



Mini Review

# Artificial Intelligence and the Disparities in Investor Return

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**Abstract:** Individual investors often trail institutional ones in investor return. Artificial intelligence (AI) has been increasingly used in investing and finance sectors. However, its impact on the disparity in investor returns is unclear. We therefore discuss how and to what extent the application of AI tools exacerbates return disparities between individual and institutional investors. Literature search and review were conducted. Hypothetical drawdowns during 2020 market crisis were simulated and reported. Our data and review of literature show that AI may worsen these disparities through additional technological and psychological edges gained by institutional (versus individual) investors and large (versus smaller) institutions. To address this concern, we propose several approaches to mitigate the increasing disparities in investor return, including increasing awareness of the risks of AI-driven tools, playing defensively in the market, actions by the law makers and law enforcement agencies and fiduciary requirement of financial advisors and brokers. However, there are several exceptions to the increasing disparities that may help individual investors and those in small institutions. In summary, AI tools will likely increase the disparity in the investor return between individual and institutional investors and that between large and smaller institutions. Yet we believe that these disparities can be prevented or mitigated through collaborative efforts of the investors, public, academics, and government officials.

**Keywords:** artificial intelligence; machine learning; investment; investor return; wealth disparity

We here discuss how and to what extent the application of artificial intelligence (AI) tools in investing and finance sectors exacerbates return disparities between individual and institutional investors. It is also hoped that various stake holders will better understand the risks and benefits of AI tools in finance sector and work together to reduce the disparities in investor returns.

Ordinary investors often earn lower returns in investment than their wealthy counterparts in the US, resulting in increased wealth disparity [1–3]. Similarly, individual investors regularly trail institutional investors (fund managers) in their returns [4,5], including the ones who invested in mutual funds [6]. On the other hand, AI influences investors' behaviors and hedge fund performances [7–9]. However, the impact of AI on these disparities in investor returns is largely unknown.

Despite the great benefits of AI in finance sector [10,11], we are deeply concerned that AI may worsen these disparities through additional technological and psychological edges gained by institutional (versus individual) investors and large (versus smaller) institutions. To address this concern, we propose several approaches to mitigate the increasing disparities in investor return and discuss several exceptions to the increasing disparities.

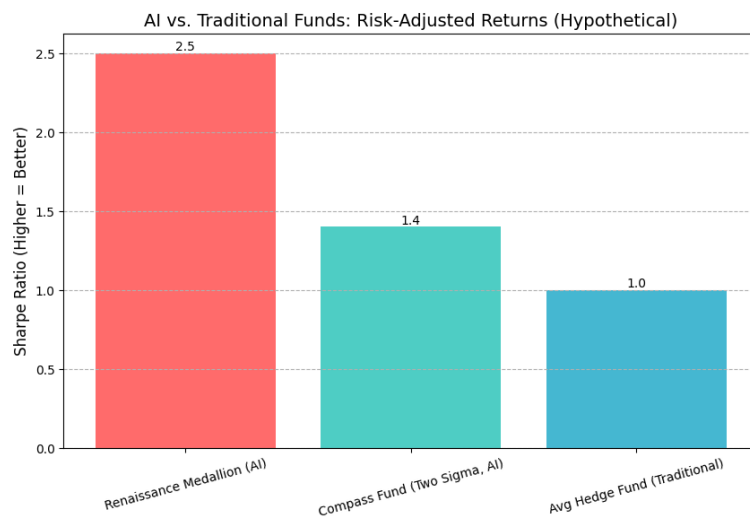


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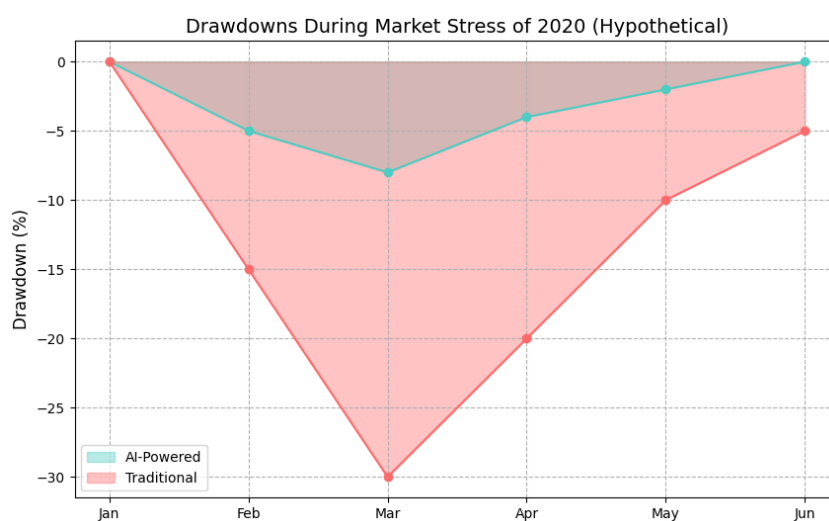
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We believe that maximizing investor return through AI tools requires gaining both technical and psychological edges, which may also impact disparities in investor return. Only if both edges are gained, can investors profit most from the AI tools. Some investors may not want to be influenced by AI tools due to the lack of access, confidence, AI literacy or required competency [12]. They will likely lose the technical edge but may still fare well in the market if hedged properly (i.e., maintain psychological edge). However, larger institutions and wealthy investors will likely beat the market more often and at a larger scale than before adopting AI tools, leading to increasing disparities in investor returns.

Indeed, AI tools can improve hedge fund performances (Figure 1, data obtained with assistance of Deepseek, figure plotted using colab of the Google) [9,13]. A quantitative back-test analysis shows that AI-drive high-frequency trading strategy outperformed manual trading (34.6% versus 12.8% annualized return and 3.7 versus 1.4 Sharpe ratio), yet with lower maximum drawdown (7.5% versus 19.3%) [14]. Similarly, a 2022 paper shows that the identified 36 AI-driven hedge funds outperformed the 790 non-AI-driven ones (0.91% versus 0.46% to 0.76% excessive returns) [9]. Our preliminary simulation study driven by AI showed that AI could significantly reduce drawdowns during the 2020 market crisis (Figure 2, plotted using colab of the Google). AI tools can also help pick hedge funds that have the best predicted performance [8]. The better returns of AI-driven funds naturally lead to not only a larger investor-return disparities between the large and smaller institution investors, but larger investor-return disparities between institutional and individual investors.



**Figure 1.** The Sharpe ratios of two AI-driven funds were higher than that of the average hedge fund.



**Figure 2.** The drawdowns during the market crisis of 2020 were simulated and generated. AI powered trading (teal area) appeared to have smaller drawdowns than traditional ones (red area).

The technical edges of AI are largely available to most data scientists and AI/software engineers. They may be earned through more data, higher data-quality, better AI algorithms, better tuning/adoption of AI algorithms,

better data scientists/engineers, more computing power and faster computing platforms. Compared with small- and medium-size institutions, large institutions have more capital to invest, obtain better, faster and more powerful AI tools, hire more capable data scientists and thus gain the technical edge. Compared with institutions, individual investors do not have direct access to high-quality data, advanced AI tools or dedicated data scientists and will thus have a technical disadvantage.

The psychological and behavioral edges are largely known to and mastered by seasoned traders [4]. For example, common psychological edges of a great trader are balancing greed and fear, being emotionless, being confident, being a life-time learner, contrarian thinking, being patient while awaiting the opportunity and being decisive in seizing the opportunity [15]. Some of these psychological edges may be gained using AI tools, but most of them cannot.

Moreover, advanced traders can even play the market, harvest their returns at an odd time and then create noises in the market as a byproduct. Thus, they may unintentionally interfere with, if not fool, other AI algorithms and data scientists. Given the nature of AI, AI tools, even generative AI, cannot process those unique traits which successful investors have.

Furthermore, contrarian traders and large institutions, who are knowledgeable, experienced, and able, can intentionally create noises in the market and fool the investors who mostly or completely rely on less advanced or slower AI algorithms. Because of the low interpretability of most AI algorithms, the “fooled” investors and their data scientists may not be able to effectively or timely trouble-shoot the issues unless they consider and effectively mitigate these noises. Thus, they are bound to having a lower investor return.

For example, at the end of a bull market, the advanced AI tool’s reading strongly and confidently suggests that a downturn of a stock is coming in one or two days. The informed investors may directly sell to harvest profits earlier than others in the next two days. Alternatively, instead of selling early, these investors would continue buying a small stake to raise the price, of course with the usual trick of first pulling down the price to wipe out stop-loss orders.

Given the momentum of rising prices, individual investors would consider the stock as bullish and thus would follow the buy or do nothing. At the same time, less advanced AI tools used by small institutions may predict the downturn in the next 1 to 7 days as predicted by the advanced AI tools did, but with less precision (1 to 7 days versus 1 to 2 days). Similar to individual investors, the less advanced AI tools will likely interpret this price rise as bullish signal which is aligned with and may augment its original (less precise) prediction. These less-well informed institutional investors will thus buy.

However, the stock’s price will drop as advanced AI tools have predicted on day two. The informed investors will sell at the highest price and the earliest moment (e.g., during premarket trading) of day two. Savvy investors may even short the stock immediately after using the settlement cash from selling. Their gain can be doubled. In other words, they are better informed and had an enormous market edge.

The others will then be trapped at the higher (buying) prices. Some investors may even consider the price drop as a normal reaction since the price rose just one day ago (day one). They will not sell until later and at even lower prices. These activities will thus lead to a return disparity in trading of this stock in this hypothetical scenario.

Finally, some investors who are true believers of AI may become overly confident and expose their assets to excessive risks even when armed with AI tools. This concern is supported by overconfidence and underperformance among the investors who used AI [16].

The investors’ investment style also has an impact on the investor-return disparity in the AI era. AI tools may be beneficial to some investing strategies, complementary to some, and neutral or not impactful to the others.

Quantitative investing strategy may benefit from AI tools more than other strategies due to the increased performance in data analyses. However, it will encounter increasing challenges as large institutions and contrarian investors start to play the market. It is noteworthy that quantitative investing strategy is available only to a small portion of individual investors (the riches) and certain institutional investors. Thus, its extraordinary returns will further increase disparities in investor returns.

AI tools may complement some investing strategies, such as macroeconomy, value, and technical analysis investing strategies. Macroeconomy based investing may use AI tools to better assess and predict the basic conditions. Value investing can also better assess a security’s intrinsic value using AI tools and are less influenced by the market noises.

However, savvy investors like Warren Buffett, who prefers a rather simple formula, will not be influenced by the AI tools. Similarly, the simple strategy of dollar cost averaging will not be impacted by the AI, either, since it is simply investing a preset amount of capital at a preset interval without sophisticated calculation or any market prediction.

Interestingly, there may be in our view several exceptions to the AI-related disparity in investor return: (1). The investors who develop and master an exceptionally innovative and accurate AI algorithm; (2). The investors who are aware of the risks of AI tools, reduce their exposure to related risks and act prudently. (3). The investors who faithfully follow a simple and repeatable investment process (e.g., dollar cost averaging). (4). When the ceiling of AI performance is reached. It may never occur, but when it occurs small- and medium-size institutions, maybe even advanced individual investors, could use AI tools to reach maximal/enhanced AI performance in related analyses including trend prediction, sentiment assessment and intrinsic value estimation. At that time, the disparity in investor return will largely depend on investor psychology and experiences and regress to the one in the era before AI was widely used. There are of course more exceptions as we start to better understand the impact of AI on disparities in investor return.

It is possible, albeit difficult, to prevent or mitigate these disparities.

First, investors, educators and government officials must be aware of the increasing disparities in investor return that is associated with AI. They can then work with the public to increase the awareness and adoption of the AI tools. Requiring disclosure of AI use in trading strategies will increase the transparency and public awareness of AI-associated trading risks, and thus reduce or stabilize the disparities in investor returns. Moreover, additional research and education funded by the government on AI-driven trading strategies will also help educate individual investors and fund managers at smaller institutions. Furthermore, government officials and law makers cannot interference the market activities but can better regulate AI-driven trading through professional organizations. For example, these organizations can implement an additional AI-trading related credentialing process that can better prepare financial advisors to protect individual investors. They may also increase the requirement of reserve funds or set the limit of leverage levels for AI-driven trading. Finally, fiduciary requirement should be enforced to best protect individual investors. This will be discussed in more details later.

Second, one can play defensively. To achieve this, individual investors can choose the strategy that is unlikely to be influenced by AI. For example, dollar-cost-averaging investing strategy can help hedge the influence of AI tools on the investor returns. Similarly, AI-driven strategies will fluctuate or be influenced by stock's prices but cannot change its intrinsic values. Hence, the value investing strategy, that relies on the firm's intrinsic values, will not be influenced and may stead benefit from fluctuation of stock prices.

Third, law makers and law enforcement agencies must be aware of the risks and market manipulations associated with AI. The worse scenario of AI associated risks will be enormous market turmoil and recessions. Thus, the public must be informed of the risks and potential crimes. To achieve this, timely and full disclosure of AI use in the trading must be released to the public and investors. The fund's performance including drawdowns must be reported with additional warning on the AI-driven trading. However, some investors may favorably consider AI-driven trading and aggressively, if not blindly, bet on these trading strategies and funds. More research on the risks and public education therefore appears warranted.

Finally, the fiduciary requirement of financial advisors and brokers may greatly protect individual investors and reduce the disparity in investor return [17,18]. The role of this requirement in protecting individual investors will become more important in the AI era than before since AI will help squeeze individual investors more than ever.

It is possible that advanced AI tools may not be understood or utilized by all financial advisors. But financial advisors still have more resources and better financial literacy than individual investors. They can also be better educated, credentialed and prepared by professional organizations than individual investors. Therefore, they are better position to meet the challenges associated AI-driven trading than individual investors. However, their best interest may not be completely aligned with that of their clients. Thus, only when financial advisors act fiducially, individual investor's interest can be effectively protected and the investor disparity will be stabilized or reduced. This is particularly true and important in the AI era.

However, it must be emphasized that these proposed approaches are preliminary and rudimentary. More and better approaches and policies will certainly emerge as more data are produced and more research is conducted.

In summary, AI tools will likely increase the disparity in the investor return between individual and institutional investors and that between large and smaller institutions. Yet we are hopeful that these disparities can be prevented or mitigated through collaborative efforts of the investors, public, academics, and government officials.

### Author Contributions

Article conceptualization and manuscript writing (I.Z.S. and L.Z.). Both authors contributed to the writing or revision of the article and approved the final publication version.

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## Data Availability Statement

Not applicable.

## Conflicts of Interest

The authors declare no other conflict of interests.

## Compliance with Ethical Standards

Not applicable. We used AI tools (Deepseek and ChatGPT) to collect data and generate graphs.

## References

1. Winston, E. Unequal Investment: A Regulatory Case Study. *Cornell L. Rev.* **2021**, *107*, 781.
2. Barber, B.M.; Odean, T. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *J. Financ.* **2000**, *55*, 773–806. <https://doi.org/10.1111/0022-1082.00226>.
3. Kacperczyk, M.; Nosal, J.; Stevens, L. Investor sophistication and capital income inequality. *J. Monet. Econ.* **2019**, *107*, 18–31. <https://doi.org/10.1016/j.jmoneco.2018.11.002>.
4. Barber, B.M.; Odean, T. The behavior of individual investors. In *Handbook of the Economics of Finance*; Elsevier: Amsterdam, The Netherlands, 2013. pp. 1533–1570. <https://doi.org/10.1016/B978-0-44-459406-8.00022-6>.
5. Gompers, P.A.; Metrick, A. Institutional investors and equity prices. *Q. J. Econ.* **2001**, *116*, 229–259. <https://doi.org/10.1162/003355301556392>.
6. Friesen, G.C.; Sapp, T.R.A. Mutual fund flows and investor returns: An empirical examination of fund investor timing ability. *J. Bank. Financ.* **2007**, *31*, 2796–2816. <https://doi.org/10.1016/j.jbankfin.2007.01.024>.
7. Rehman, M.; Dhiman, B.; Cheema, S.C. Minds and Machines: Impact of Emotional Intelligence on Investment Decisions with Mediating the Role of Artificial Intelligence. *Int. J. Eng. Bus. Manag.* **2024**, *8*, 1–10. <https://doi.org/10.22161/ijebm.8.1>.
8. Ma, T.; Wang, W.; Jiang, F. Machine learning the performance of hedge fund. *J. Int. Money Financ.* **2025**, *155*, 103332. <https://doi.org/10.1016/j.jimonfin.2025.103332>.
9. Grobys, K.; Kolari, J.W.; Niang, J. Man versus machine: On artificial intelligence and hedge funds performance. *Appl. Econ.* **2022**, *54*, 4632–4646. <https://doi.org/10.1080/00036846.2022.2032585>.
10. Hoang, D.; Wiegatz, K. Machine learning methods in finance: Recent applications and prospects. *Eur. Financ. Manag.* **2023**, *29*, 1657–1701. <https://doi.org/10.1111/eufm.12408>.
11. Aziz, S.; Dowling, M.; Hammami, H.; et al. Machine learning in finance: A topic modeling approach. *Eur. Financ. Manag.* **2021**, *28*, 744–770. <https://doi.org/10.1111/eufm.12326>.
12. Manrai, R.; Gupta, K.P. Investor’s perceptions on artificial intelligence (AI) technology adoption in investment services in India. *J. Financ. Serv. Mark.* **2023**, *28*, 1–14. <https://doi.org/10.1057/s41264-021-00134-9>.
13. Faheem, M.; Aslam, M.; Kakolu, S. Artificial Intelligence in Investment Portfolio Optimization: A Comparative Study of Machine Learning Algorithms. *Int. J. Sci. Res. Arch.* **2022**, *6*, 335–342. <https://doi.org/10.30574/ijrsra.2022.6.1.0131>.
14. Zhemerov, V. The Quantitative Edge: How High-Frequency Trading and Market Making Strategies Are Revolutionizing Financial Markets. 1 May 2025. Available online: <https://www.linkedin.com/pulse/quantitative-edge-how-high-frequency-trading-market-making-zhemerov-quhuc/> (accessed on 14 June 2025).
15. Munger, C.T. *Poor Charlie’s Almanack: The Essential Wit and Wisdom of Charles T. Munger*; Stripe Press: San Francisco, CA, USA, 2023.
16. Alp Coşkun, E.; Kahyaoglu, H.; Lau, C.K.M. Which return regime induces overconfidence behavior? Artificial intelligence and a nonlinear approach. *Financ. Innov.* **2023**, *9*, 30. <https://doi.org/10.1186/s40854-022-00446-2>.
17. Fein, M.L. FINRA’s Report on Robo-Advisors: Fiduciary Implications. *SSRN* **2016**. <https://doi.org/10.2139/ssrn.2768295>.
18. Weber, R.M. Who’s Your Fiduciary? *J. Financ. Serv. Prof.* **2024**, *78*, 24.