

Can LLM-based Financial Investing Strategies Outperform the Market in Long Run?

Weixian Waylon Li

AIAI, School of Informatics
The University of Edinburgh
Edinburgh, United Kingdom
waylon.li@ed.ac.uk

Mihai Cucuringu

Dept. of Mathematics; Dept. of Statistics & OMI
University of California, Los Angeles; University of Oxford
United States; United Kingdom
mihai@math.ucla.edu

Hyeonjun Kim

Global Finance Research Center
Sungkyunkwan University
Seoul, Republic of Korea
hjkimfin@gmail.com

Tiejun Ma

AIAI, School of Informatics
The University of Edinburgh
Edinburgh, United Kingdom
tiejun.ma@ed.ac.uk

Abstract

Large Language Models (LLMs) have recently been leveraged for asset pricing and stock trading applications, enabling AI agents to generate investment decisions from unstructured financial data. However, most evaluations of LLM timing-based investing strategies are conducted on narrow timeframes and limited stock universes, overstating effectiveness due to survivorship and data-snooping biases. We critically assess their generalisability and robustness by proposing FINSABER¹, a backtesting framework evaluating timing-based strategies across longer periods and a larger universe of symbols. Systematic backtests over two decades and 100+ symbols reveal that previously reported LLM advantages deteriorate significantly under broader cross-section and over a longer-term evaluation. Our market regime analysis further demonstrates that LLM strategies are overly conservative in bull markets, underperforming passive benchmarks, and overly aggressive in bear markets, incurring heavy losses. These findings highlight the need to develop LLM strategies that are able to prioritise trend detection and regime-aware risk controls over mere scaling of framework complexity.

CCS Concepts

- General and reference → Evaluation; Empirical studies;
- Computing methodologies → Intelligent agents.

Keywords

Automated trading, LLM investors, Backtest, Benchmark

ACM Reference Format:

Weixian Waylon Li, Hyeonjun Kim, Mihai Cucuringu, and Tiejun Ma. 2026. Can LLM-based Financial Investing Strategies Outperform the Market in Long Run?. In *Proceedings of the 32nd ACM SIGKDD Conference on Knowledge Discovery and Data Mining V.1 (KDD '26)*, August 09–13, 2026, Jeju Island,

¹Data and code available at <https://github.com/waylonli/FINSABER>.



This work is licensed under a Creative Commons Attribution 4.0 International License.
KDD '26, Jeju Island, Republic of Korea
© 2026 Copyright held by the owner/author(s).
ACM ISBN 979-8-4007-2258-5/2026/08
<https://doi.org/10.1145/370854.3785702>

Republic of Korea. ACM, New York, NY, USA, 15 pages. <https://doi.org/10.1145/370854.3785702>

1 Introduction

Large language models (LLMs) are increasingly used in financial decision-making, especially for generating investment actions such as Buy, Hold, or Sell [11, 18]. These so-called LLM *timing-based investing strategies* leverage LLMs' ability to interpret historical and real-time data to autonomously trade. From sentiment-driven trading [53] to sophisticated multi-agent systems [51, 54], a growing body of work has explored the potential of LLMs as autonomous financial agents.

Backtesting is the standard method for assessing investment strategies, simulating them on historical data to evaluate profitability and robustness [7, 33]. However, current LLM investing research suffers from fragmented, underdeveloped evaluation practices. Most studies assess performance over short periods, on few stock symbols, and often omit code release, limiting reproducibility. As summarised in Table 1, several recent methods evaluate over under a year, with fewer than ten stocks, and benchmark only against naïve baselines like Buy-and-Hold. Such short horizons and narrow stock universes lead to three sources of bias: **survivorship bias** [21], where delisted or failed stocks are omitted; **look-ahead bias** [7], where future information inadvertently influences past decisions; and **data-snooping bias** [1], where strategy performance is inflated through repeated testing on the same data. These biases can result in misleading performance assessments and undermine the validity of claimed improvements over traditional methods. This raises a central question: **Can LLM-based investing strategies survive longer and broader robustness evaluations?**

While recent efforts such as Wang et al. [44] and Hu et al. [26] have addressed benchmarking for deep learning (DL)-based trading and LLM-based time-series forecasting, comprehensive evaluation of LLM-based investing strategies remains unaddressed. Separately, FinBen [48] provides a thorough FinLLM benchmark covering multiple tasks, including decision-making. However, as a broad FinLLM benchmark, FinBen's backtesting still relies on a limited, hand-picked symbol set, which contains the aforementioned biases and lacks a professional backtesting pipeline or systematic comparison with traditional strategies. To fill this gap, we introduce **FINSABER**,

Method	Eval Period	Eval Symbols	Code
MarketSenseAI	1 year 3 months	100	✗
TradingGPT	N/A	N/A	✗
FinMem	6 months	5	✓
FinAgent	6 months	6	✓
FinRobot	N/A	N/A	✓
TradExpert	1 year	30	✗
FinCon	8 month	8	✗
TradingAgents	3 months	3	✗
MarketSenseAI 2.0	2 years	100	✗

Table 1: Summary of current LLM-based investing strategies.

a comprehensive framework for benchmarking LLM timing-based investing strategies that supports **longer backtesting periods**, a **broader and more diverse symbol universe**, and **explicit bias mitigation**. Specifically, our main contributions are:

- (1) We propose FINSABER, the first comprehensive evaluation framework for LLM-based investing strategies that supports 20 years of multi-source data, including unstructured inputs such as news and filings, expands symbol coverage via unbiased selection, and mitigates survivorship, look-ahead, and data-snooping biases.
- (2) We empirically reassess prior claims and show that LLM advantages reported in recent studies often vanish under broader and longer evaluations, indicating that many conclusions are driven by selective or fragile setups.
- (3) We conduct regime-specific analysis and reveal that LLM strategies underperform in bull markets due to excessive conservatism and suffer disproportionate losses in bear markets due to inadequate risk control.
- (4) We offer guidance for future LLM strategy design, arguing that regime-awareness and adaptive risk management are more critical than increasing architectural complexity.

Altogether, our work provides empirical guidance for LLM-based investment research, advocating for the development of strategies that are able to adjust to dynamically-changing market conditions.

2 Related Works

Recent work using LLMs as investors directly employ LLMs to make investing decisions [11]. The most common approach leverages LLMs' sentiment analysis capabilities, using either general-purpose LLMs (e.g., GPT, LLaMA, Qwen) or fine-tuned financial variants like FinGPT [49] to generate sentiment scores for trading decisions [31, 38, 46, 53]. However, these approaches stop short of forming complete trading strategies, which require not only directional forecasts, but also realistic liquidity sizing for mitigating impact, development of execution rules for trade timing and risk management, and incorporation of trading costs.

More advanced approaches move beyond sentiment scores by summarising and reasoning over multi-source financial text. For example, Fatouros et al. [19] introduce a memory module that stores summarised financial data, retrieved during trading to guide decisions. Similarly, LLMFactor [43] learns to extract profitable factors from historical news aligned with price movements and applies them to future market forecasts.

A growing body of work incorporates LLM-based agents [24], where either one specialised agent or multiple collaborative agents are employed to perform financial analysis or predictions. Notable examples include FinMem [51], FinAgent [54], FinRobot [50], TradExpert [12], FinCon [52], TradingAgents [47] and MarketSenseAI 2.0 [18]. Some models also incorporate reinforcement learning (RL) for iterative self-improvement [13, 32].

3 Definitions of Investing Strategies

Timing-Based Strategies. Timing-based strategies generate daily Buy (+1), Sell (-1), or Hold (0) signals based on market data such as prices and technical indicators. The objective is to capture short-term price movements through systematic trading rules.

Selection-Based Strategies. Selection-based strategies identify subsets of assets expected to outperform based on ranking signals. Assets are selected periodically using top- k or thresholding. These strategies focus on cross-sectional alpha.

4 Biases and Robustness Challenges in Backtesting LLM Investors

Robust evaluation of financial strategies demands carefully designed backtests. Unlike typical machine learning tasks with large, clean datasets, financial data is noisy, nonstationary, and limited in scope. As a result, backtests are especially prone to three major sources of bias: **survivorship bias**, **look-ahead bias**, and **data-snooping bias**, each of which can inflate perceived performance and lead to misleading conclusions [7].

Survivorship Bias. This occurs when backtests include only currently active stocks while ignoring delisted or bankrupt assets. Such omissions systematically overstate returns and understate risk [28]. A common cause is using today's S&P 500 constituents as the historical investment universe. This practice introduces what Garcia and Gould [21] call "preinclusion bias", also a form of look-ahead bias where future index membership influences past decisions. The impact is well-documented: Grinblatt and Titman [23] and Elton et al. [16] estimate annual return distortions between 0.1% and 0.9%, and Brown et al. [5] show that even small distortions can misrepresent performance persistence.

Look-ahead Bias. Look-ahead bias arises when a strategy uses information that would not have been known at the time of decision-making [7]. This includes selecting features, parameters, or symbols based on full-period outcomes, thereby introducing future knowledge into the backtest.

Data-snooping Bias. Also known as multiple testing bias, this occurs when repeated experimentation on the same dataset leads to overfitting. In finance, where sample sizes are small and the signal-to-noise ratio is very low, this bias is particularly problematic. Bailey et al. [1] showed that evaluating strategies on overlapping data inflates false positive rates, and that standard hold-out validation techniques often fail to guard against this issue.

Bias-Mitigation Requires Broader and Longer Evaluation. Addressing these biases requires evaluating strategies across longer periods and broader asset universes. For daily trading, at least 3 years of data is generally recommended, while weekly and monthly strategies

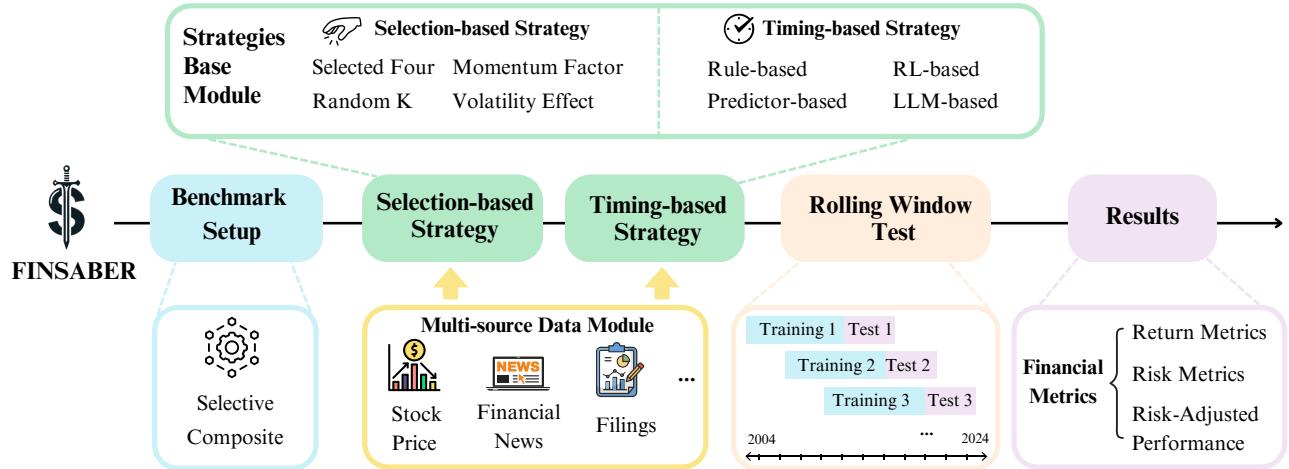


Figure 1: Overview of the FINSABER Backtest Framework. The central pipeline illustrates the backtesting process. The framework includes a Strategies Base Module (green), which covers both selection-based and timing-based strategies, and a Multi-source Data Module (yellow), integrating diverse financial data inputs.

benefit from 10 to 20 years or more [1]. Gatev et al. [22] tested pairs trading on 40 years of daily data, but Do and Faff [14] extended this to 48 years and found profitability declined, highlighting the need for long-term evaluation. Likewise, recent deep learning models in finance rely on multi-year datasets to ensure robustness [20, 42].

Stock selection is another critical factor. Many LLM-based investing studies selectively use only a small number of well-known stocks such as TSLA and AMZN. These are both historical winners, which limits generalisability and embeds both survivorship and look-ahead bias into the evaluation. Omitting delisted or under-performing stocks distorts performance metrics and presents an incomplete picture of real-world investing conditions.

Therefore, **backtests must address survivorship bias, look-ahead bias, and data-snooping bias explicitly**. Broader and longer evaluations, using historically accurate stock universes and spanning multiple market regimes, are essential for producing reliable, generalisable results that reflect real investing conditions.

5 FINSABER

As discussed in §4, existing evaluations of LLM-based investors suffer from survivorship bias, look-ahead bias, and data-snooping bias. These issues are largely due to limited evaluation periods and narrow stock selections. In this study, all subsequent findings and analyses are derived from our meticulously constructed backtesting framework, FINSABER², which systematically addresses biases and meets the practical needs of LLM-based strategies, including the integration of unstructured, multi-source data. FINSABER comprises three core modules: (1) a multi-source data module, (2) a modular strategies base, and (3) a bias-aware two-step backtesting pipeline. Figure 1 illustrates the framework.

Multi-source Data. LLM-based investing strategies utilise both structured and unstructured data such as historical stock prices, financial news, and company filings (10-K, 10-Q), spanning from 2000 to 2024. To prevent **look-ahead bias**, all data inputs are aligned with each backtest window using only information available prior to the start date. **Survivorship bias** is addressed by explicitly including delisted stocks, and open-source equivalents are provided for reproducibility (more detail in Appendix A).

Strategies Base. We incorporate a comprehensive collection of strategies across multiple paradigms to ensure robust benchmarking. The *timing-based strategies* include open-source LLM investors (FinMem [51], FinAgent [54]), traditional rule-based approaches (Buy and Hold, Moving Average Crossover, Bollinger Bands [3], Trend Following [45]), ML/DL forecaster-based methods (ARIMA, XGBoost), and RL-based strategies (A2C, PPO, TD3, SAC implemented via FinRL [36] framework). Selection-based strategies encompass random K selection, Momentum Factor Selection (based on past returns), Volatility Effect Selection (selecting low-volatility stocks), and the stocks selection agent from the FinCon [52] framework. This diverse strategy base enables comprehensive performance comparison across different methodological approaches while maintaining extensibility for custom implementations. More technical details of the strategies are available in Appendix B.

Two-Step Pipeline for Bias Mitigation. FINSABER applies a two-step pipeline. First, *selection-based strategies* operate on regularly updated, historically accurate constituent lists, for example, the S&P 500 including delisted symbols, at each window. This further mitigates **survivorship bias** from the stock selection process, ensuring the evaluation is not restricted to a limited or selectively surviving set of stocks. Subsequently, *timing-based strategies* which covers rule-based, ML, RL, and LLM-driven approaches will be used to execute daily trading decisions. The modular strategy base is easily extensible for custom methods (see Appendix B). To mitigate **data-snooping bias**, rolling-window evaluations are performed over

²Financial INvesting Strategy Assessment with Bias mitigation, Expanded time, and Range of symbols

Type	Strategy	TSLA				NFLX				AMZN				MSFT			
		SPR↑	CR↑	MDD↑	AV↓	SPR↑	CR↑	MDD↑	AV↓	SPR↑	CR↑	MDD↑	AV↓	SPR↑	CR↑	MDD↑	AV↓
FinMem Selection (2022-10-06 to 2023-04-10)																	
Rule Based	Buy and Hold	-0.342	-20.483	-52.729	55.910	1.326	43.079	-20.184	41.523	-0.460	-13.250	-31.546	35.624	0.974	21.171	-14.192	28.327
	SMA Cross	-0.293	-5.540	-18.517	38.602	-1.020	-8.285	-15.942	20.477	-0.420	-4.433	-18.910	27.084	1.515	18.289	-8.746	20.821
	WMA Cross	0.215	3.741	-18.492	42.062	-0.803	-6.004	-14.290	19.826	-0.563	-6.121	-21.030	26.831	1.334	16.576	-8.883	21.503
	ATR Band	-0.595	-19.142	-39.599	42.161	0.150	2.992	-12.231	19.314	0.622	11.007	-15.842	23.272	1.036	12.979	-7.709	15.005
	Bollinger Bands	-0.769	-24.747	-44.655	45.366	-0.558	-4.996	-13.244	16.754	-0.402	-7.105	-20.615	26.559	2.115	31.619	-3.475	18.243
Predictor	Turn of The Month	0.219	3.639	-11.642	31.042	0.559	8.833	-10.641	17.194	-0.037	0.039	-14.892	20.722	-0.034	0.970	-11.955	15.097
	ARIMA	0.601	15.007	-24.446	41.402	1.159	23.783	-15.043	25.749	-0.225	-4.752	-20.046	26.899	2.245	44.777	-7.121	22.636
	XGBoost	0.331	6.213	-35.374	37.729	0.770	10.134	-11.246	14.928	1.955	42.468	-8.816	25.135	0.895	12.678	-10.734	16.721
RL	A2C	-0.201	-15.876	-52.642	56.172	1.262	36.760	-20.436	37.542	-0.093	-3.253	-24.042	30.903	1.166	24.804	-13.437	26.743
	PPO	-0.254	-18.223	-52.609	57.301	1.420	40.181	-18.036	35.170	-0.576	-9.485	-22.761	24.169	1.149	25.752	-14.444	28.503
	SAC	-0.320	-20.598	-53.614	57.665	1.325	42.872	-20.121	41.448	-0.440	-13.215	-32.145	36.533	1.004	22.304	-14.522	28.904
	TD3	-0.343	-20.423	-52.592	55.859	1.325	42.872	-20.121	41.448	-0.440	-13.215	-32.145	36.533	0.973	21.026	-14.099	28.073
LLM	FinMem (GPT-4o-mini)	0.927	19.940	-30.144	48.638	1.704	32.549	-13.018	34.766	0.297	2.800	-2.744	10.247	-0.554	-7.104	-14.588	25.969
	FinMem (GPT-4o)	0.404	5.312	-36.351	54.434	0.896	16.244	-15.234	38.209	-0.968	-20.091	-31.164	40.896	0.792	12.834	-13.555	33.884
	FinMem (reported)	2.679	61.776	-10.800	46.865	2.017	36.449	-15.850	36.434	0.233	4.885	-22.929	42.658	1.440	23.261	-14.989	32.562
	FinAgent	-	-	-	-	1.543	41.167	-20.417	51.030	-1.108	-6.113	-9.317	13.257	1.252	21.438	-14.502	32.952

Table 2: Backtest performance over the previously reported period (2022-10-06 to 2023-04-10) where LLM investing strategies were shown to be effective. “-” metrics indicate no trading activities were triggered. Top in red and second-best in blue.

diverse and dynamically changing asset selections and extended time horizons. Window size and step are customisable, enabling realistic simulation across different market regimes. Together, this pipeline ensures broad symbol coverage and prevents overfitting to narrow datasets or short evaluation horizons.

Evaluation Metrics. FINSABER adopts three categories of evaluation metrics: *return*, *risk*, and *risk-adjusted performance*. Return metrics measure profitability, including Annualised Return (AR) and Cumulative Return (CR). Risk metrics quantify uncertainty and downside exposure, including Annualised Volatility (AV) and Maximum Drawdown (MDD). Risk-adjusted metrics assess capital efficiency, including the Sharpe Ratio (SPR) and Sortino Ratio (STR).

High returns alone do not imply strategy quality. Risk-adjusted metrics such as SPR and STR are more informative, especially in finance where capital efficiency and downside risk are critical [7]. These metrics are standard in the literature [9, 10] and widely used in recent LLM-based investing benchmarks [52, 54]. Formal definitions and formulas are provided in Appendix C.

6 Experiments

Our experiments address methodological flaws in prior LLM-based investing evaluations identified in §4, specifically survivorship and data-snooping biases from selective stock choices and short evaluation periods. We demonstrate how these practices inflate results and illustrate how FINSABER enables fairer assessments.

Specifically, our experiments include two parts: (1) **Pitfalls of selective evaluation:** Replicating previously reported results on select periods and symbols, then extending this evaluation period to demonstrate performance deterioration. (2) **Fair and robust comparisons:** Implementing systematic stock-selection methods to explicitly mitigate survivorship and data-snooping biases for fairer LLM assessments. We only consider go-long positions, aligning with current LLM strategies. Technical details, including hyperparameter configurations, are provided in Appendix E.

6.1 Pitfalls of Selective Evaluation

Revisiting Reported Claims. We begin by replicating earlier evaluation setups that demonstrated the effectiveness of LLM investing strategies on TSLA, NFLX, AMZN, and MSFT during the previously reported period (6 October 2022 to 10 April 2023). Additionally, we incorporate broader benchmarks, including traditional rule-based, ML, and DL methods. Previous studies omit key details such as exact risk-free rates and transaction costs. Thus, we set a historical average risk-free rate of 0.03 and use Moomoo’s³ standard US commission fee (\$0.0049/share, minimum \$0.99/order), comparable to HSBC and TradeUp⁴.

Table 2 summarises these results. Our analysis indicates that **LLM investors are not universally superior, even in their preferred setups.** Specifically, *FinMem* only consistently outperforms for TSLA, while traditional benchmarks remain competitive or superior for other symbols. These results caution against overly optimistic interpretations from selective evaluations. *FinAgent*, the other LLM-based method, performs similarly to *FinMem* on NFLX and MSFT but generally lacks consistent improvements across the set. Furthermore, **LLM-based strategies exhibit high annual volatility and significant maximum drawdowns**, indicating a high-risk profile. This highlights the necessity of explicit risk assessments when evaluating such strategies.

Further evidence in Appendix D supports the instability of short-period evaluations, where even a slight two-month extension of the evaluation period results in substantial variation for LLM-based strategies.

Extending the Evaluation Period. To further illustrate the limitations of short evaluation horizons, We extend the evaluation period (2004–2024) using the same four symbols (TSLA, NFLX, AMZN, MSFT) to assess LLM performance robustness over the long term.

³https://www.moomoo.com/ca/support/topic10_122

⁴<https://www.tradeup.com/pricing/detail>

Type	Strategy	TSLA					NFLX				
		SPR↑	STR↑	AR↑	MDD↑	AV↓	SPR↑	STR↑	AR↑	MDD↑	AV↓
Rule Based	Buy and Hold	0.630	0.915	37.767	-50.839	45.243	0.622	0.952	23.919	-48.119	41.703
	SMA Cross	0.680	1.013	23.681	-23.707	24.680	0.087	0.160	5.514	-28.689	21.836
	WMA Cross	0.664	0.955	21.158	-25.135	24.087	0.004	0.071	1.447	-32.409	23.074
	ATR Band	0.022	0.066	-0.005	-38.536	26.609	0.186	0.377	2.202	-35.603	23.922
	Bollinger Bands	0.193	0.294	4.282	-37.157	26.267	0.075	0.381	0.286	-34.002	23.088
	Trend Following	0.815	1.356	36.289	-28.113	28.628	0.403	0.646	11.868	-29.179	25.368
Predictor	Turn of The Month	0.207	0.353	7.872	-27.902	23.595	0.287	0.487	7.097	-21.646	17.166
	ARIMA	0.681	1.003	24.138	-30.450	27.612	0.659	1.035	19.022	-27.567	25.514
	XGBoost	0.142	0.370	10.877	-22.901	19.537	0.202	0.355	4.957	-21.301	17.302
RL	A2C	0.172	0.249	3.875	-27.367	22.890	0.171	0.243	4.359	-20.960	16.129
	PPO	0.469	0.663	28.189	-46.810	40.156	0.541	0.814	19.279	-39.615	33.630
	SAC	0.119	0.190	6.654	-11.042	9.902	0.186	0.285	8.397	-9.545	9.216
	TD3	0.417	0.604	23.336	-33.725	30.233	0.291	0.431	10.900	-21.451	19.304
LLM	FinMem	0.641	1.069	42.153	-34.234	35.030	0.293	0.622	12.566	-27.721	26.876
	FinAgent	0.206	0.649	38.591	-36.930	38.302	-0.419	0.621	22.543	-20.466	22.838
Type		AMZN					MSFT				
Type	Strategy	SPR↑	STR↑	AR↑	MDD↑	AV↓	SPR↑	STR↑	AR↑	MDD↑	AV↓
		0.551	0.829	15.997	-36.842	30.860	0.461	0.620	11.238	-25.463	21.791
Rule Based	Buy and Hold	0.057	0.205	3.896	-22.096	17.520	-0.263	-0.314	0.192	-17.656	11.840
	SMA Cross	0.175	0.300	5.702	-19.309	17.178	-0.363	-0.437	-1.664	-19.075	11.932
	WMA Cross	0.443	0.998	5.452	-19.990	15.130	0.317	0.637	5.725	-11.893	10.885
	ATR Band	0.019	0.125	0.895	-23.757	15.763	-0.054	-0.029	1.578	-16.101	11.931
	Bollinger Bands	0.019	0.125	0.895	-23.757	15.763	-0.054	-0.029	1.578	-16.101	11.931
	Trend Following	0.649	1.111	16.018	-19.120	20.130	0.205	0.321	5.438	-17.515	13.419
Predictor	Turn of The Month	-0.029	-0.009	1.534	-20.422	15.728	-0.263	-0.343	-0.177	-14.308	10.438
	ARIMA	0.339	0.504	7.523	-20.612	19.115	0.304	0.466	8.207	-15.227	13.819
	XGBoost	-0.587	-0.366	1.200	-13.659	11.106	0.171	0.322	5.890	-10.523	10.335
RL	A2C	0.165	0.247	3.925	-14.841	11.654	0.279	0.380	7.478	-13.447	11.933
	PPO	0.505	0.767	13.831	-29.128	24.392	0.344	0.463	8.589	-16.697	14.410
	SAC	0.179	0.257	4.438	-14.093	11.665	0.216	0.288	5.329	-14.866	11.835
	TD3	0.382	0.597	11.738	-21.942	19.149	0.050	0.070	1.405	-9.491	6.648
LLM	FinMem	0.188	0.340	5.695	-28.296	24.786	0.203	0.293	4.567	-19.270	17.891
	FinAgent	0.364	0.663	12.699	-25.516	25.390	0.285	0.432	11.123	-18.596	18.863

Table 3: Backtest performance for previously reported LLM-selected symbols over an extended period (2004-01-01 or earliest available to 2024-01-01). Top in red and second-best in blue.

Table 3 summarises these extended period results. Crucially, extending the evaluation horizon significantly diminishes the perceived superiority of LLM investors. Over two decades, traditional strategies like *Buy and Hold* consistently rank among the top performers across most symbols. TSLA is the only case where LLM investors (*FinMem*, *FinAgent*) clearly lead in AR, while for NFLX, AMZN, and MSFT, *Buy and Hold* or other strategies match or outperform them. This further supports that **previously reported LLM advantages are likely short-lived, potentially hand-picked, and highly sensitive to the evaluation period**.

It is crucial to note that we cannot yet conclude that benchmark strategies cannot outperform the market. As mentioned, backtesting only on popular stocks may inadvertently introduce survivorship bias, as these stocks have gained popularity due to past success during prolonged bull markets. Thus, expanding the range of symbols is essential to ensure a more systematic and unbiased evaluation.

6.2 Fair Comparisons with Composite Approach

To overcome the aforementioned biases, we introduce the **Composite** evaluation setup within FINSABER. This setup integrates systematic *selection-based strategies* to expand and diversify the stock universe, explicitly addressing survivorship and data-snooping biases. Specifically, we use four unbiased stock selection approaches from the strategies base (details in Appendix B): RANDOM FIVE, MOMENTUM FACTOR [40], VOLATILITY EFFECT [2], and the FINCON SELECTION AGENT in the FinCon [52] framework.

For each rolling window, the selection strategy identifies a set of K symbols. Each *timing-based strategy* is then applied independently to each selected symbol, generating separate trades and performance records. The reported results for each timing strategy reflect the average performance across all selected symbols within the window, as these models operate on individual stocks and do not construct or manage a coordinated portfolio across symbols.

Type	Timing Strategy	RANDOM 5 (91 symbols)					MOMENTUM FACTOR (84 symbols)				
		SPR ↑	STR ↑	AR ↑	MDD ↑	AV ↓	SPR ↑	STR ↑	AR ↑	MDD ↑	AV ↓
Rule Based	Buy and Hold	0.315	0.456	6.694	-35.130	27.410	0.384	0.694	9.916	-32.596	37.421
	SMA Cross	-0.298	-0.290	0.446	-22.292	15.774	-0.251	0.008	2.109	-19.438	20.050
	WMA Cross	-0.299	-0.305	0.232	-22.754	15.528	-0.169	0.051	3.674	-18.651	20.330
	ATR Band	0.232	0.425	5.119	-21.535	16.113	0.197	0.595	4.314	-19.407	20.038
	Bollinger Bands	0.129	0.288	3.521	-22.487	16.290	0.114	0.702	1.881	-19.451	21.555
	Trend Following	-0.389	-0.198	2.525	-8.587	8.223	0.119	0.531	6.380	-15.726	18.696
Predictor	Turn of The Month	0.015	0.072	2.870	-18.582	13.542	0.056	0.662	3.197	-18.108	18.055
	ARIMA	0.255	0.434	6.928	-21.691	17.504	0.542	1.043	13.257	-18.277	22.892
	XGBoost	-0.055	0.028	3.089	-17.160	13.075	0.094	1.525	6.131	-12.754	17.238
RL	A2C	0.086	0.122	1.902	-9.220	6.887	0.105	0.171	2.488	-14.452	14.815
	PPO	0.179	0.256	3.282	-18.395	13.783	0.185	0.308	1.939	-23.177	25.527
	SAC	0.097	0.142	1.389	-16.058	12.375	0.195	0.321	5.591	-12.235	16.144
	TD3	0.173	0.248	3.682	-14.471	11.565	0.186	0.293	3.464	-14.593	14.953
LLM	FinMem	-0.253	0.114	-0.094	-24.243	21.214	0.025	0.170	3.649	-23.335	28.078
	FinAgent	0.094	0.323	4.477	-28.059	26.387	0.104	0.534	13.950	-20.675	30.635
Type	Timing Strategy	VOLATILITY EFFECT (63 symbols)					FINCON SELECTION AGENT (80 symbols)				
		SPR ↑	STR ↑	AR ↑	MDD ↑	AV ↓	SPR ↑	STR ↑	AR ↑	MDD ↑	AV ↓
Rule Based	Buy and Hold	0.703	1.291	7.898	-14.146	14.720	0.389	0.671	6.940	-30.943	41.710
	SMA Cross	-0.568	-0.544	0.781	-9.296	8.665	-0.346	-0.351	-4.187	-21.095	20.765
	WMA Cross	-0.665	-0.348	1.908	-8.481	8.573	-0.176	-0.129	-1.683	-19.432	21.141
	ATR Band	-0.026	0.120	2.798	-8.032	7.951	0.181	0.539	4.469	-18.827	24.820
	Bollinger Bands	-0.077	0.029	2.503	-7.618	7.774	0.116	0.333	7.155	-19.145	27.250
	Trend Following	0.230	0.619	5.503	-8.115	9.297	-0.008	0.189	1.358	-19.500	20.400
Predictor	Turn of The Month	-0.156	-0.095	2.881	-6.889	7.233	0.013	0.141	2.020	-15.871	16.862
	ARIMA	0.325	0.838	4.898	-9.111	9.807	0.532	0.841	10.662	-16.018	19.181
	XGBoost	-0.108	-0.055	2.775	-6.676	7.077	0.116	0.325	8.057	-15.320	18.078
RL	A2C	0.421	0.795	4.620	-4.428	5.149	-0.004	-0.061	0.823	-12.557	11.767
	PPO	0.514	0.972	5.805	-8.757	9.461	0.132	0.147	2.327	-9.744	10.257
	SAC	0.402	0.810	3.527	-4.821	5.030	0.180	0.279	2.661	-11.979	14.210
	TD3	0.269	0.394	4.610	-5.442	5.992	0.130	0.334	0.695	-14.621	21.693
LLM	FinMem	-0.228	0.483	4.061	-10.860	11.641	-0.292	0.135	-1.686	-20.809	24.948
	FinAgent	0.241	0.527	4.954	-10.268	11.502	-0.076	0.381	5.168	-15.563	22.565

Table 4: Backtest performance under the Composite setup, using three different selection strategies across historical S&P 500 constituents (2004–2024), including delisted symbols. Top in red and second-best in blue.

To mitigate survivorship bias, we use historical constituent lists, specifically S&P 500 for US market, at each evaluation period's start and explicitly include delisted symbols. To address data-snooping bias, we evaluate a large and diversified symbol universe: 91, 84, 63, and 80 total distinct symbols for RANDOM FIVE, MOMENTUM-based, VOLATILITY-based selection, and FINCON SELECTION AGENT respectively. These counts reflect all unique symbols encountered across rolling windows, where stocks are reselected in each window, preventing cherry-picking and short-horizon bias.

Table 4 summarises these comprehensive evaluations. Results obtained through this unbiased and systematic approach **further validate our previous findings from the selected-four evaluation**. Specifically, both the RANDOM FIVE and MOMENTUM-based selections reinforce the conclusion that the previously claimed superiority of LLM investors is largely driven by selective evaluation setups. For instance, in the RANDOM FIVE setup, *Buy and Hold*, *ATR Band* and *ARIMA* outperform *FinMem* and *FinAgent* in terms of risk-adjusted metrics. Similarly, *ARIMA* and simple rule-based strategies

often perform better than LLM-based methods under the MOMENTUM-based selection. In the VOLATILITY-based selection, traditional methods dominate even more clearly: *Buy and Hold* achieves the highest Sharpe (0.703), Sortino (1.291), and AR (7.898%), while *PPO* and *ARIMA* again show strong all-round performance. LLM-based methods lag behind, with *FinAgent* offering moderate returns but lower Sharpe (0.241) and larger drawdowns. Notably, our reported LLM performances do not adjust for potential data leakage: given the use of pretrained models like GPT-4o, the LLMs may have seen parts of the data during training, but they still fail to outperform traditional strategies under fair evaluation, casting further doubt on their real-world advantage.

Nevertheless, it is important to acknowledge **LLM-based strategies still show potential regarding absolute annual returns**. For instance, *FinAgent* achieves the highest AR (13.950%) in the MOMENTUM-based selection setup. However, the relatively weaker performance observed in SPR (0.104) and MMD metrics suggests

a clear need for improved risk management within LLM-driven approaches before they can be reliably adopted in practice.

Moreover, by comparing *Buy and Hold* with different selection strategies, we clearly identify the relative effectiveness of each selection strategy: VOLATILITY EFFECT selection (Sharpe 0.703) outperforms FINCON SELECTION AGENT (0.389) and MOMENTUM FACTOR (0.384), which in turn surpass RANDOM FIVE (0.315). RL-based methods exhibit the clearest alignment with selection quality. Strategies like PPO, SAC, and TD3 systematically achieve their best performance under the VOLATILITY selection and degrade under the other three. This suggests **RL methods are more dependent on the quality of the stock candidates**. Among LLM strategies, *FinAgent* exhibits a greater dependency on selection quality than *FinMem*.

Overall, these results not only confirm our earlier insights but also underscore the critical importance of unbiased, systematic stock-selection methodologies for accurately assessing the true capabilities of LLM-based investing strategies.

6.3 Statistical Validation and Behavioural Diagnostics of LLM Agents

To validate our findings from the composite backtests and diagnose the underlying drivers of LLM agent performance, we conduct a unified statistical and behavioural analysis. First, we conduct paired t-tests comparing *Buy and Hold*, *FinMem*, and *FinAgent* across both **Selected 4** (Table 3) and **Composite** (Table 4) setups. Second, we dissect the agents' behavioural characteristics by examining their drawdown profiles, alpha (α) and beta (β) decomposition, and trading turnover across the different selection environments. These metrics are obtained by regressing the strategy's excess returns against the market's excess returns based on the Capital Asset Pricing Model (CAPM) [41]. The model is defined as: $R_s - R_f = \alpha + \beta(R_m - R_f) + \epsilon$, where R_s is the return of the strategy, R_m is the market return, R_f is the risk-free rate, and ϵ is the idiosyncratic residual. In this model, β measures the strategy's systematic risk or volatility relative to the market, while α represents the portion of the return not explained by market exposure, often considered a measure of strategy-specific skill.

Setup	B&H vs FinMem	B&H vs FinAgent	FinMem vs FinAgent
<i>Selective symbols, expanded period (Selected four; Table 3)</i>			
TSLA	0.3643	0.1663	0.2258
NFLX	0.0436	0.0363	0.1493
AMZN	0.0127	0.0984	0.4023
MSFT	0.0005	0.2252	0.5549
<i>Bias-mitigated (Composite; Table 4)</i>			
Random 5	3.0e-6	7.7e-4	4.0e-3
Momentum	4.0e-5	0.0117	0.2001
Volatility Effect	4.0e-6	5.9e-4	3.8e-3

Table 5: Paired t-test p-values comparing B&H, FinMem, and FinAgent under Selected 4 and Composite setups.

Table 5 reports t-tests and p-values for the previous results, testing the null hypothesis of equal performance distributions. Under the selective period, statistical significance is inconsistent and limited mostly to individual stocks. However, after mitigating biases through the composite setup, the p-values drop substantially, indicating the market baseline (B&H) significantly outperforms

both LLM strategies across all robust setups. Notably, while *FinAgent* tends to outperform *FinMem* when biases are controlled, both still underperform simple market baselines. Furthermore, the behavioural analysis in Table 6 reveals that this underperformance is rooted in a lack of genuine skill; **neither LLM agent generates statistically significant alpha**, with all measured p-values exceeding 0.34. This finding robustly supports our main thesis that the claimed superiority of these models does not hold under rigorous evaluation, aligning with the Efficient Market Hypothesis [37].

A clear behavioural hierarchy emerges between the two agents. *FinMem* consistently shows a more pathological trading profile, marked by excessive turnover and poor risk management. Its commission ratio is five to nine times higher than *FinAgent*'s across both contexts, and its drawdown durations are substantially longer. This overtrading leads to persistent value destruction, reflected in *FinMem*'s negative alpha in all scenarios. In contrast, *FinAgent* follows a more restrained, though still unskilled, trading strategy. Appendix F provides a comparative analysis with visualisations to further highlight the behavioural differences between *FinMem* and *FinAgent* as supplementary evidence.

These behaviours are directly modulated by the selection strategy, which acts as a powerful environmental filter. The **Momentum selection** strategy elicits the most engaged market posture from the agents, prompting their highest β values. *FinMem*'s performance improves in this context relative to other environments, but it still yields a negative alpha of -1.34%. This is the only scenario where *FinAgent* produces a large positive alpha of +6.57%. Although this result lacks statistical significance ($p=0.35$), it suggests that the LLMs' primary strength may not be in *discovering* novel signals but rather in *exploiting* strong, pre-existing market trends. In contrast, the **Low Volatility** environment takes a risk-averse posture. Here, *FinMem* remains ineffective with a -1.04% alpha and a very low β of 0.20. *FinAgent* also becomes highly conservative, with its risk profile improving (e.g., its average drawdown duration falls to 38.71 days) but at the cost of performance, generating a negative alpha.

In summary, this unified analysis statistically validates the underperformance of LLM agents and reveals that their behaviour is not monolithic. It is highly dependent on the characteristics of the asset universe they operate within, reinforcing the need for bias-mitigated evaluation frameworks like FINSABER.

Strategy	Avg Max Drawdown (Days)	Avg Regular Drawdown (Days)	Alpha (%)	Beta	Alpha p-value
MOMENTUM FACTOR					
FinMem	210	80	-1.343	0.518	0.477
FinAgent	150	59	6.571	0.758	0.345
VOLATILITY EFFECT					
FinMem	177	71	-1.036	0.199	0.430
FinAgent	123	39	-0.196	0.354	0.368

Table 6: Behavioural analysis of LLM timing strategies, highlighting drawdown duration, alpha (α) and beta (β) decomposition, and trading turnover (commission ratio).

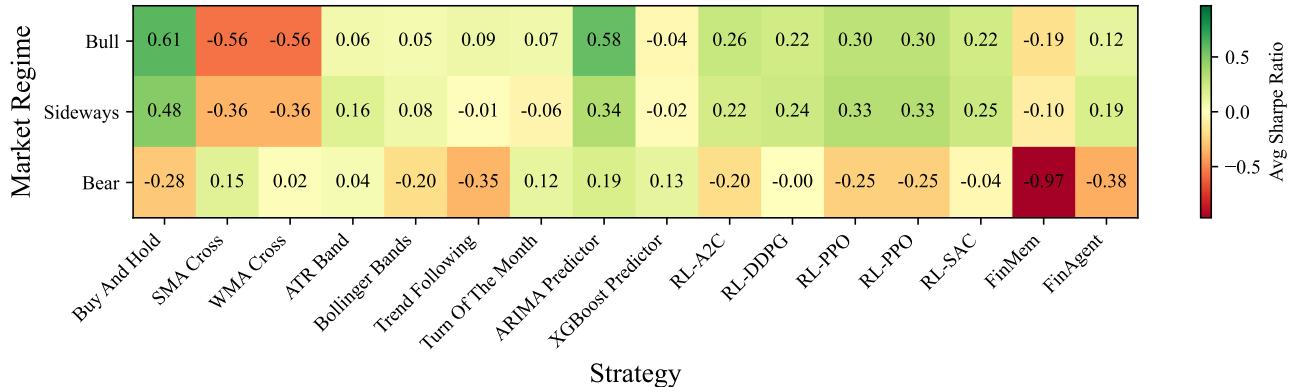


Figure 2: Average Sharpe ratio by regime for all benchmarking strategies. Green = strong, red = weak.

7 Market Regime Analysis

Another key question in evaluating LLM-based investing strategies is whether they adapt appropriately across varying market conditions. Financial markets exhibit time-varying predictability and uncertainty across different economic, and political regimes [30]. Some strategies may exploit these variations, while others may struggle to adapt. Distinct market environments—bull, bear, and sideways—present unique challenges and opportunities: bull markets reward aggressive positioning and high exposure, bear markets require effective risk management, and sideways markets test a strategy’s ability to navigate uncertainty in the absence of clear trends. By decomposing performance across these regimes, it is possible to determine whether strategies are overly conservative and miss opportunities during bullish periods, or excessively aggressive and incur significant losses during downturns. Understanding these regime-specific behaviours is essential for interpreting the strengths and weaknesses of LLM-based investing strategies [27].

We label each calendar year based on the annual return of the S&P 500: $R_y = \frac{P_T - P_0}{P_0}$, where P_0 and P_T are the adjusted closing prices on the first and last trading days of year y . A year is classified as **bull** if $R_y \geq +20\%$, **bear** if $R_y \leq -20\%$, and **sideways** otherwise. The $\pm 20\%$ threshold follows standard industry convention [55].

To analyse regime-specific performance, we employ our composite setup using the three selection strategies outlined in §6.2. For each timing strategy, we retrieve the SPR within each 1-year window from Table 4. These are then averaged per $\{\text{strategy}, \text{regime}\}$ pair to produce stable performance indicators across market conditions. Figure 2 illustrates the results, with **green** indicating strong SPR and **red** signifying the opposite.

Traditional rule-based and predictor-based methods still set the standard. *ATR Band*, *Turn of the Month* and *ARIMA* deliver positive Sharpe in every regime, while *Buy and Hold*, our passive yardstick, posts 0.61 in bulls, 0.48 in sideways markets and only -0.28 in bears. No active strategy surpasses this passive SPR in the bull regime, suggesting that many strategies, including the LLM ones, may struggle to fully capitalise on strong up-trends.

RL algorithms sit in the middle. *A2C* and *DDPG* pick up part of the upside and limit losses; *PPO* and *SAC* swing with volatility and underperform *ARIMA* once conditions turn.

LLM strategies perform poorly. *FinAgent* records Sharpe 0.12 in bulls and -0.38 in bears; *FinMem* gets -0.19 and -0.97. Both are too cautious when risk is rewarded and too aggressive when it is penalised. *FinAgent* is better, halving the bear-market shortfall relative to *Buy and Hold* and keeping a small positive Sharpe in neutral conditions, but it still trails rule-based or predictor benchmark.

These results suggest two directions for future LLM investors. First, trend-detection capabilities to ensure that the strategy can at least match passive equity beta during upward market phases. Second, incorporating explicit regime-aware risk controls that reduce exposure as volatility or drawdown risk increases. Balancing risk-taking and risk management, rather than simply increasing model size, appears the key to closing the gap with traditional methods.

8 Findings and Takeaways

Our investigation via the FINSABER framework offers several novel findings that challenge the prevailing narrative on LLM-based investors and set a new baseline for future research.

First, we find that **LLM-derived alpha is likely a methodological artefact of narrow, biased evaluations**. The performance advantages reported in short-term, selective studies vanish under our bias-mitigated backtests, which reveal a consistent and statistically significant failure to generate alpha (§6.3). This suggests that current LLMs do not overcome the Efficient Market Hypothesis [17] in reality, and that prior gains stemmed from survivorship and look-ahead biases rather than genuine market inefficiency.

Second, **model complexity does not equate to market competence**. The scaling laws of natural language processing [29] do not translate effectively to financial markets, which impose intrinsic limits on extractable signals [25]. We show that larger models do not reliably outperform smaller ones, and both are consistently bettered by simpler models like *ARIMA* on risk-adjusted metrics (Table 4). Without encoded financial logic, architectural complexity appears to add noise rather than value.

Third, we diagnose “how” LLM agents fail, revealing a **fundamental misalignment with market regimes**. Our further analysis (§7, Appendix F) shows that agents are pathologically miscalibrated: they are too conservative in bull markets and too aggressive in bear markets. This behavioural flaw contradicts the Adaptive Markets Hypothesis [37], shifting the issue from merely

a lack of profitability to a more profound failure in the agents' decision-making policies.

Synthesising these points, our work establishes that the primary barrier to successful LLM investors is not model scale, but a **lack of domain-aware financial logic**. The path forward is designing smarter, more adaptive agents, and FINSABER provides the framework to rigorously test such designs, moving the field beyond flawed evaluations toward practical and robust financial agents.

9 Conclusion

We reassess the robustness of LLM *timing-based investing strategies* using FINSABER, a comprehensive framework that mitigates backtesting biases and extends both the evaluation horizon and symbol universe. Results show that the perceived superiority of LLM-based methods deteriorates under more robust and broader long-term testing. Regime analysis further reveals that current strategies miss upside in bull markets and incur heavy losses in bear markets due to poor risk control.

We identify two priorities for future LLM-based investors: (1) enhancing uptrend detection to match passive exposure, and (2) including regime-aware risk controls to dynamically adjust aggression. Addressing these dimensions rather than increasing framework complexity is the key to building practical, reliable strategies.

A remaining limitation is potential data leakage, as some evaluation data may have been included in the pretraining corpora of proprietary LLMs and cannot be fully verified. However, any such leakage would bias results in favour of LLMs and therefore does not alter our central findings.

Finally, our cost analysis (Appendix G) shows that large-scale LLM backtesting is financially intensive. Future work should pursue cost-efficient model designs and incorporate API costs into performance evaluation.

Limitations

There are several limitations to our current study. First, we did not individually tune the traditional rule-based strategies for each rolling evaluation window. Typically, applying domain-specific market insights to optimise parameters can significantly enhance the performance of these methods. However, we argue that our current configuration remains valid and effectively demonstrates the competitive disadvantage faced by LLM strategies. Indeed, tuning the parameters of traditional rule-based strategies would likely elevate their performance further, reinforcing rather than undermining our main conclusions.

Second, our evaluation has not fully eliminated look-ahead bias. Pre-trained LLMs, due to their inherent training corpus, may inadvertently contain stock-related information from historical periods overlapping our test sets. Despite this potential data leakage, the observed underperformance of LLM strategies strengthens our critical assessment. Explicitly addressing this look-ahead concern through controlled model training or careful exclusion of financial data from training corpora will be an important avenue for future research.

Third, to ensure experiment reproducibility, we restricted our analysis to publicly available data, excluding proprietary sources such as private newsfeeds, earning transcripts, or expert analyses. Nonetheless, the FINSABER framework was deliberately designed

to be modular and extensible, allowing researchers with access to private data to easily integrate additional information sources. Our primary goal remains providing a rigorous, long-term evaluation pipeline that minimises selective reporting. Researchers lacking proprietary data can fully replicate our results using openly accessible resources.

Acknowledgements

We thank the reviewers and the area chair for their useful feedback. The authors acknowledge the use of resources provided by the Edinburgh Compute and Data Facility⁵ (ECDF).

References

- [1] David H. Bailey, Jonathan Michael Borwein, Marcos M. López de Prado, and Qiji Jim Zhu. 2015. The Probability of Backtest Overfitting. *ERN: Econometric Modeling in Financial Economics (Topic)* (2015).
- [2] David Blitz and Pim Vliet. 2007. The Volatility Effect: Lower Risk without Lower Return. *The Journal of Portfolio Management* 34 (2007).
- [3] J. Bollinger. 2002. *Bollinger on Bollinger Bands*.
- [4] George Edward Pelham Box and Gwilym Jenkins. 1990. *Time Series Analysis, Forecasting and Control*.
- [5] Stephen J Brown, William Goetzmann, Roger G Ibbotson, and Stephen A Ross. 1992. Survivorship bias in performance studies. *The Review of Financial Studies* 5, 4 (1992), 553–580.
- [6] Mark M. Carhart. 1997. On Persistence in Mutual Fund Performance. *The Journal of Finance* 52, 1 (1997), 57–82.
- [7] E.P. Chan. 2021. *Quantitative Trading: How to Build Your Own Algorithmic Trading Business*.
- [8] Tianqi Chen and Carlos Guestrin. 2016. XGBoost: A Scalable Tree Boosting System. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, August 13–17, 2016*, Balaji Krishnapuram, Mohak Shah, Alexander J. Smola, Charu C. Aggarwal, Dou Shen, and Rajeev Rastogi (Eds.), 785–794.
- [9] Rama Cont. 2001. Empirical properties of asset returns: stylized facts and statistical issues. *Quantitative Finance* 1, 2 (2001), 223–236.
- [10] Victor DeMiguel, Lorenzo Garlappi, and Raman Uppal. 2007. Optimal Versus Naive Diversification: How Inefficient is the 1/N Portfolio Strategy? *The Review of Financial Studies* 22, 5 (2007), 1915–1953.
- [11] Han Ding, Yinheng Li, Junhao Wang, and Hang Chen. 2024. Large Language Model Agent in Financial Trading: A Survey.
- [12] Qianggang Ding, Haochen Shi, and Bang Liu. 2024. TradExpert: Revolutionizing Trading with Mixture of Expert LLMs.
- [13] Yujie Ding, Shuai Jia, Tianyi Ma, Bingcheng Mao, Xiuze Zhou, Liulin Li, and Dongming Han. 2023. *Integrating Stock Features and Global Information via Large Language Models for Enhanced Stock Return Prediction*. Papers 2310.05627. arXiv.org.
- [14] Binh Do and Robert Faff. 2010. Does simple pairs trading still work? *Financial Analysts Journal* 66, 4 (2010), 83–95.
- [15] Zihai Dong, Xinyu Fan, and Zhiyuan Peng. 2024. FNSPID: A Comprehensive Financial News Dataset in Time Series. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, KDD 2024, Barcelona, Spain, August 25–29, 2024*, Ricardo Baeza-Yates and Francesco Bonchi (Eds.), 4918–4927.
- [16] Edwin J Elton, Martin J Gruber, and Christopher R Blake. 1996. Survivor bias and mutual fund performance. *The review of financial studies* 9, 4 (1996), 1097–1120.
- [17] Eugene F Fama. 1970. Efficient capital markets. *Journal of Finance* 25, 2 (1970), 383–417.
- [18] George Fatouros, Kostas Metaxas, John Soldatos, and Manos Karathanassis. 2025. MarketSenseAI 2.0: Enhancing Stock Analysis through LLM Agents.
- [19] Georgios Fatouros, Konstantinos Metaxas, John Soldatos, and Dimosthenis Kyriazis. 2024. Can Large Language Models Beat Wall Street? Unveiling the Potential of AI in Stock Selection.
- [20] Fuli Feng, Xiangnan He, Xiang Wang, Cheng Luo, Yiqun Liu, and Tat-Seng Chua. 2019. Temporal Relational Ranking for Stock Prediction. *ACM Trans. Inf. Syst.* 37, 2, Article 27 (2019), 30 pages.
- [21] CB Garcia and FJ Gould. 1993. Survivorship bias. *Journal of Portfolio Management* 19, 3 (1993), 52.
- [22] Evan Gatev, William N. Goetzmann, and K. Geert Rouwenhorst. 2006. Pairs Trading: Performance of a Relative-Value Arbitrage Rule. *The Review of Financial Studies* 19, 3 (2006), 797–827.
- [23] Mark Grinblatt and Sheridan Titman. 1989. Mutual fund performance: An analysis of quarterly portfolio holdings. *Journal of business* (1989), 393–416.

⁵<http://www.ecdf.ed.ac.uk/>

- [24] Taicheng Guo, Xiuying Chen, Yaqi Wang, Ruidi Chang, Shichao Pei, Nitesh V. Chawla, Olaf Wiest, and Xiangliang Zhang. 2024. Large Language Model Based Multi-agents: A Survey of Progress and Challenges. In *Proceedings of the Thirty-Third International Joint Conference on Artificial Intelligence, IJCAI 2024, Jeju, South Korea, August 3-9, 2024*. 8048–8057.
- [25] Campbell Harvey and Yan Liu. 2013. Backtesting. *SSRN Electronic Journal* 42 (2013).
- [26] Yifan Hu, Yuante Li, Peiyuan Liu, Yuxia Zhu, Naiqi Li, Tao Dai, Shu tao Xia, Dawei Cheng, and Changjun Jiang. 2025. FinTSB: A Comprehensive and Practical Benchmark for Financial Time Series Forecasting.
- [27] Eddie Hui and Ka Kwan Kevin Chan. 2018. Optimal trading strategy during bull and bear markets for Hong Kong-listed stocks. *International Journal of Strategic Property Management* 22 (2018), 381–402.
- [28] Jacques Joubert, Dragan Sestovic, Illya Barziy, Walter Distaso, and Marcos Lopez de Prado. 2024. The three types of backtests. *Available at SSRN* (2024).
- [29] Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B. Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. 2020. Scaling Laws for Neural Language Models.
- [30] Jae H Kim, Abul Shamsuddin, and Kian-Ping Lim. 2011. Stock return predictability and the adaptive markets hypothesis: Evidence from century-long US data. *Journal of Empirical Finance* 18, 5 (2011), 868–879.
- [31] Kemal Kirtac and Guido Germano. 2024. Sentiment trading with large language models. *Finance Research Letters* 62 (2024), 105227.
- [32] Kelvin J. L. Koa, Yunshan Ma, Ritchie Ng, and Tat-Seng Chua. 2024. Learning to Generate Explainable Stock Predictions using Self-Reflective Large Language Models. In *Proceedings of the ACM on Web Conference 2024, WWW 2024, Singapore, May 13-17, 2024*, Tat-Seng Chua, Chong-Wah Ngo, Ravi Kumar, Hady W. Lauw, and Roy Ka-Wei Lee (Eds.), 4304–4315.
- [33] Weixian Waylon Li and Tiejun Ma. 2025. Learn to Rank Risky Investors: A Case Study of Predicting Retail Traders' Behaviour and Profitability. *ACM Trans. Inf. Syst.* 44, 1, Article 15 (Nov. 2025), 33 pages. doi:10.1145/3768623
- [34] Xiao-Yang Liu, Ziyi Xia, Hongyang Yang, Jiechao Gao, Daochen Zha, Ming Zhu, Christina Dan Wang, Zhaojun Wang, and Jian Guo. 2024. Dynamic Datasets and Market Environments for Financial Reinforcement Learning. *Machine Learning - Springer Nature* (2024).
- [35] Xiao-Yang Liu, Hongyang Yang, Jiechao Gao, and Christina Dan Wang. 2021. FinRL: Deep reinforcement learning framework to automate trading in quantitative finance. *ACM International Conference on AI in Finance (ICAIF)* (2021).
- [36] Xiao-Yang Liu, Hongyang Yang, Jiechao Gao, and Christina Dan Wang. 2022. FinRL: deep reinforcement learning framework to automate trading in quantitative finance. In *Proceedings of the Second ACM International Conference on AI in Finance (Virtual Event) (ICAIF '21)*. Article 1, 9 pages.
- [37] Andrew Lo. 2004. The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective. *The Journal of Portfolio Management* 30, 5 (2004), 15–29.
- [38] Alejandro Lopez-Lira and Yuehua Tang. 2023. Can ChatGPT Forecast Stock Price Movements? Return Predictability and Large Language Models.
- [39] John J. McConnell and Wei Xu. 2008. Equity Returns at the Turn of the Month. *Financial Analysts Journal* 64, 2 (2008), 49–64.
- [40] C Muller and M Ward and. 2010. Momentum Effects in Country Equity Indices. *Studies in Economics and Econometrics* 34, 1 (2010), 111–127.
- [41] William F. Sharpe. 1964. Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *The Journal of Finance* 19, 3 (1964), 425–442.
- [42] Heyuan Wang, Tengjiao Wang, Shun Li, Jiayi Zheng, Shijie Guan, and Wei Chen. 2022. Adaptive Long-Short Pattern Transformer for Stock Investment Selection. In *Proceedings of the Thirty-First International Joint Conference on Artificial Intelligence, IJCAI 2022, Vienna, Austria, 23–29 July 2022*, Luc De Raedt (Ed.), 3970–3977.
- [43] Meiyun Wang, Kiyoshi Izumi, and Hiroki Sakaji. 2024. LLMFactor: Extracting Profitable Factors through Prompts for Explainable Stock Movement Prediction.
- [44] Saizhuo Wang, Hao Kong, Jiadong Guo, Fengrui Hua, Yiyuan Qi, Wanrun Zhou, Jiahao Zheng, Xinyu Wang, Lionel M. Ni, and Jian Guo. 2025. QuantBench: Benchmarking AI Methods for Quantitative Investment.
- [45] Cole Wilcox, Eric Crittenden, and Blackstar Funds. 2005. Does Trend Following Work on Stocks. In *The Technical Analyst*, Vol. 14. 1–19.
- [46] Ruoxi Wu. 2024. Portfolio Performance Based on LLM News Scores and Related Economical Analysis. *SSRN Electronic Journal* (2024).
- [47] Yijia Xiao, Edward Sun, Di Luo, and Wei Wang. 2024. TradingAgents: Multi-Agents LLM Financial Trading Framework. *ArXiv preprint abs/2412.20138* (2024).
- [48] Qianqian Xie, Weiguang Han, Zhengyu Chen, Ruoyu Xiang, Xiao Zhang, Yueru He, Mengxi Xiao, Dong Li, Yongfu Dai, Duanyu Feng, Yijing Xu, Haoqiang Kang, Ziyuan Kuang, Chenhan Yuan, Kailai Yang, Zheheng Luo, Tianlin Zhang, Zhiwei Liu, Guojun Xiong, Zhiyang Deng, Yuechen Jiang, Zhiyuan Yao, Haohang Li, Yangyang Yu, Gang Hu, Jiajia Huang, Xiao-Yang Liu, Alejandro Lopez-Lira, Benyou Wang, Yanzhao Lai, Hao Wang, Min Peng, Sophia Ananiadou, and Jimin Huang. 2024. FinBen: A Holistic Financial Benchmark for Large Language Models. In *Advances in Neural Information Processing Systems 38: Annual Conference on Neural Information Processing Systems 2024, NeurIPS 2024, Vancouver, BC, Canada, December 10 - 15, 2024*, Amir Globersons, Lester Mackey, Danielle Belgrave, Angela Fan, Ulrich Paquet, Jakub M. Tomczak, and Cheng Zhang (Eds.).
- [49] Hongyang Yang, Xiao-Yang Liu, and Christina Dan Wang. 2023. FinGPT: Open-Source Financial Large Language Models. *FinLLM Symposium at IJCAI 2023* (2023).
- [50] Hongyang Yang, Boyu Zhang, Neng Wang, Cheng Guo, Xiaoli Zhang, Likun Lin, Junlin Wang, Tianyu Zhou, Mao Guan, Runjia Zhang, and Christina Dan Wang. 2024. FinRobot: An Open-Source AI Agent Platform for Financial Applications using Large Language Models.
- [51] Yangyang Yu, Haohang Li, Zhi Chen, Yuechen Jiang, Yang Li, Denghui Zhang, Rong Liu, Jordan W. Suchow, and Khaldoun Khashanah. 2023. FinMem: A Performance-Enhanced LLM Trading Agent with Layered Memory and Character Design.
- [52] Yangyang Yu, Zhiyuan Yao, Haohang Li, Zhiyang Deng, Yuechen Jiang, Yupeng Cao, Zhi Chen, Jordan W. Suchow, Zhenyu Cui, Rong Liu, Zhaozhuo Xu, Denghui Zhang, Kuduvayur Subbalakshmi, Guojun Xiong, Yueru He, Jimin Huang, Dong Li, and Qianqian Xie. 2024. FinCon: A Synthesized LLM Multi-Agent System with Conceptual Verbal Reinforcement for Enhanced Financial Decision Making. In *Advances in Neural Information Processing Systems 38: Annual Conference on Neural Information Processing Systems 2024, NeurIPS 2024, Vancouver, BC, Canada, December 10 - 15, 2024*, Amir Globersons, Lester Mackey, Danielle Belgrave, Angela Fan, Ulrich Paquet, Jakub M. Tomczak, and Cheng Zhang (Eds.).
- [53] Haohan Zhang, Fengrui Hua, Chengjin Xu, Hao Kong, Ruifing Zuo, and Jian Guo. 2023. Unveiling the Potential of Sentiment: Can Large Language Models Predict Chinese Stock Price Movements?
- [54] Wentao Zhang, Lingxuan Zhao, Haochong Xia, Shuo Sun, Jiaze Sun, Molei Qin, Xinyi Li, Yuqing Zhao, Yilei Zhao, Xinyu Cai, Longtao Zheng, Xinrun Wang, and Bo An. 2024. A Multimodal Foundation Agent for Financial Trading: Tool-Augmented, Diversified, and Generalist. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, KDD 2024, Barcelona, Spain, August 25–29, 2024*, Ricardo Baeza-Yates and Francesco Bonchi (Eds.), 4314–4325.
- [55] Jason Zweig. 2019. Where Did This 'Bull Market' Come From, Anyway? *The Wall Street Journal* (2019).

A Data Collection

Our multi-source data comprises daily stock prices, daily financial news, and 10-Q and 10-K filings.

Daily Stock Prices. We collect daily price data for over 7,000 U.S. equities spanning from 2000 to 2024. Additionally, our dataset includes delisted symbols that were historically part of the S&P 500 index, based on the archived constituent list. This inclusion enhances the historical completeness of our dataset and mitigates survivorship bias within the context of index-based evaluations.

Financial News. The financial news dataset, initially compiled by Dong et al. [15], comprises 15.7 million records pertaining to 4,775 S&P 500 companies, spanning the years 1999 to 2023. We have organised the news by aligning it with the respective companies and indexing it by date.

10K & 10Q Filings. We collect 10-K and 10-Q filings for companies included in the Russell 3000 index, sourced from the US Securities and Exchange Commission (SEC) EDGAR database. These filings are publicly available and accessed via the SEC-API⁶, which allows programmatic retrieval and parsing. We preprocess the HTML documents and segment them into standardized sections, such as Risk Factors, MD&A, and Financial Statements, to support fine-grained analysis. Each filing is indexed by company identifier and filing date to enable alignment with other datasets.

Extensibility. All datasets used in this framework can be seamlessly substituted with proprietary or higher-resolution alternatives

⁶<https://sec-api.io/>

if available. Researchers may incorporate paid datasets such as premium financial news (e.g., Alpaca Markets⁷, Refinitiv⁸), earnings call transcripts, analyst research reports, or other modalities including video or audio. Integration is supported through the implementation of a custom dataset class, allowing modular and flexible replacement of any data stream within the pipeline.

B FinSABER Strategies Base

B.1 Timing-based Strategies

Open-Source LLM investors. This category includes *FinMem* [51] and *FinRobot* [50]. We acknowledge other works, such as *FinCon* [52] and *MarketSenseAI* [18], but they are not (yet) open-source, which prevents us from generating backtesting results.

Traditional Rule-Based (Indicator-Based) Strategies. We implement and cover several well-known traditional rule-based (indicator-based) investing strategies, such as *Buy and Hold*, *Simple Moving Average Crossover*, *Weighted Moving Average Crossover*, *ATR Band*, *Bollinger Bands* [3], *Trend Following* [45], and *Turn of the Month* [39]. These strategies typically rely on one or multiple technical indicators or domain-based rules to generate timely buy/sell signals, aiming to exploit identifiable market patterns or anomalies.

It is noteworthy that **traditional strategies are often overlooked**, with many existing works focusing solely on *Buy and Hold*. However, other established strategies listed above have also endured over time and demonstrated their effectiveness.

ML/DL Forecaster-Based Strategies. In contrast to fixed rules or indicator-based triggers, these strategies rely on data-driven models (statistical or neural network forecasters) to predict future price movements. Specifically, they buy or hold if an uptrend is indicated and sell (or go short) otherwise. This can be viewed as a relatively naive application of ML/DL forecasters, but it is widely used as a benchmark method for such models. Although one could consider the forecast output as a type of “indicator”, the reliance on predictive algorithms capable of uncovering complex patterns sets these methods apart from purely rule-based approaches. We include the well-known ARIMA [4] and XGBoost [8] in this category and also cover forecasters based on LLMs, but these are not LLM investors.

RL-Based Strategies. We also implement widely used RL algorithms for financial markets, including Advantage Actor-Critic (A2C), Proximal Policy Optimisation (PPO), Twin Delayed Deep Deterministic Policy Gradient (TD3), and Soft Actor-Critic (SAC), utilising the FinRL framework [34, 36]. Each agent learns investing policies by interacting with a simulated trading environment based on the OpenAI Gym API, using real historical market data.

B.2 Selection-based Strategies

This section details the implementation of the primary selection strategies used in our composite backtesting framework. Each selector operates on the historical S&P 500 constituents available at the start of a given rolling-window period to produce a list of tickers for the timing-based strategies.

⁷<https://alpaca.markets/>

⁸<https://www.lseg.com/en>

RANDOM FIVE. This strategy serves as a simple baseline for performance comparison. At the beginning of each evaluation period, it selects five stocks at random, without replacement, from the list of all available historical S&P 500 constituents for that period.

MOMENTUM FACTOR. Following the well-documented momentum factor [40], this strategy selects the stocks with the highest recent price appreciation. For each candidate stock, we calculate a momentum score based on its historical price data. Specifically, the score is the percentage return over a “momentum period” (e.g., 100 trading days), but we exclude the most recent “skip period” (e.g., 21 trading days) from the calculation. This practice is common in momentum strategies to avoid the “short-term reversal” effect [6]. The score for a given stock is calculated as: Momentum Score = $(\text{Price}_{t-\text{skip_period}})/(\text{Price}_{t-\text{momentum_period}}) - 1$. t is the selection date. All candidate stocks are then ranked in descending order by this score, and the top- k stocks (e.g., $k = 5$) are selected.

VOLATILITY EFFECT. This strategy is based on the “volatility effect” anomaly, where low-volatility stocks have been empirically shown to generate higher risk-adjusted returns [2]. For each candidate stock, we measure its historical volatility over a recent “look-back period” (e.g., 21 trading days). The volatility is calculated as the standard deviation of its weekly log returns within this period. We use weekly returns ($\ln(P_t/P_{t-5})$) rather than daily returns to smooth out daily noise. Candidate stocks are then ranked in ascending order by their calculated volatility, and the top- k stocks with the lowest volatility are selected for the portfolio.

FINCON SELECTION AGENT. Unlike the single-factor methods above, the FINCON SELECTION AGENT [52] aims to construct a **diversified portfolio** by explicitly considering both performance and inter-stock correlation. Its selection process is more sophisticated:

- (1) **Metric Calculation:** For all candidate stocks over a “look-back years” period (e.g., 2 years), the agent calculates daily returns to derive a full correlation matrix and a suite of performance metrics for each stock, including the Sharpe ratio.
- (2) **Primary Selection:** The agent first ranks each stock using a combined score that balances risk-adjusted return (Sharpe ratio) and its potential for diversification (low average correlation with all other stocks, $\bar{\rho}$). The score is calculated as: Score = Sharpe Ratio $\times (1 - \bar{\rho})$. The top- k stocks based on this score form the initial portfolio.
- (3) **Diversification Check &Fallback:** The agent then assesses the average correlation *within* the selected k -stock portfolio. If this internal correlation is above a predefined threshold (e.g., 0.7), it indicates poor diversification. In this case, the agent discards the initial selection and triggers a fallback algorithm. This second algorithm uses a greedy, diversification-first approach: it starts with the single stock with the highest Sharpe ratio and then iteratively adds the available stock that has the lowest average correlation to the already-selected members until a k -stock portfolio is formed.

C Evaluation Metrics

We group evaluation metrics into three categories, each targeting a distinct aspect of strategy performance. In the following definitions, T represents the total number of trading days, and R_t is the portfolio's return on day t .

C.1 Return Metrics

Annualised Return (AR). Measures the geometric average return of the portfolio on a yearly basis. It is calculated from the total cumulative return C as:

$$R_{\text{annual}} = (1 + C)^{\frac{252}{T}} - 1 \quad (1)$$

where 252 is the approximate number of trading days in a year.

Cumulative Return (CR). Measures the total return of the portfolio over the entire test period. It is calculated as:

$$C = \prod_{t=1}^T (1 + S_t \cdot R_{m,t}) - 1 \quad (2)$$

where S_t is the position taken by the strategy on day t (+1 for long, 0 for neutral) and $R_{m,t}$ is the market return of the asset on day t .

C.2 Risk Metrics

Annualised Volatility (AV). Measures the standard deviation of the portfolio's returns, scaled to a yearly figure. It is defined as:

$$\sigma_{\text{annual}} = \sigma_{\text{daily}} \times \sqrt{252} \quad (3)$$

where σ_{daily} is the standard deviation of the portfolio's daily returns, R_t .

Maximum Drawdown (MDD). Measures the largest peak-to-trough decline in portfolio value, representing the worst-case loss from a previous high. It is defined as:

$$\text{MDD} = \max_{t \in [1, T]} \left(\frac{P_t - V_t}{P_t} \right) \quad (4)$$

where V_t is the portfolio value on day t , and P_t is the peak portfolio value recorded up to day t ($P_t = \max_{i \in [1, t]} V_i$).

C.3 Risk-adjusted Performance Metrics

Sharpe Ratio (SPR). Measures the excess return of the portfolio per unit of its total volatility. It is calculated as:

$$\text{SPR} = \frac{\bar{R}_t - R_{f,\text{daily}}}{\sigma_{\text{daily}}} \times \sqrt{252} \quad (5)$$

Sortino Ratio (STR). Similar to the Sharpe ratio, but it only penalises for downside volatility, measuring the excess return per unit of downside risk. It is defined as:

$$\text{STR} = \frac{\bar{R}_t - R_{f,\text{daily}}}{\sigma_{\text{downside}}} \times \sqrt{252} \quad (6)$$

where \bar{R}_t is the average daily portfolio return, $R_{f,\text{daily}}$ is the daily risk-free rate (i.e., the annual rate divided by 252), and σ_{downside} is the standard deviation of only the negative daily returns.

D Extra Results on Selective Symbols

Tables 2 and 7 further substantiate our findings by highlighting the performance instability of *FinMem* and *FinAgent* when extending evaluation periods even marginally. Specifically, extending the evaluation by just two months beyond the originally reported periods [51] results in notable inconsistencies in critical performance metrics. It should be noted that the results for the LLM strategies are retrieved from Yu et al. [52], while the traditional rule-based results presented are based on our implementations.

For instance, *FinMem* exhibited a drastic change in cumulative returns for MSFT from a reported 23.261% down to -22.036%, and a reduction in Sharpe ratios from 1.440 to -1.247. Similarly, for NFLX, the Sharpe ratio for *FinMem* shifted dramatically from a reported 2.017 to -0.478. These examples underscore the sensitivity of LLM-based investing strategies to minor shifts in market conditions and reinforce our argument about the necessity of comprehensive and temporally robust evaluations to accurately assess the reliability and generalisability of these models.

E Technical Details

FINSABER Implementation. The backtesting framework and traditional rule-based strategies in FINSABER are implemented using BackTrader⁹ and Papers With Backtest¹⁰. Reinforcement learning-based methods are implemented using FinRL [35]. FINSABER supports two operational modes: “LLM” mode and “BT” mode. The “LLM” mode is tailored for strategies that leverage multi-modal inputs, including financial news and regulatory filings. In contrast, the “BT” mode is built directly on BackTrader, offering robust support for traditional rule-based strategies while maintaining a familiar interface to facilitate easy migration from standard BackTrader workflows.

Experiment Rolling Windows. We apply a rolling-window evaluation setup to ensure temporal robustness and reduce data-snooping bias. For the **Selected 4** evaluation, we use a 2-year rolling window with a 1-year step, and allow strategies to use up to 3 years of prior data for training. For the **Composite** setup, we adopt a more frequent rebalancing scheme with a 1-year rolling window and a 1-year step, allowing up to 2 years of prior data. This adjustment reflects the observation that rebalancing every two years may be too infrequent to capture changing market dynamics. All experiments span the benchmark period from 2004 to 2024.

Parameters of Strategies. Table 8 summarises the key hyperparameters used for each benchmark strategy in our experiments. These settings are largely drawn from standard defaults commonly used in the public implementations. For traditional rule-based strategies, optimal parameter selection often requires domain expertise or practitioner experience. Our goal is not to optimise each strategy's absolute performance, but to provide a fair and consistent baseline under a unified evaluation framework. We encourage future researchers to explore parameter optimisation techniques (e.g., grid search, Bayesian tuning) if desired.

⁹<https://www.backtrader.com/>

¹⁰<https://paperswithbacktest.com/>

Type	Strategy	TSLA			AMZN			NIO			MSFT		
		SPR	CR	MDD									
FinCon Selection (2022-10-05 to 2023-06-10)													
Rule Based	Buy And Hold	0.247	2.056	-54.508	0.150	2.193	-32.177	-0.858	-51.569	-53.563	1.071	32.629	-14.452
	SMA Cross	-0.151	-3.973	-23.173	0.599	13.731	-18.910	0.810	22.047	-17.976	1.641	32.057	-8.746
	WMA Cross	1.104	32.058	-18.492	0.513	11.765	-21.030	-0.771	-9.412	-18.732	1.526	30.344	-8.883
	ATR Band	-0.554	-22.136	-39.599	0.494	11.007	-15.842	0.681	24.684	-21.229	0.827	12.979	-7.709
	Bollinger Bands	-0.249	-12.756	-44.655	-0.381	-7.105	-20.615	0.940	25.476	-16.623	1.759	31.619	-3.475
LLM	Turn of The Month	0.928	27.850	-11.642	0.123	3.487	-14.892	0.874	31.344	-17.995	0.407	7.744	-11.955
	FinGPT	0.044	1.549	-42.400	-1.810	-29.811	-29.671	-0.121	-4.959	-37.344	1.315	21.535	-16.503
	FinMem	1.552	34.624	-15.674	-0.773	-18.011	-36.825	-1.180	-48.437	-64.144	-1.247	-22.036	-29.435
	FinAgent	0.271	11.960	-55.734	-1.493	-24.588	-33.074	0.051	0.933	-19.181	-1.247	-27.534	-39.544
	FinCon	1.972	82.871	-29.727	0.904	24.848	-25.889	0.335	17.461	-40.647	1.538	31.625	-15.010
Type	Strategy	AAPL			GOOG			NFLX			COIN		
		SPR	CR	MDD									
FinCon Selection (2022-10-05 to 2023-06-10)													
Rule Based	Buy And Hold	0.906	24.558	-19.508	0.683	20.884	-20.278	1.594	77.367	-20.421	0.024	-23.761	-54.402
	SMA Cross	1.423	21.054	-6.030	0.382	8.497	-17.035	-0.855	-8.393	-18.545	0.232	1.286	-35.559
	WMA Cross	1.648	25.257	-6.114	0.635	13.659	-14.985	-1.009	-9.479	-18.531	0.087	-7.461	-40.883
	ATR Band	0.241	4.522	-5.159	0.067	2.616	-13.522	0.522	10.739	-12.231	0.777	25.169	-22.906
	Bollinger Bands	-	-	-	0.365	7.526	-13.522	-0.182	-0.710	-13.244	-0.705	-24.371	-40.733
LLM	Turn of The Month	0.098	3.337	-12.498	0.343	7.188	-13.519	0.987	18.942	-10.641	-0.020	-8.999	-33.895
	FinGPT	1.161	20.321	-16.759	0.011	0.242	-26.984	0.472	11.925	-20.201	-1.807	-99.553	-74.967
	FinMem	0.994	12.397	-11.268	0.018	0.311	-21.503	-0.478	-10.306	-27.692	0.017	0.811	-50.390
	FinAgent	1.041	20.757	-19.896	-1.024	-7.440	-10.360	1.960	61.303	-20.926	-0.106	-5.971	-56.882
	FinCon	1.597	27.352	-15.266	1.052	25.077	-17.530	2.370	69.239	-20.792	0.825	57.045	-42.679

Table 7: Backtest performance of traditional rule-based (indicator-based) strategies and *FinCon* over the selective period (2022-10-05 to 2023-06-10), as presented in Yu et al. [52], evaluated using four metrics: cumulative return (CR), Sharpe ratio (SPR), annual volatility (AV), and maximum drawdown (MDD). The best metrics are highlighted in red, while the second best are marked in blue. “-” metrics across the board indicate no trade signals were triggered.

Strategies	Parameters
SMA Cross	short_window=10, long_window=20
WMA Cross	short_window=10, long_window=20
ATR Band	atr_period=14, multiplier=1.5
Bollinger Band	period=20, devfactor=2.0
Trend Following	atr_period=10, period=20
Turn of the Month	before_end_of_month_days=5, after_start_of_month_business_days=3
ARIMA	order=(5,1,0)
XGBoost	num_boost_round=10, n_estimators=1000
RL-A2C	learning_rate=1e-5, ent_coef=0.1, vf_coef=0.5, max_grad_norm=0.5, gae_lambda=0.95, gamma=0.99
RL-PPO	batch_size=64, learning_rate=2.5e-4, ent_coef=0.1, clip_range=0.2, gae_lambda=0.95, gamma=0.99
RL-SAC	learning_rate=2e-2, buffer_size=1000000, batch_size=256, learning_starts=100, ent_coef=0.1, tau=0.005, gamma=0.99, action_noise="normal"
RL-TD3	learning_rate=3e-2, buffer_size=1000000, tau=0.005, gamma=0.99, policy_delay=2, target_policy_noise=0.5, target_noise_clip=0.5, action_noise="normal"
FinMem	model=gpt-4o-mini, top_k=3, embedding_model=text-embedding-ada-002, chunk_size=5000
FinAgent	model=gpt-4o-mini, trader_preference=aggressive_trader, top_k=5, previous_action_look_back_days=14

Table 8: Default parameter settings for benchmark strategies.

F Comparative Drawdown Analysis via Underwater Plots

This appendix provides a visual analysis of strategy risk profiles through **underwater plots**. An underwater plot visualises the drawdown of a portfolio over time, offering an intuitive way to assess the depth, duration, and frequency of its losses.

The plots are derived by calculating the percentage loss of a portfolio’s equity curve from its running maximum value (its previous peak). At any given point in time, the drawdown D_t is calculated as: $D_t = (\text{Current Value}_t - \text{Previous Peak}_t)/\text{Previous Peak}_t$.

A value of 0% indicates the portfolio is at a new all-time high, while a negative value shows how far it is “underwater”. When interpreting the plots, two key features should be considered:

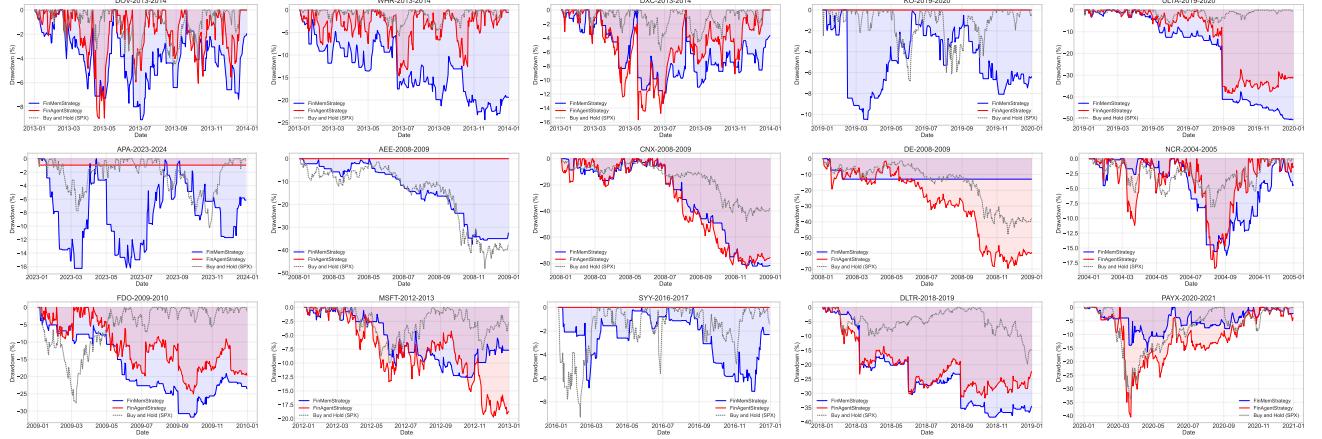


Figure 3: Comparative underwater plots for the FinMem (blue) and FinAgent (red) strategies against the Buy and Hold (SPX) benchmark across individual stocks selected in the Composite setup. The plots are grouped by the market regime of the period shown: bull markets (top two rows), bear market (third row), and sideways markets (bottom two rows).

- **Depth:** The magnitude of the drawdown, indicated by how low the line drops on the y-axis. Deeper drawdowns represent larger losses and greater risk.
- **Duration:** The length of time the line stays below the 0% axis. Longer durations represent slower recoveries and more prolonged periods of underperformance for the investor.

A superior strategy will exhibit shallower and briefer drawdowns compared to its benchmark.

The visual case studies shown in Figure 3 complement the aggregated quantitative results in the main paper, offering a granular perspective on the agents' behavioural patterns under different market conditions.

Bull Markets. The top two rows of the figure display strategy performance during bull market years, revealing a stark divergence in the agents' approaches. The *FinAgent* strategy (red) sometimes exhibits an **overly conservative posture**, as seen in KO (2019–2020) and APA (2023–2024). Its drawdowns are shallower than the benchmark's, or it may not trigger any trading activities. While this appears safe, it visually confirms the low beta values from our quantitative analysis and indicates a missed opportunity to capitalise on market gains. However, this risk-averse behaviour is fragile; in the case of ULTA (2019–2020), *FinAgent* experiences a catastrophic drawdown, revealing its risk model to be unreliable and poorly calibrated.

In contrast, the *FinMem* strategy (blue) consistently **fails to manage single-stock volatility**. In most bull-market cases (DOV, WHR, DXC), its drawdowns are significantly deeper and more prolonged than *FinAgent*'s. This demonstrates an inability to handle the inherent risk of the underlying asset, leading to the significant underperformance identified in the main paper.

Bear Markets. The third row, depicting the 2008 Global Financial Crisis, provides the most critical insight into the agents' flaws. While a single stock is expected to be more volatile than the index during a crash, the LLM strategies, particularly *FinMem*, **catastrophically amplify this downside risk**. For DE, the *FinMem*

strategy's drawdown approaches -75%, a far more severe loss than the SPX benchmark's -50%. Rather than providing any form of risk mitigation, the agents appear to make pro-cyclical decisions that accelerate losses. The *FinAgent* strategy, true to its more conservative nature, often mitigates some of these losses relative to *FinMem*, yet it still fails to generate a positive outcome. For instance, while its drawdown for CNX is shallower than *FinMem*'s, it remains severe and prolonged. This relative outperformance is insufficient and aligns with our market regime analysis (§7), which finds that both agents are poorly calibrated for bear markets and ultimately succumb to losses [9].

Sideways Markets. The final two rows illustrate performance in sideways, where the primary challenge is managing idiosyncratic stock risk without a clear market tailwind. Generally (but not consistently), the *FinAgent* strategy (red) exhibits shallower and less severe drawdowns than *FinMem* (blue), as seen in cases like NCR (2004–2005), FDO (2009–2010), and SYY (2016–2017). However, *FinAgent*'s conservative nature can also lead to periods of complete inactivity where no trades are triggered (observed before in bull market and bear market), causing it to miss minor recovery opportunities that the benchmark captures, as seen in FDO (2009–2010).

In summary, these visual case studies reinforce the quantitative conclusions in §6.3 and §7. LLM agents are poorly calibrated to distinct market regimes, behaving too timidly in uptrends and too recklessly in downturns, ultimately failing to provide the adaptive risk management necessary for consistent performance.

G LLM Strategies Cost Analysis

To better understand the practical deployment of LLM-based investing strategies, we monitor the API costs associated with running backtests on the **Composite** experiment with VOLATILITY EFFECT selection as a representative example. The cost for backtesting *FinAgent* was \$198.24, while *FinMem* incurred a significantly lower cost

of \$31.79 using GPT-4o mini. This reflects the higher prompt complexity and more frequent calls involved in FinAgent’s multi-agent decision-making process.

Extrapolating from these numbers, we estimate that completing all **Composite** experiments required approximately \$700 in LLM API costs. The **Selected 4** setup likely incurred even greater cost, given its larger rolling window size and the increased volume of financial news associated with these selectively popular symbols.

FinAgent was roughly 6 times more expensive than FinMem in our tests. Importantly, these figures only account for LLM generation costs (i.e., chat/completions endpoints), and do not include the cost of generating embeddings (e.g., via *text-embedding-ada-002*¹¹), which would further increase the total budget.

This observation raises a practical consideration for future research: when evaluating LLM-driven strategies, computational cost should be factored into the financial metrics, particularly for real-world deployment scenarios. Incorporating API usage cost into risk-adjusted performance metrics (e.g., Sharpe or Sortino) could provide a more holistic picture of strategy efficiency.

Recommendation. For researchers with limited budget, we recommend adopting open-source LLMs (e.g., LLaMA, Qwen, Mistral) for benchmarking and prototyping. These models can be deployed locally or via cost-effective cloud infrastructure, significantly reducing evaluation costs while enabling reproducible experimentation.

¹¹<https://platform.openai.com/docs/models/text-embedding-ada-002>