effects</i>	Dummies for region of headquarters	Refinitiv	–



Analysis



Named Entity
Recognition

ESG Severity Index (ESGSI) Construction

Text Pre-processing (1)

Texts are lowercased, tokenized, lemmatized, and stripped of stopwords and boilerplate content using NLTK

ESG Term Frequency (3)

Lexicon of ESG-specific terms constructed based on established standards (GRI, SASB, ...) with TF-IDF weighting

Sentiment Analysis (2)

TextBlob library applied to extract sentiment polarity score (-1 to +1) capturing overall tone and optimism

ESGSI Calculation (4)

$ESGSI = \text{Normalized Sentiment Score} - \text{Normalized ESG Term Density}$

Higher values indicate excessive positivity relative to ESG content

ESGSI Construction



Textual ESG sentiment

Computed using TextBlob sentiment polarity on cleaned company reports.



Sustainability term density

Calculated using TF-IDF scores of a curated ESG keyword dictionary.



ESGSI

Computed as:

$$\text{ESGSI} = \text{Normalized Sentiment Score} - \text{Normalized Sustainability Score}$$

The ESG Severity Index (ESGSI)



Text Preprocessing

Lowercasing, tokenization, lemmatization, and removal of stopwords



Sentiment Analysis

Extract sentiment polarity score ranging from -1 to +1



ESG Term Frequency

Compute sustainability relevance score using TF-IDF weighting



ESGSI Calculation

Difference between normalized sentiment and ESG term density

Higher ESGSI values indicate excessive positivity relative to ESG content, signaling potential ESG washing. This metric captures the decoupling between narrative tone and substantive ESG discourse, offering a granular measure of disclosure integrity.

Methodology

Example: Input Text

Bank of Example offers premium Banking services. Visit us at www.bankofexample.com!

- **Text Normalization**

"bank of example offers premium banking services visit us"

- **Tokenization**

["bank", "of", "example", "offers", "premium", "banking", "services", "visit", "us"]

- **Stopword Removal**

Exclude common stopwords to focus on relevant terms.["bank", "example", "offers", "premium", "banking", "services", "visit"]

- **Lemmatization**

Simplify words to their base or dictionary form.["bank", "example", "offer", "premium", "bank", "service", "visit"]

- **Vectorization (TF-IDF)**

Convert text data into a numerical format using TF-IDF, which reflects the importance of each word within the document and the corpus.

Methodology

Sentiment Analysis

- Assesses the emotional tone of texts.
- Uses **TextBlob library** for calculating sentiment scores.
- **Polarity**: Ranges from negative to positive, indicating sentiment tone.
- **Subjectivity**: Measures if sentiment is an opinion or factual.

Sustainability Content Analysis

- Analyzes presence of sustainability-related terms using **TF-IDF vectorization**.
- Calculates sustainability score based on term prominence.
- Provides an objective measure of substantive content on sustainability.

- TEXTBLOB: Loria, S. (2018). TextBlob: Simplified Text Processing. <https://textblob.readthedocs.io/en/dev/>
- TF-IDF: Salton, G., & Buckley, C. (1988). Term-weighting approaches in automatic text retrieval. *Information Processing & Management*, 24(5), 513–523. [https://doi.org/10.1016/0306-4573\(88\)90021-0](https://doi.org/10.1016/0306-4573(88)90021-0)
- SHAP: Lundberg, S. M., & Lee, S.-I. (2017). A Unified Approach to Interpreting Model Predictions. *Advances in Neural Information Processing Systems*, 30, 4765–4774.

Descriptive Statistics of Textual Indicators

Variable	Mean	Std. Dev.	Min	Max
ESG Severity Index (ESGSI)	-0.2587	0.1501	-0.7008	0.8116
Normalized Sustainability Score	0.5737	0.1342	0.0307	1.0000
Normalized Sentiment Score	0.3150	0.0638	0.0000	1.0000
Sentiment Polarity	0.0932	0.0301	-0.0556	0.4167
Sentiment Subjectivity	0.3506	0.0465	0.0000	0.5379

The ESG Severity Index exhibits considerable variation across firms, with values ranging from approximately -0.70 to +0.81, reflecting both negative and positive imbalances between sentiment and sustainability content.

Econometric Implementation

Our core OLS specification is given by:

$$\begin{aligned} \text{ESGSI}_i = & \alpha + \beta_1 \text{FamilyControl}_i + \beta_2 \text{FundControl}_i + \beta_3 \text{InstitutionalOwnership}_i + \beta_4 \text{ROA}_i \\ & + \beta_5 \text{RefinitivESGScore}_i + \beta_6 \log(\text{TotalAssets}_{i,t-1}) + \beta_7 \text{Employees}_{i,t-1} + \beta_8 \text{NetIncome}_{i,t-1} \\ & + \beta_9 (\text{FamilyControl}_i \times \text{RefinitivESGScore}_i) + \beta_{10} (\text{FundControl}_i \times \text{RefinitivESGScore}_i) \\ & + \beta_{11} (\text{InstitutionalOwnership}_i \times \text{RefinitivESGScore}_i) + \beta_{12} (\text{FamilyControl}_i \times \text{FreeFloat}_i) \\ & + \beta_{13} (\text{FundControl}_i \times \text{FreeFloat}_i) + \beta_{14} (\text{InstitutionalOwnership}_i \times \text{FreeFloat}_i) \\ & + \beta_{15} \text{FreeFloat}_i + \beta_{16} \text{FreeFloat}_i^2 + \varepsilon_i \end{aligned}$$

We also implement a binary indicator of ESG-washing exposure ($\text{ESGSI} > 0$) using logistic regression and apply machine learning techniques for further analysis.

Machine Learning and SHAP Analysis

To investigate non-linear relationships driving ESGSI:

- *Implemented RandomForest model for its robustness to multicollinearity*
- *Applied SHapley Additive exPlanations (SHAP) for model interpretation*
- *Quantified marginal contribution of each feature to predictions*
- *Provided both global and local interpretability*

RandomForest achieved an R^2 of 0.0541 on the test set, indicating foundational predictive capability for this complex phenomenon.

OLS Regression Results

Variable	Coefficient	Std. Error
Family Control	0.1584***	(0.034)
Fund Control	0.0717	(0.086)
InstitutionalOwnership	0.0020	(0.001)
ESGScore (Refinitiv)	0.0261***	(0.006)
TotalAssets t-1	-0.0020***	(0.000)
Family × FreeFloat	-0.0050***	(0.001)
FreeFloat	0.9693***	(0.051)
FreeFloat ²	-1.0725***	(0.063)

Observations: 1,525 | Adjusted R²: 0.417 | F-statistic: 69.10***

*** p<0.01



Family Control

Higher ESGSI values indicating greater ESG-washing tendency



Free Float Interaction

Family × FreeFloat is negative and significant ($\beta = -0.0050$, $p < 0.001$)

ESG-washing tendency mitigated as externally shares increases



Market Discipline

Inverted U-shape relationship between free float and ESGSI

ESG-washing peaks at moderate levels of market scrutiny
but diminishes under intense external pressure

Family Control and ESGSI

- Family-controlled firms exhibit significantly higher ESGSI levels
- Indicates greater narrative-substance gaps in ESG reporting
- Supports Hypothesis H1
- Challenges assumption that family firms engage in more authentic communication

Machine Learning Results

Model	R ² CV	R ² Test	RMSE	MAE	Top Variables
Lasso	0.0043	-0.0076	0.1462	0.1147	TotalAssets t-1, Family × ESG, ROA
Ridge	-0.0028	-0.0090	0.1463	0.1143	FreeFloat, FreeFloat ² , Family
ElasticNet	0.0043	-0.0075	0.1462	0.1147	Control TotalAssets t-1, Family × ESG, ROA
Random Forest	0.0708	0.0541	0.1416	0.1092	TotalAssets t-1, ESGScore, InstitutionalOwners hip
Gradient Boosting	0.0721	0.0480	0.1421	0.1092	ESGScore, TotalAssets t-1, NetIncomet-1

Confirm OLS results
Tree-based models outperform penalized regressions, with Random Forest yielding the best performance.

Top Predictors by SHAP and Permutation Importance



Total Assets

Firm size exerts strongest influence—larger firms face higher reputational stakes

Institutional Ownership

External monitoring significantly shapes disclosure credibility



ESG Score

Third-party ratings correlate with ESGSI, revealing potential decoupling

Free Float²

Nonlinear market discipline effects confirmed through quadratic term

*SHAP values provide transparent, feature-level decomposition of ESG-washing propensity. Convergence between SHAP rankings and permutation importance validates model insights. The prominence of **Total Assets and Institutional Ownership** underscores governance factors as primary drivers.*

Subsample Analysis by Continent

1

North America

Higher free float exhibits significantly higher ESGSI values

Refinitiv ESG score negatively associated with ESGSI

Family × ESG interaction positive and significant

2

Europe

Only significant predictor is firm size (Total Assets), which has a negative effect

Larger firms tend to disclose ESG information more proportionately to actual ESG performance

3

Asia

Strong explanatory power ($R^2 = 0.1918$) despite small sample size

Negative effect of ESG score and positive moderation by institutional ownership

Hypothesis Testing Summary

1

H1: Family Firms → Higher ESGSI

Supported. Family Control coefficient +0.158*** in multivariate OLS. Family firms exhibit greater narrative-substance gaps.

2

H2: Institutional Ownership → Lower ESGSI

Supported. Negative Pearson correlation significant; OLS coefficient negative and significant in full specification.

3

H3: Free Float → Lower ESGSI

Supported. Negative Pearson correlation; inverted U-shape in regression confirms market discipline effect.

4

H4: Family Firms—ESG Performance → Lower ESGSI

Supported. Subsample regression shows negative ESG Score coefficient among family firms.

5

H5: Institutional Ownership Moderates Family Effect

Supported. Family×Institutional Ownership interaction negative and significant, confirming mitigating role.

Key Takeaways

Family firms are more prone to ESG-washing

Despite presumed sustainability orientation, reputational concerns and SEW priorities drive excessive ESG rhetoric relative to substantive content.

Higher ESG scores reflect form and not substance

Higher third-party ESG scores correlate with higher ESGSI—suggesting ratings may reward disclosure narrative over ESG content. Investors need complementary tools.

Governance mechanisms matter

Ownership dispersion (free float) and institutional monitoring constrain symbolic disclosure. Market discipline and external scrutiny mitigate ESG-washing tendencies.

Context shapes behavior

Institutional environment, industry norms, and firm characteristics create heterogeneous ESG-washing patterns. One-size-fits-all regulation insufficient.

Implications for Stakeholders



Investors & Asset Managers

ESGSI can serve as a red flag mechanism in ESG due diligence and portfolio screening

Helps reduce misallocation of sustainable finance capital



Family Firms

Cautionary note about overreliance on rhetorical strategies

Need to ensure ESG claims are backed by verifiable action



Policymakers & Regulators

Support for more stringent ESG disclosure requirements and third-party verification

ESGSI offers a data-driven method to detect early signs of ESG-washing



Standard Setters

Importance of coupling quantitative indicators with linguistic analysis

Consider incorporating textual inconsistency checks in frameworks

Contributions and Limitations

Contributions

- *Novel ESG Severity Index (ESGSI) combining sentiment and content analysis*
- *Nuanced view of ESG-washing as strategic behavior influenced by governance characteristics*
- *Bridge between narrative and numeric analysis with practical applications*

Limitations

- *Based on English-language disclosures only*
- *Sentiment analysis does not capture sarcasm, irony, or nuanced rhetoric*
- *Classification of family firms relies on available ownership data*
- *Refinitiv ESG performance scores*
- *Refine ESGSI with transformer-based models for deeper contextual understanding*

Thank you!

PRIN 2022: Tackling social-and green-washing: is the current EU regulatory framework enough?



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