Assessing the Performance of AI-managed Portfolios

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joint with Iván Simon

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Introduction I

- 18/10/2017 AIEQ was launched (first AI-powered public fund)

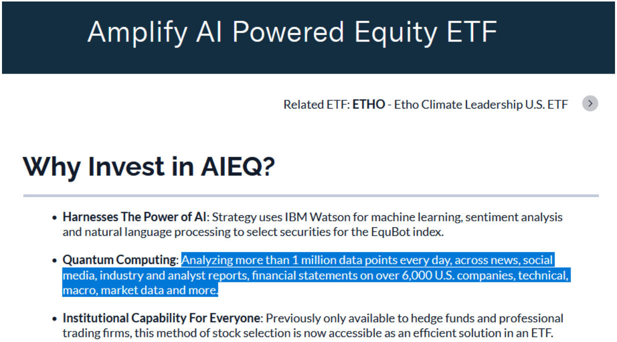

Figure: Screenshot: Amplify ETFs (2024)

Introduction I

- 18/10/2017 AIEQ was launched (first AI-powered public fund)
- AI has several advantages over human fund managers (as described e.g. Chen and Ren, 2022)
  - higher computational power
  - no behavioural biases (Linnainmaa et al., 2021)
  - human fund performance is declining (Barras et al., 2010)
  - extreme cases of AI strategies claim to produce SR of above 2.0 and alphas over 13% (Chen et al., 2024, Cong et al., 2021)
- AI also has some disadvantages
  - limited *marginal* predictive power (Gu et al., 2020)
  - high turnover or trade assets with low liquidity (Avramov et al., 2023, Chen and Velikov, 2023)

Introduction II

- Are those AI strategies actually profitable?
- $\longrightarrow$ hands-on real fund approach: investigate funds that use AI to outperform (similar to Chen and Ren, 2022)

Preview

- Are they profitable?
  - Not more than conventional funds or the market.
- What about skill?
  - AI (for allocations) trades excessively or illiquid stocks
  - good at market timing, bad at stock picking

Identifying AI funds

1. download all SEC 497-K filings from EDGAR
2. screen filings for AI-related keywords
3. review/verify all matches manually

Data Sources Further Information

⚠ AI-labelled rather than AI-enhanced?

Identifying Rival Funds

adapt Hoberg et al. (2018):

- match funds w/similar fund characteristics
- specify distance metric
  - z-scores or ranks
  - orthogonalize
- compute Euclidean distances
- cut off at a certain distance

Cumulative Returns I

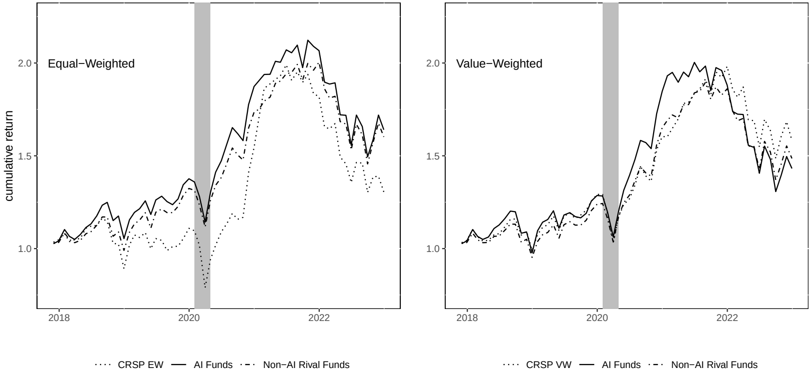

Figure: Return over time, equal- and value-weighted portfolio of AI and rival non-AI funds, incl. market benchmark

Distribution AuM | incl small funds | w/alternative rival funds

Summary Stats - Performance

	Sharpe Ratios									
	Equal Weighted Portfolios					Value Weighted Portfolios				
	SR	SR_{ann}	ΔSR_{AI-Rv}	se	pval	SR	SR_{ann}	ΔSR_{AI-Rv}	se	pval
AI	0.122	0.422				0.051	0.178			
Rivals (ew)	0.153	0.531	-0.032	0.031	0.300	0.132	0.456	-0.080	0.050	0.108
Rivals (dw)	0.155	0.537	-0.033	0.031	0.276	0.129	0.447	-0.078	0.048	0.103
Mkt	0.082	0.284	0.040	0.073	0.583	0.144	0.500	-0.093	0.063	0.141

Notes: Standard Errors for SR following Ledoit and Wolf (2008) based on the prewhitened Parzen kernel.

returns

Factor regressions

	Dependent variable:									
	AI fund returns (ew)					AI fund returns (vw)				
	Rivals (ew)	Rivals (dw)	CAPM	FFC4	FFC6	Rivals (ew)	Rivals (dw)	CAPM	FFC4	FFC6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	−0.157	−0.166	−0.017	0.008	0.100	−0.452	−0.439	−0.423	−0.379	−0.213
	(0.173)	(0.181)	(0.272)	(0.229)	(0.176)	(0.337)	(0.320)	(0.390)	(0.284)	(0.216)
rvex	1.089***					1.116***				
	(0.062)					(0.068)				
rvvx		1.089***					1.117***			
		(0.060)					(0.064)			
mkt			1.026***	0.989***	1.026***			1.053***	0.996***	1.053***
			(0.065)	(0.076)	(0.077)			(0.073)	(0.078)	(0.049)
smb				0.181***	0.056				0.397***	0.194*
				(0.069)	(0.087)				(0.117)	(0.102)
hml				−0.219***	−0.187***				−0.311***	−0.239***
				(0.043)	(0.069)				(0.055)	(0.066)
rmw					−0.267***					−0.422***
					(0.075)					(0.101)
cma					0.041					0.020
					(0.091)					(0.071)
mom				−0.021	−0.046				0.026	−0.007
				(0.053)	(0.052)				(0.070)	(0.071)
Observations	62	62	64	64	64	62	62	64	64	64
Adjusted R^2	0.935	0.935	0.903	0.927	0.932	0.877	0.885	0.840	0.894	0.909

Note: Newey and West (1994) Standard Errors are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Cumulative Returns II

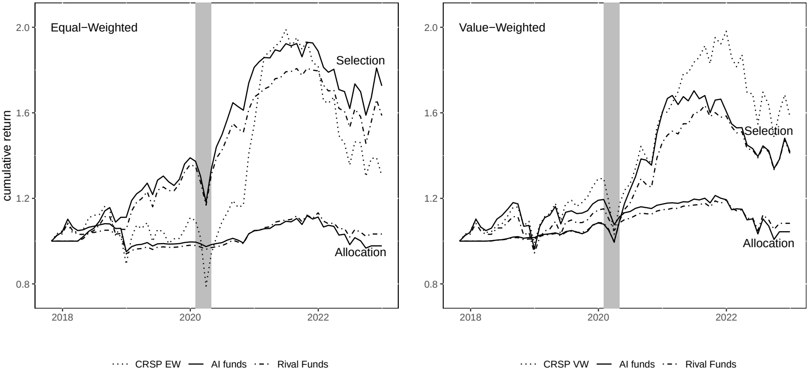

Figure: Return over time, sub-groups: AI in screening universe, AI in portfolio computation

incl small funds

Activeness & Skill

Pástor et al. (2020):

$$r = \mu g(T, L),$$

where μ reflects skill and

$g(T, L) = TL^{-1/2}$ how actively a fund applies skill

Activeness

Table: following Pástor et al. (2020), $FundActiveness = TL^{-1/2}$, where T is the turnover ratio and L is a liquidity measure.

	Dependent variable:	
	Fund Activeness	
	(1)	(2)
ai_fund	-5.4700^{***}	
	(2.1005)	
ai_in_stock_sel		-9.1556^{***}
		(1.6843)
quant_strat		7.9256^{*}
		(4.0933)
Observations	151,456	151,456
Adjusted R^2	-0.0002	-0.0002
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Skill I

Table: following Kacperczyk et al. (2014),

$$Timing_t^j = \sum_{i=1}^{N^j} \left(w_{i,t}^j - w_{i_t}^m \right) \left(\beta_{i,t} R_{t+1}^m \right)$$

	Dependent variable: Timing					
	(1)	(2)	(3)	(4)	(5)	(6)
ai_fund	0.0045***		0.0028***		0.0033***	
	(0.0007)		(0.0009)		(0.0009)	
ai_in_stock_sel		0.0048***		0.0025**		0.0028***
		(0.0009)		(0.0011)		(0.0010)
quant_strat		0.0038***		0.0041***		0.0050***
		(0.0010)		(0.0015)		(0.0015)
Controls	×	×	✓ (w/o MV)	✓ (w/o MV)	✓	✓
Observations	485,137	485,137	217,707	217,707	212,512	212,512
Adjusted R^2	−0.0001	−0.0001	0.0034	0.0034	0.0147	0.0147

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Skill II

Table: following Kacperczyk et al. (2014),

$$Picking_t^j = \sum_{i=1}^{N^j} \left(w_{i,t}^j - w_{i_t}^m \right) \left(R_{t+1}^i - \beta_{i,t} R_{t+1}^m \right)$$

	Dependent variable: Picking					
	(1)	(2)	(3)	(4)	(5)	(6)
ai_fund	−0.0058***		−0.0034*		−0.0038**	
	(0.0015)		(0.0018)		(0.0016)	
ai_in_stock_sel		−0.0059***		−0.0034		−0.0036*
		(0.0020)		(0.0022)		(0.0020)
quant_strat		−0.0055***		−0.0033*		−0.0043**
		(0.0015)		(0.0020)		(0.0021)
Controls	×	×	✓ (w/o MV)	✓ (w/o MV)	✓	✓
Observations	485,137	485,137	217,707	217,707	212,512	212,512
Adjusted R^2	0.0001	0.0001	−0.00003	−0.00004	0.0080	0.0080

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

What else?

- Persistence
- Fund Flows
- Robustness
  - Tiny funds ▸ w/tiny funds
  - Alternative variables to matching rival funds ▸ w/ranks ▸ w/z-scores

Conclusion

AI funds ...

- perform similar than traditional funds.
- are less active than traditional funds
- tend to exhibit timing abilities but lack them at picking stocks.

Thank you for your feedback

References I

Avramov, D., S. Cheng, and L. Metzker (2023). "Machine Learning vs. Economic Restrictions: Evidence from Stock Return Predictability". In: *Management Science* 69.5, pp. 2587–2619.

Barras, L., O. Scaillet, and R. Wermers (2010). "False Discoveries in Mutual Fund Performance: Measuring Luck in Estimated Alphas". In: *Journal of Finance* 65.1, pp. 179–216.

Chen, A. Y. and M. Velikov (2023). "Zeroing in on the Expected Returns of Anomalies". In: *Journal of Financial and Quantitative Analysis* 58.3, pp. 968–1004.

Chen, L., M. Pelger, and J. Zhu (2024). "Deep Learning in Asset Pricing". In: *Management Science* 70.2, pp. 714–750.

Chen, R. and J. Ren (2022). "Do AI-powered Mutual Funds Perform Better?" In: *Finance Research Letters* 47, p. 102616.

References II

- Cong, L. W., K. Tang, J. Wang, and Y. Zhang (2021). "AlphaPortfolio: Direct Construction Through Deep Reinforcement Learning and Interpretable AI". In: *Available at SSRN 3554486*.
- ETFs, A. (2024). *Amplify AI Powered Equity ETF*. https://amplifyetfs.com/aieq/ [Accessed: 14/08/2024].
- Gu, S., B. Kelly, and D. Xiu (2020). "Empirical Asset Pricing via Machine Learning". In: *Review of Financial Studies* 33.5, pp. 2223–2273.
- Hoberg, G., N. Kumar, and N. Prabhala (2018). "Mutual Fund Competition, Managerial Skill, and Alpha Persistence". In: *Review of Financial Studies* 31.5, pp. 1896–1929.
- Kacperczyk, M., S. V. Nieuwerburgh, and L. Veldkamp (2014). "Time-varying Fund Manager Skill". In: *Journal of Finance* 69.4, pp. 1455–1484.

References III

- Ledoit, O. and M. Wolf (2008). "Robust Performance Hypothesis Testing with the Sharpe Ratio". In: *Journal of Empirical Finance* 15.5, pp. 850–859.
- Linnainmaa, J. T., B. T. Melzer, and A. Previtero (2021). "The Misguided Beliefs of Financial Advisors". In: *Journal of Finance* 76.2, pp. 587–621.
- Newey, W. K. and K. D. West (1994). "Automatic Lag Selection in Covariance Matrix Estimation". In: *Review of Economic Studies* 61.4, pp. 631–653.
- Pástor, L., R. F. Stambaugh, and L. A. Taylor (2020). "Fund Tradeoffs". In: *Journal of Financial Economics* 138.3, pp. 614–634.