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Title: Man versus machine: on artificial intelligence and hedge funds performance

Year: 2022

Version: Accepted manuscript

Please cite the original version:

Grobys, K., Kolari, J. W. & Niang, J. (2022). Man versus machine: on artificial intelligence and hedge funds performance. *Applied Economics* 54(40), 4632-4646. https://doi.org/10.1080/00036846.2022.2032585

Man Versus Machine:

On Artificial Intelligence and Hedge Funds Performance

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Employing partially hand-collected data, sample hedge funds are formed into four categories depending on their level of automation. We find that hedge funds with the highest level of automation outperform other hedge funds with more reliance on human involvement. Also, we find that a man versus machine zero-cost strategy that is long hedge funds portfolio with highest level of automation and short those with highest level of human involvement yields a highly significant spread of at least 50 basis points per month. We conclude that automation plays an important role in the profitability of the hedge fund industry.

JEL Classification: G10, G11, G12, G14.

Keywords: artificial intelligence, asset pricing, automation, machine learning, hedge funds.

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[*]The authors would like to thank an anonymous reviewer for providing helpful and useful comments.

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1. Introduction

According to Agarwal, Green, and Ren (2018), hedge funds are pooled investment funds that engage in short-selling, leverage, and derivatives in an effort to improve risk-managed performance Their clientele consists mainly of institutional investors, wealthy individuals, and other sophisticated investors. Despite their niche investment style, hedge funds have gained considerable market share in the investment industry. As of 2020, the Preqin Global Hedge Fund Report (2021a) lists the global assets under management (AUM) of the hedge fund industry at $3.87 trillion. With approximately 18,000 active hedge fund managers, the forecasted annual growth rate of AUM is expected to be 3.5 percent with approximately $4.28 trillion by 2025.

Hedge funds compete with traditional investment companies. In this regard, the total net assets of passive exchange traded funds (ETFs) in the U.S. grew fourfold over the past decade surpassing $4 trillion (Investment Company Fact Book, 2021). Also, U.S equity mutual funds have similarly expanded over time, of which approximately 40 percent are passively managed index funds (Grégoire, 2020). Fact Book data indicate declining expense ratios for both ETFs and index mutual funds due to increasing competition as well as the inherently low cost fee structure of passive management relative to active management. Exploring the relationship between fees and performance, Kooli and Stetsyuk (2020) found that hedge funds outperform their more traditional equity investment counterparts but only before fees. They observed that increasing competition has tended to put pressure on hedge fund fee structures.

Competitive trends among institutional investors pose a serious challenge to the hedge fund industry. One possible way to improve the competitiveness of hedge funds vis-à-vis traditional investment companies is through technological advances. Computerized trading dates back to the early 1970s, but as observed by Kim (2010), automated trading systems have become progressively more complex over time. In this regard, Ray Dalio (2017), founder of Bridgewater Associates, has cautioned: "The main thrust of machine learning in recent years has gone in the direction of data mining, in which powerful computers ingest massive amounts of data and look for patterns … Investment systems built on machine learning that is not accompanied by deep understanding are dangerous …" (Dalio, 2017, p. 263). Gerlein, McGinnity, Belatreche, and Coleman (2016) have posited that AI is an evolutionary process from simple automation to more sophisticated algorithms that come close to (or even replace) the end user. Harvey, Rattray, Sinclair, and Van Hemert (2017) have commented that, while algorithms are already commonplace among hedge funds, their roles differ. They divided hedge funds into discretionary hedge funds that make trading decisions manually and systematic hedge funds that primarily utilize algorithms for decision making. As technology advances, the authors conjectured that it would become more difficult to distinguish between these two types of hedge funds, such that a combined approach was recommended.

A natural question that arises is: How does automation affect the performance of hedge funds? To answer this question, the present study investigates the performance of hedge funds using different technologies. If less direct interaction with trading decisions and more control by advanced trading algorithms yield better returns, hedge funds should progress to fully automated decision making. In this case human managers would become observers, with less involvement in day-to-day trading decisions. Unfortunately, a major problem in studying automation and hedge funds is that, as noted by Capocci and Hübner (2004), secrecy is a common practice in the industry. Treleaven, Galas, and Lalchand (2013) have argued that trading algorithms of varying sophistication used by hedge funds make it difficult to find details on their investment processes. Also, according to Fung and Hsieh (2000), regulators and financial supervisory authorities (FSAs) do not impose material restrictions on the types of investments that hedge funds pursue or their mandated disclosures.

In an effort to better understand how automation affects hedge funds, the present study employs the Preqin Hedge Fund Database (2021b) containing the population of 59,438 funds. Using specific search criteria, we gather a select sample of 826 hedge funds. By means of manual procedures, we create a data library that contains information about hedge funds' size, fee structure, and AI usage. This data set enables us to make inferences about automation with respect to the population of hedge funds. As a replication exercise, we revisit the Harvey et al. study. Hou, Xue, and Zhang (2020) have estimated that approximately 80 percent of scientific studies in financial economics fail scientific replication. Hence, replication is important to verify the results of testable research hypotheses. Additionally, we extend Harvey et al. by introducing a fourth category of hedge funds – namely, AI funds that combine elements from the other categories but use an advanced technological framework that sets them apart from others. Lastly, to our knowledge no previous studies carry out similar performance comparisons of hedge funds. Given the growing influence of automation and AI on various fields – from medicine to self-driving cars – our study yields insights into their impacts on the financial industry.

Based on four clusters of hedge funds depending on the level of human involvement in the decision-making process, we find that hedge funds with the highest level of automation in terms of using AI and machine learning in their investment process generate the highest average risk-adjusted returns ranging from 74 to 79 basis per month. Notably, the returns of highly automated hedge funds are correlated with the excess market factor but lack correlations to other risk factors, such as size, profitability and momentum. Confirming evidence in Harvey et al., we find that more traditional hedge funds are not only exposed to the market factor but the aforementioned risk factors also. Interestingly, hedge funds that exhibit the highest level of human involvement in decision-making invest in small, unprofitable loser stocks. Given that this cluster of hedge funds generates risk-adjusted average payoffs varying between 23 and 28 basis points per month, we infer that hedge fund managers take bets involving high risks that, on average, pay off. In view of these findings, we construct a man-versus-machine strategy that is long hedge funds with highest level of automation in their investment decision process and short hedge funds with lowest level of automation. This strategy generates statistically significant average payoffs that range from 50 to 56 basis points per month. Surprisingly, hedge funds that employ a medium combination of both automation and human involvement underperform other clusters. Apparently, blending human decision-making with automated processes is an inferior investment strategy.

Section 2 describes the formation of hedge fund clusters. Section 3 gives details of our data. Section 4 discusses the empirical results and robustness checks. The last section concludes.

2. Clustering hedge funds

2.1 Discretionary funds

As described by Fung and Hsieh, the discretionary approach to investing involves the use of mechanical trading rules performed by humans. While growth in technology has influenced the discretionary approach, this type of fund uses technology in a support role. They place a greater emphasis and weight on their managers in general and their professionalism and skill in particular (Kooli and Stetsyuk, 2020). Discretionary funds are the closest to the traditional hedge fund. Hence it is not surprising that they are most common hedge funds class. The Preqin Report (2021a, p. 96) lists 6,960 active discretionary funds managed by 2,636 fund managers with 1,152 investors.

Harvey et al. showed that discretionary funds exhibit a relatively stronger exposure than other funds with respect to well-known risk factors in asset pricing models. They found that the returns of these funds are less homogenous with more easily understood strategies than systematic funds. From a psychological perspective, Dietvorst, Simmons, and Massey (2015) observed that some investors are averse to investing in technology driven funds due to fears related to the use of algorithms and related wrong perceptions. According to Treleaven et al., while discretionary funds utilize multiple technologies in their pre-trade analyses (e.g., data cleaning and signal generation), human involvement dominates their investment process. Nevertheless, Harvey et al. have discerned that historical differences between discretionary funds and systematic funds have narrowed over time due to increasing similarities in their automated processes (e.g., macroeconomic and company specific factors).

Whereas algorithms other than AI would need to be specifically programmed to take into account different sources of information (e.g., meetings with company management), humans are more adaptive and can utilize direct conversations. In turn, behavioral biases can arise, as fund managers subjectively weight some information. One of the main factors setting discretionary funds apart from more automated funds is their reduced use of mathematical models for implementing trading strategies. Therefore, discretionary funds are considered to be skill-focused as opposed to model-focused, thereby creating inherent differences in their return and volatility dynamics (Preqin Report, 2021a, pp. 106-109). Relatedly, behavioral factors may explain the added return volatility of these funds.

Finally, Chincarini (2014) found that discretionary funds are more illiquid and place more restrictions on investor withdrawals than other funds. While these two characteristics are connected (e.g., a stable asset base is essential for investing in illiquid securities), Aragon (2007) documented that these practices are linked to higher average returns for hedge funds (i.e., a premium as compensation for holding illiquid securities). In sum, the main differences between discretionary and other funds stem from their quantitative models, investment philosophies, and liquidity.

2.2 Systematic funds

Systematic funds typically employ an extensive quantitative framework grounded in statistical methods in their trading strategies, which are automated using different types of algorithms. Because the involvement of a human manager is greatly reduced relative to discretionary funds, Chincarini inferred that behavioral errors are eliminated for the most part. Consistent with substantially fewer systematic than discretionary funds, the Preqin Report (2021a, p. 96) lists 2,173 systematic funds managed by 1,161 fund managers with 776 investors.

According to Chincarini, while management and performance fees do not differ between discretionary and systematic funds, the latter funds demand a higher minimum investment from their investors. Moreover, the average size of a systematic fund is considerably larger than a discretionary fund, which tends to reduce their trading costs due to economies of scale. Relatedly, automated trading tends to result in relatively more trading by systematic funds that further increases economies of scale.

Treleaven et al. divided the trading process of systematic funds into four steps. First, data are collected, including financial time series and economic fundamentals. Since these data need to be automatically retrieved, cleaned, organized, and sorted prior to usage, pre-processing is an important step. Second, the resultant data are input into trading algorithms. This step also involves data analysis to assess overall trends and signal generation. Third, trade execution is implemented as market orders based on the levels of supply and demand. Fourth, and last, post-trade analyses evaluate the profitability of trades as well as the decision process.

Because unexpected events can take place, a fund manager in a discretionary fund may well deviate from the original trading strategy. This adaptability enables discretionary funds to exhibit a higher degree of flexibility than other funds. However, as noted by Chincarini, even though systematic funds are less able to adapt, they have lower return volatility than discretionary funds.[1] Also, systematic funds tend to perform better during periods of market stress, which might be due to their ability to better manage pressure at such times.

2.3 Combined funds

[1] In a recent paper, Abis (2020) employed machine learning techniques to study the payoffs of discretionary and systematic funds. He argued that quantitative investors who rely on computer models exhibit more learning capacity but lack flexibility to adapt to changing market conditions.

As differentiated by Chincarini and Harvey et al., discretionary and systematic funds have their own advantages and disadvantages that can affect their performance. Therefore, they posited that a combined approach using the best parts of both trading styles would improve outcomes. These funds employ a hybrid approach, wherein the process is highly automated but the human manager is still involved. Because they incorporate a mixture of methods, it is not possible to clearly perceive the investment process. As an example, a combined fund might emphasize a systematic trading style but manually choose when trades are closed. Also, in their search for outperformance, Chincarini conjectured that combined funds might take advantage of the market timing ability of systematic funds.

In terms of correlations between different trading styles, combined funds are expected to be fairly similar to both systematic and discretionary funds. As such, their return dynamics will tend to follow similar patterns. Due to their joint nature, decision elements are cherry-picked to include both automation and emotionless execution as well as adaptability and human involvement. Even so, combined funds are recorded in the Preqin hedge fund database as their own trading style.

2.4 Artificial intelligence and machine learning (AIML) funds

AI funds are listed in the Preqin database as discretionary funds using AI, systematic funds using AI, and combined funds using AI. We group these three funds using into one cluster for artificial intelligence and machine learning (AIML).

AIML funds have a number of distinct characteristics. For example, Matias and Reboredo (2012) noted that AI models are well suited for dealing with nonlinear market data. Also, according to Gerlein et al., AI models excel in forecasting asset prices as well as uncovering hidden patterns in data that can lead to the creation of completely different strategies than human traders. Commenting on AI models, Mullainathan and Spiess (2017) mentioned that AI models do not require specific programming, as they are simply given an input along with a desired output, and the model itself determines the best course of action via a mathematical function. By implication, AIML funds could do a better job than systematic funds in terms of uncovering unique trading strategies (among a large number of combinations of strategies) that generate outperformance. If this is true, then AIML funds should not have strong commonalities with conventional hedge fund trading styles. Unlike systematic funds, AI models are able to learn and adapt. Also, unlike discretionary funds, AIML do not need to find an optimal level of human involvement that could impose possible behavioral biases.

With respect to potential AIML disadvantages, Chen, Hong, Huang, and Kubik (2004) opined that unique strategies may be difficult to scale up. Because AIML funds are small in terms of AUM, they could be exposed to the same risks as exotic trading strategies. As deduced by Dietvorst, Simmons, and Massey (2015), one potential reason for the small size of AIML funds in terms of AUM is algorithm aversion by investors. Moreover, Gerlein et al. highlighted that AI models and therefore AIML funds need to periodically retrain their models to keep up with market dynamics.

In sum, due to their distinctively different investment strategies, AIML funds are fundamentally different from conventional style funds. As observed by Stein (2009) and Sun, Wang, and Zheng (2012), the uniqueness of trading strategies is especially important for performance, whereas traditional strategies' abnormal returns will tend to disappear due to competition. In the next section, we explore whether these differences are reflected in the performance of AIML funds relative to their conventional fund counterparts.

3. Data

Hedge fund data is downloaded from the Preqin database with industry coverage on a global scale. Founded in 2003, the company started hedge fund records in 2007. Information is gathered from multiple sources, including open datahouses, SEC disclosures and other such regulatory filings, and direct contributions by funds. The latter source of direct information is obtained from fund managers as well as investors and service providers. Within the database, cross-referencing information from these multiple sources is emphasized to maintain high data quality and accuracy.

For most funds, data is available on the amount of leverage, management and performance fees, and fund performance and AUM figures. A variety of filters are available, including (for example) fund type, status, asset types traded, etc. Relevant to the present study, it contains a filter for whether a fund uses AI methods in its trading strategies. Moreover, the database differentiates between liquidated funds and funds withdrawing from reporting. The dates of inception and liquidation as well as current status of an active fund are reported. The database contains over 350 AIML funds. Also, almost all funds report a trading style, viz., systematic, discretionary, or combined.

The process of creating our data library is summarized in Figure 1. First, the overall database of 59,438 funds is culled by excluding different share classes that relate to the same underlying fund, which leaves 35,885 funds. Second, by selecting only funds with performance figures, the sample decreases to 11,944 funds of which 8,729 are hedge funds. Commodity Trading Advisors (CTAs) are not included to better focus on individual hedge funds. Third, the sample of funds is reduced to 1,476 by choosing those that trade equities, operate within North American markets (i.e., mainly the U.S.), and report U.S. dollar denominated returns.

We next manually filter funds. For example, North American funds are culled to contain those with U.S. investments. Also, because funds that trade equities may well trade other asset classes, we manually chose funds that mainly focus on equities (based on written descriptions and asset type information). Lastly, we remove funds with missing trading style information (i.e., systematic, discretionary, or combined).

Our final sample contains 826 individual hedge funds. Table 1 summarizes information on their trading styles and equity strategies. Potential survivorship bias is handled by the inclusion of both active and liquidated funds in the analyses. Sample period returns consist of monthly series from

September 2006 to January 2021 (or 173 months). In rare cases for which a fund is marked as liquidated but no specific date is provided, the fund is considered liquidated after it stops reporting in the database.

The classification of the final sample of hedge funds by trading style categories is based both on the trading style filter and other information available in the database about the use of AI in their investment process. Systematic funds include funds with this trading style and negative or no AI usage. Combined funds include funds with trading styles of both systematic and discretionary and negative or no AI usage. Discretionary funds include funds with this trading style and again negative or no AI usage. Finally, AIML funds include all funds with the usage of AI being positive regardless of their trading style being systematic, discretionary, or combined. For each of these trading styles, we form an equally-weighted portfolio across the full sample period of 173 monthly observations. Tables 2 and 3 provide descriptive information for these four trading style categories. As shown there, AIML funds generate lower maximum losses and gains compared to more traditional counterparts. This finding suggests that AI algorithms generate relatively stable performance outcomes. Also, AIML funds generate substantially higher cumulative returns and higher Sharpe ratios compared to other hedge fund trading styles.

4. Empirical results

4.1. Risk-adjusting the hedge funds portfolios

Agarwal et al. have observed that there is little or no consensus on the most appropriate model of hedge fund performance. In this respect, Capocci and Hübner posited that several different models can fulfill this purpose. Also, Sun, Wang, and Zheng (2012) proposed that the dynamic nature of hedge fund strategies requires models that have additional factors beyond the CAPM market factor of Sharpe (1964), Lintner (1965), and Mossin (1966). Contrarily, for mutual funds, Berk and Van Binsbergen (2016) and Barber, Huang, and Odean (2016) found that the CAPM was sufficient. In the present study, we follow Fung and Hsieh as well as Ammann and Moerth (2005) by employing multiple asset pricing models to evaluate hedge fund performance. More specifically, we use the CAPM market model, Fama and French (1993) three-factor model, Carhart (1997) four-factor model, and Fama and French (2015) five-factor model, which are specified as follows:

$$R_{i,t}^{e} = a_i + b_i MKT_t^{EX} + u_t, \tag{1}$$

$$R_{i,t}^{e} = a_i + b_i MKT_t^{EX} + s_i SMB_t + h_i HML_t + u_t, \tag{2}$$

$$R_{i,t}^{e} = a_i + b_i MKT_t^{EX} + s_i SMB_t + h_i HML_t + m_i UMD_t + u_t, \tag{3}$$

$$R_{i,t}^{e} = a_i + b_i MKT_t^{EX} + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + u_t, \tag{4}$$

where $R_{i,t}^{e}$ is the hedge fund portfolio excess return over the one-month U.S. Treasury bill rate, MKT_t^{EX} is the value-weighted (VW) market index return minus the Treasury rate at time *t*, SMB_t (small minus big) is the size factor, HML_t (high minus low book-to-market equity) is the value factor, RMW_t (robust minus weak) is the profitability factor, CMA_t (conservative minus aggressive) is the capital investment factor, and UMD_t (winners minus minus losers) is the momentum factor. Data for these risk factors are retrieved from Kenneth French's online data library.

Table 4 reports the regression estimates for our sample hedge fund portfolios. To take into account autocorrelation in hedge fund returns, we use the heteroscedasticity-and-autocorrelation-robust covariance (HAAC) matrix estimator of Newy-West (1987) with one lag (see Hwang, Xu, In, and Kim, 2017; Liew and French, 2005). In Panel A we see that, after controlling for the market risk factor, discretionary and AIML funds generate statistically significant risk-adjusted returns equal to 23 and 79 basis per month, respectively. In all categories of hedge funds, the market factor is statistically significant.

In Panel B of Table 4, we regress hedge fund portfolio excess returns on the popular three-factor model, which is often used as a benchmark model in the empirical asset pricing literature. Both discretionary and combined systematic and discretionary hedge funds are positively and significantly exposed to the size factor. This positive size exposure indicates that their excess returns are sensitive to small stocks' returns. Also, all but systematic funds generate statistically significant risk-adjusted returns (intercepts).

Panel C of Table 4 contains the regression results for the four-factor model. The size factor is positive and significant for discretionary and combined funds, which suggests sensitivity to small stocks' returns. With the exception of AIML funds, all hedge funds are significantly exposed to the momentum factor. Concerning mixed coefficient signs, systematic hedge funds are sensitive to winner stocks, whereas discretionary and combined funds are sensitive to loser stocks. Moreover, after controlling for all four risk factors, risk-adjusted returns (intercepts) for all but systematic funds are significant at the 5 percent level.

Finally, Panel D of Table 4 reports the results for the five-factor model. None of the hedge fund portfolios is significantly exposed to the value, profitability, and investment factors. Discretionary and combined funds are positively and significantly exposed to the size factor with sensitivity to small stocks' returns, which is consistent with our findings in Panels B and C. Additionally, discretionary hedge funds are at least marginally exposed to stocks that are unprofitable as implied by the nominally significant negative loading on the profitability factor. We infer that managers of discretionary funds bet aggressively on small and unprofitable stocks.

A number of patterns emerge from our asset pricing model findings in Table 4. First, AIML funds generate the highest risk-adjusted average returns (intercepts) ranging from 74 and 79 basis points per month with highly significant *t*-statistics between 3.96 and 4.50. Second, at least for AIML funds, our results confirm those for mutual funds by Van Binsbergen (2016) and Barber, Huang, and Odean (2016) in the sense that augmentation of the CAPM with other factors does not change our main results. In Table 4 we see that the market factor is the only factor that matters for all hedge funds irrespective of the level of automation; nonetheless, AIML hedge fuds exhibit the least exposure to the market factor. Third, and last, as we move from the AIML mutual fund category to discretionary funds, exposures to the size factor and estimated R-square values increase.[2] These findings corroborate Harvey et al., who found that discretionary funds exhibit a stronger exposure to traditional risk factors than other funds.

One may wonder if the results could be a manifestation of employing equal-weighted returns in each hedge funds cluster. Note from Table 4, that the excess returns of the AIML cluster are not exposed to the size factor in any asset pricing model because the *t*-statistic varying between 1.39 and 1.60 indicate statistical insignificances. Hence, we infer that the superiority of the AIML cluster is not a manifestation of some potential size exposure.

4.2. The artificial intelligence premium

Given our findings from Table 4, an interesting question is whether the higher risk-adjusted average returns of AIML hedge funds are systematically higher than those of discretionary hedge funds with the most human involvement. To answer this question, we form a man-versus-machine strategy that is long the AIML hedge fund portfolio and short the discretionary hedge fund portfolio. Using this long/short zero-investment portfolio as the dependent variable, we repeat the asset pricing model regression analyses in the previous section. Referring to Table 5, the man-versus-machine strategy generates payoffs ranging from 50 to 56 basis points per month with highly significant *t*-statistics ranging from 2.81 to 3.10. We infer from these findings that machines outperform humans in terms of risk-adjusted investment performance. Second, machines prefer to invest in stocks that are relatively larger than the stocks that humans choose.

4.3. Are the results robust?

[2] There may be several explanations for the observed differences in R-square values. For example, one explanation could be the use of portfolios in each category as opposed to individual funds. That is, if the cross-section of AIML funds is heterogeneous, it could be that a high alpha is the result of a mechanical relation. To explore this issue in more detail, one could use the empirical density of alphas in each fund categories and compare moments of this density. Since this exceeds the scope of our study, this is left for future research.

To ensure against false discoveries, Harvey, Liu, and Zhu (2016) evaluated over 300 cross-sectional asset pricing anomalies by means of a multiple testing framework to derive threshold levels for testing statistical significance. Their results indicated false discoveries account for 27% to 53% of empirical findings. Following these authors, we utilize the higher cut-off corresponding to 3.39 to assess the significance of test statistics. As shown in Table 4, payoffs for AIML hedge funds remain significant as *t*-statistics vary from 3.94 to 4.50 across different model specifications. Hence, our conclusions are unchanged.

As a further robustness check, following Hou et al., we perform a scientific replication. Since the returns of hedge fund categories are highly correlated (see Appendix Table A.1), we use a seemingly unrelated regression (SUR) approach. Extending our earlier results, we employ the Fama and French (2018) six-factor model, which augments their five-factor model with the momentum factor. The resultant system of equations is as follows:

$$R_t^{AIML} = a_1 + b_1 MKT_t^{EX} + s_1 SMB_t + h_1 HML_t + r_1 RMW_t + c_1 CMA_t + m_1 UMD_t + u_{1t},$$

$$R_t^{SYS} = a_2 + b_2 MKT_t^{EX} + s_2 SMB_t + h_2 HML_2 + r_2 RMW_t + c_2 CMA_t + m_2 UMD_t + u_{2t},$$

$$R_t^{COM} = a_3 + b_3 MKT_t^{EX} + s_3 SMB_t + h_3 HML_t + r_3 RMW_t + c_3 CMA_t + m_3 UMD_t + u_{3t},$$

$$R_t^{DIS} = a_4 + b_4 MKT_t^{EX} + s_4 SMB_t + h_4 HML_t + r_4 RMW_t + c_4 CMA_t + m_4 UMD_t + u_{4t}.$$

Here R_t^{AIML}, R_t^{SYS}, R_t^{COM}, and R_t^{DIS} denote the excess returns of AIML, systematic, combined, and discretionary hedge funds, respectively, in excess of the one-month U.S. Treasury bill rate. Using a two-step optimization procedure, SUR accounts for contemporaneous correlation across hedge funds categories. The results are reported in Table 6. Intercept estimates (denoted as alpha) are virtually the same as in Panel D of Table 4. Whereas the *t*-statistic with respect to the average payoffs of AIML hedge funds is exactly the same, *t*-statistics for alphas of other hedge funds increase after taking into account contemporaneous correlation and adding the momentum factor. Hence, our main conclusions are again unchanged.

Next, using the SUR approach, we re-test the statistical significance of the man-versus-machine strategy introduced in Subsection 3.2. Specifically, the research hypotheses are:

$$H_0\colon\ (a_1 - a_4) = 0 \qquad \text{versus} \qquad H_1\colon\ (a_1 - a_4) \neq 0.$$

The test statistic λ under the null hypothesis is asymptotically distributed as $\chi^2(1)$. Since the test statistic is estimated at $\hat{\lambda} = 8.61 > 3.84 = \chi^2_{0.95}(1)$ (p-value 0.0033), we clearly reject the null hypothesis. This statistical test strongly confirms our previous results. The artificial intelligence premium corresponds to 50 basis point per month and is statistically significant at any level.

Also, consistent with Harvey et al., Table 6 shows that discretionary hedge funds are significantly correlated with the size, profitability, and momentum factors. As such, discretionary funds exhibit a stronger exposure to traditional risk factors than other funds. Only AIML funds do not exhibit any significant factor exposure, with the exception of market factor. Furthermore, the sign of discretionary funds factor exposures indicates that they are, on average, exposed to small and unprofitable stocks that are losers. Lastly, the six-factor model does of good job of explaining variation in discretionary funds' returns with an estimated R-squared value of 93%.

4.4. On limitations

The results of the present study avoid a number of potential econometric pitfalls. First, there is no potential survivorship bias within the dataset, as both currently live and liquidated funds are included in the sample. Second, the biased effects of backfilling of return data, as discussed in Fung and Hsieh (2000) and Aggarwal and Jorion (2009), are negligible. Third, the case for return smoothing is not likely due to the fact that all our funds trade equities and most are publicly traded. Fourth, as pointed out by Hwang, Xu, In, and Kim (2017) and Liew and French (2005), serial correlation is not an issue in our study due to the use of robust *t*-statistics. It is true that, due to data availability, our sample period from September 2006 to January 2021 is relatively short. Despite this short sample period, our *t*-statistics are close to four and, hence, indicate a very high level of significance.[3]

In general, we find that AI and ML investment strategies have been highly successful relative to other funds in the recent past. However, as alluded to earlier, Ray Dalio (a highly successful manager of large hedge funds) has cautioned that automated methods are prone to rapidly changing financial markets.[4] In a Bloomberg seminar covering the topic of safe havens, Mark Spitznagel (2020), a hedge fund manager at *Universa* which posted an incredible return of 3,600% in March 2020, stressed that "stock markets are non-ergodic" in the sense that the future does not look like the past. Of course, successful hedge fund managers with different views of the world will shape the future of strategic hedge fund investment. It will be interesting to see if AIML funds can continue to outperform their less automated counterparts in the future.

This paper identifies hedge funds using artificial intelligence and machine learning (AIML funds) based on a filter whether a fund uses AI methods in the investment strategies from the Preqin Database. If a fund reports the use of AI in its investment strategy, no matter it is originally a systemic, combined, or discretionary fund, it would be grouped into a new cluster– AIML fund. Relying on this method, our paper identified 36 AIML funds out of 826 funds in total. However, hedge funds may use artificial intelligence and machine learning for different purposes and at different levels. For example, a hedge fund may use a machine learning algorithm to collect and analyze masses of data, predict corrections in supply and demand imbalances, forecast market movements, or execute trades. Furthermore, a fund manager may use AI in a support role to make investment decisions if the fund is associated with a discretionary style or launch the fund as an AI pure play fund with little human

[3] We acknowledge that there may typically be a possibility for some backfill bias in the performance figures of the database; however, since no return data is excluded due to our relatively small time series sample such effects can be presumed to be negligible. Further, a potential survivorship bias is accounted for by the inclusion of both active and liquidated funds into the analysis which is detailed by Chincarini (2014) and Fung and Hsieh (2009).

[4] Harvey (2021) has recently argued that, if unexperienced researchers use systematic tools, backtests are often overfit, which results in disappointing performance in live trading.

involvement. For instance, in 2018, Barclay Hedge's Hedge Fund Sentiment Survey found that over half of hedge fund respondents (56%) used AI to inform investment decisions.[5] We acknowledge that using the definition of AIML funds in our study, the percentage of AIML funds identified is lower than the percentage found in Barclay Hedge's survey. Note, that our study explicitly employs the Preqin database's filter as a reliable tool for classification. However, future studies are encouraged to use other filters.

Next, this study employs well-known and often-used asset pricing models to explore hedge funds performance. The literature has, however, introduced more risk factor models as performance benchmarks. For example, other risk factors that could be accounted for may account for the bond market, credit market, currency carry, or volatility as used in Harvey et al. (2017) for equity hedge funds. One could also consider the Fung and Hsieh seven-factor model or combined twelve-factor model a model accounting for a timing factor which have been also used in some hedge fund studies (Agarwal, Green and Ren, 2018). This exceeds, however, the scope of our study and is left for future research.

5. Conclusion

AI and ML are increasingly impacting many areas of society. This study sought to investigate the influence of automation on the financial industry. AI and ML are revolutionary new tools that have the potential to disrupt the management of traditional hedge funds. Using the Preqin database, we manually construct a data set of hedge funds grouped into four clusters: discretionary, systematic, combined, and AIML (automated). Subsequently, we tested whether AIML funds outperform other funds on a risk-adjusted basis. Using the CAPM market model as well as Fama and French three-factor and Carhart four-factor models, we found that AIML funds generated superior average returns compared to hedge funds with higher levels of human involvement. Testing a man-versus-machine

[5] See https://www.barclayhedge.com/insider/majority-of-hedge-fund-pros-use-ai-machine-learning-in-investment-strategies.

investment strategy that is long AIML fund portfolio returns and short discretionary fund portfolio returns, we documented significant average payoffs ranging from 50 to 56 basis points per month. Paradoxically, hedge funds with a medium level of both automation and human involvement perform the worst among different fund clusters. We infer that mixing human decision-making with automated processes is inferior to relying predominantly on either human or machine decision-making. This puzzle is left for future research. As there is a difference in the performance between AIML funds and other funds, it also would be interesting to explore potential exposures to other risks that are not captured in the common risk factor models such as idiosyncratic risk and tail risk. Since this exceeds to scope of our current research, future research is encouraged to investigate these issues.

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Figure 1. Process of data retrieval using the Preqin database

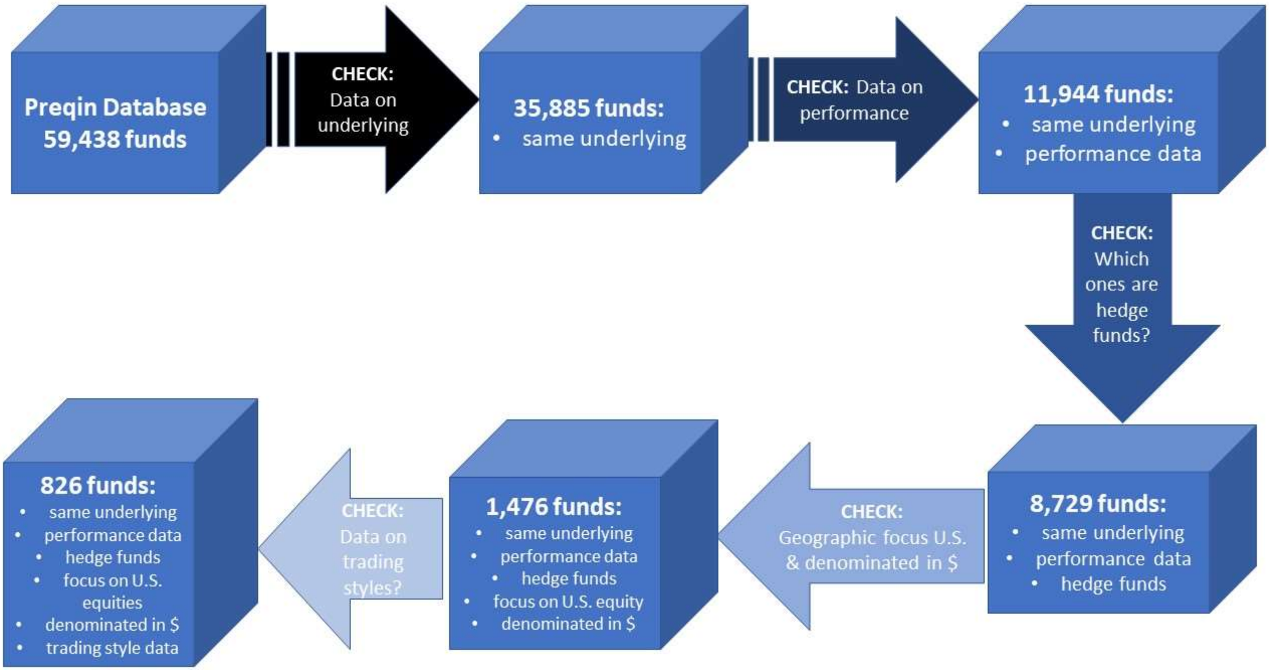

Table 1. Number of funds by trading style and common equity strategy

Hedge funds trading style and strategy	No. of funds
Panel A. AIML	36
AIML: Long/short equity	18
AIML: Equity market neutral	6
AIML: Long bias	3
Panel B. Systematic	117
Systematic: Long/short equity	56
Systematic: Equity market neutral	18
Systematic: Bias	18
Panel C. Combined systematic and discretionary	184
Combined: Long/short equity	118
Combined: Value-oriented	13
Combined: Long bias	26
Panel D. Discretionary	489
Discretionary: Long/short equity	294
Discretionary: Value-oriented	41
Discretionary: Long bias	80
All	826

Table 2. Descriptive statistics of hedge funds by trading style

Hedge funds trading style	Min. investment (thousand $)	Management fee	Performance fee	Leverage	Excess return	Cumulative return	Sharpe ratio	AUM (million $)
Panel A. AIML								
Min	25.00	0.40%	0.00%	0.00	-33.67%	-12.04%	-0.16	0.02
Mean	836.36	1.61%	17.81%	2.75	0.91%	52.83%	0.20	45.26
Median	500.00	1.75%	20.00%	1.50	0.63%	20.68%	0.14	15.53
Max	10,000.00	2.50%	25.00%	9.00	40.60%	358.36%	0.92	443.60
Panel B. Systematic								
Min	1.00	0.00%	0.00%	0.00	-66.66%	-92.26%	-0.55	0.05
Mean	3,528.35	1.38%	19.25%	16.74	0.46%	53.07%	0.14	747.72
Median	250.00	1.50%	20.00%	2.00	0.60%	20.07%	0.12	24.60
Max	100,000.00	3.00%	50.00%	400.00	91.20%	693.00%	1.44	35,662.00

Table 2. continued

Hedge funds trading style	Min. investment (thousand $)	Management fee	Performance fee	Leverage	Excess return	Cumulative return	Sharpe ratio	AUM (million $)
Panel C. Combined								
Min	1.00	0.00%	0.00%	0.00	-63.01%	-94.25%	-0.37	0.02
Mean	1,804.50	1.39%	17.88%	1.71	0.70%	94.79%	0.13	45.26
Median	500.00	1.50%	20.00%	2.00	0.58%	35.17%	0.13	15.53
Max	25,000.00	2.75%	50.00%	5.00	164.62%	2,913.01%	1.12	443.60
Panel D. Discretionary								
Min	1.00	0.00%	0.00%	0.00	-57.82%	-84.92%	-1.35	0.05
Mean	1,239.77	1.41%	18.50%	6.94	0.73%	116.52%	0.16	747.72
Median	625.00	1.50%	20.00%	1.05	0.69%	59.21%	0.15	24.60
Max	25,000.00	2.35%	30.00%	175.00	88.59%	2,718.63%	1.16	35,662.00

Table 3. Descriptive statistics of hedge fund trading style portfolios

This table provides descriptive statistics for hedge funds used in our sample. The statistics are reported for each cluster separately. For instance, across all hedge funds in the cluster AIML the generated minimum return is -9.82% over the sample period. In the same manner, across all hedge funds in the cluster AIML the lowest generated cumulative return is -2.11% over the sample period. Sample period returns consist of monthly series from September 2006 to January 2021 (or 173 months).

Hedge fund trading style	Excess return	Cumulative return	Sharpe ratio	AUM (million $)	No. of funds	Time series observations
Panel A. AIML						173
Min	-9.82%	-2.11%	-0.14	1.50	1	
Mean	0.93%	178.02%	0.57	354.72	12	
Median	0.82%	176.86%	0.41	110.89	10	
Max	10.82%	392.29%	1.68	1,448.48	30	
Panel B. Systematic						173
Min	-11.48%	-23.72%	-0.46	93.62	23	
Mean	0.44%	40.83%	0.36	12,646.46	53	
Median	0.71%	35.68%	0.42	8.668.94	53	
Max	4.96%	112.21%	1.28	37,478.94	78	
Panel C. Combined						173
Min	-9.81%	-18.08%	-0.53	1,701.48	49	
Mean	0.59%	64.39%	0.38	10,997.39	111	
Median	0.73%	72.06%	0.37	7,985.64	115	
Max	12.19%	177.29%	1.31	28,552.60	152	
Panel D. Discretionary						173
Min	-12.07%	-17.64%	-0.56	10,809.28	163	
Mean	0.70%	82.94%	0.46	34,055.09	312	
Median	1.04%	92.60%	0.31	37,115.04	336	
Max	10.72%	236.35%	1.58	59,269.66	395	

Table 4. Risk-adjusted regression tests by hedge fund trading style

This table reports the risk-adjusted regression tests for hedge funds with different trading styles. Regression analyses employ the CAPM market model, Fama and French (1993) three-factor model, Carhart (1997) four-factor model, and Fama and French (2015) five-factor model to risk-adjust hedge fund portfolio excess returns as follows:

$$R_{i,t}^{e} = a_i + b_i MKT_t^{EX} + u_t,$$
$$R_{i,t}^{e} = a_i + b_i MKT_t^{EX} + s_i SMB_t + h_i HML_t + u_t,$$
$$R_{i,t}^{e} = a_i + b_i MKT_t^{EX} + s_i SMB_t + h_i HML_t + m_i UMD_t + u_t,$$
$$R_{i,t}^{e} = a_i + b_i MKT_t^{EX} + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + u_t,$$

where $R_{i,t}^{e}$ is the hedge fund portfolio excess return over the one-month U.S. Treasury bill rate, MKT_t^{EX} is the value-weighted (VW) market index return minus the Treasury rate at time *t*, SMB_t (small minus big) is the size factor, HML_t (high minus low book-to-market equity) is the value factor, RMW_t (robust minus weak) is the profitability factor, CMA_t (conservative minus aggressive) is the capital investment factor, and UMD_t (winners minus minus losers) is the momentum factor. The sample period is from September 2006 to January 2021 (or 173 months). Newey-West (1987) *t*-statistics accounting for first-order autocorrelation are shown in parentheses.

Panel A. CAPM market model								
	Alpha	MKT	SMB	HML	RMW	CMA	UMD	Adj R-squared
AIML	0.79***	0.19***						0.13
	(3.94)	(3.56)						
Systematic	0.07	0.46***						0.79
	(0.57)	(10.17)						
Combined	0.12	0.60***						0.89
	(1.41)	(27.44)						
Discretionary	0.23**	0.60***						0.87
	(2.16)	(22.39)						
Panel B. Three-factor model								
AIML	0.74***	0.18***	0.11	-0.10				0.15
	(4.26)	(4.43)	(1.60)	(-1.01)				
Systematic	0.02	0.48***	0.02	-0.08***				0.80
	(0.16)	(10.76)	(0.43)	(-2.66)				
Combined	0.14*	0.56***	0.17***	0.01				0.91
	(1.82)	(32.26)	(5.69)	(0.37)				
Discretionary	0.24***	0.55***	0.29***	-0.00				0.92
	(3.38)	(32.87)	(11.23)	(-0.07)				

* Statistically significant at the 10% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 1% level.

Table 4. continued

	Alpha	MKT	SMB	HML	RMW	CMA	UMD	Adj R-squared
Panel C. Four-factor model								
AIML	0.74***	0.18***	0.18	-0.11			-0.01	0.15
	(4.25)	(3.84)	(1.60)	(-0.96)			(-0.25)	
Systematic	0.01	0.49***	0.02	-0.05			0.05***	0.81
	(0.13)	(11.45)	(0.55)	(-1.45)			(2.76)	
Combined	0.14**	0.54***	0.17***	-0.03			- 0.06***	0.91
	(2.00)	(35.49)	(6.10)	(-0.63)			(-2.96)	
Discretionary	0.24**	0.54***	0.28***	-0.03			-0.04**	0.93
	(3.61)	(27.94)	(11.83)	(-0.55)			(-237)	
Panel D. Five-factor model								
AIML	0.79***	0.16***	0.11	-0.03	-0.02	-0.23		0.17
	(4.50)	(3.94)	(1.39)	(-0.20)	(-0.16)	(-1.58)		
Systematic	0.03	0.47***	0.01	-0.07*	-0.04	-0.02		0.80
	(0.35)	(13.78)	(0.23)	(-1.91)	(-0.44)	(-0.21)		
Combined	0.17**	0.55***	0.16***	0.03	-0.04	-0.05		0.91
	(1.99)	(30.71)	(5.90)	(0.63)	(-1.04)	(-1.13)		
Discretionary	0.28***	0.53***	0.27***	0.03	-0.09*	-0.10		0.93
	(3.85)	(32.31)	(10.08)	(0.38)	(-1.76)	(-1.51)		

* Statistically significant at the 10% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 1% level.

Table 5. Pricing the zero-cost strategy man-versus-machine

This table reports asset pricing results for a man-versus-machine strategy that is long the AIML hedge funds portfolio and short the discretionary portfolio. Regression analyses employ the CAPM market model, Fama and French (1993) three-factor model, Carhart (1997) four-factor model, and Fama and French (2015) five-factor model to risk-adjust hedge fund portfolio excess returns as follows:

$$R_{i,t}^{e} = a_i + b_i MKT_t^{EX} + u_t,$$
$$R_{i,t}^{e} = a_i + b_i MKT_t^{EX} + s_i SMB_t + h_i HML_t + u_t,$$
$$R_{i,t}^{e} = a_i + b_i MKT_t^{EX} + s_i SMB_t + h_i HML_t + m_i UMD_t + u_t,$$
$$R_{i,t}^{e} = a_i + b_i MKT_t^{EX} + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + u_t,$$

where $R_{i,t}^{e}$ is the return on the zero-cost, man-versus-machine hedge fund strategy, MKT_t^{EX} is the value-weight (VW) market portfolio return minus the risk-free rate at time t, SMB_t (small minus big) is the size factor, HML_t (high minus low book-to-market equity) is the value factor, RMW_t (robust minus weak) is the profitability factor, CMA_t (conservative minus aggressive) is the capital investment factor, and UMD_t (winners minus minus losers) is the momentum factor. The sample period is from September 2006 to January 2021 (or 173 months). Newey-West (1987) *t*-statistics accounting for first-order autocorrelation are shown in parentheses.

	Alpha	MKT	SMB	HML	RMW	CMA	UMD	Adj R-squared
CAPM market model	0.56***	-0.42***						0.43
	(3.10)	(-10.92)						
Three-factor model	0.50***	-0.36***	-0.18***	-0.09				0.46
	(2.81)	(-9.97)	(-3.02)	(-1.39)				
Four-factor model	0.50***	-0.36***	-0.18***	-0.07			0.03	0.46
	(2.81)	(-8.58)	(-2.97)	(-0.98)			(0.76)	
Five-factor model	0.51***	-0.37***	-0.16**	-0.05	0.07	-0.13		0.46
	(3.02)	(-10.45)	(-2.36)	(-0.62)	(0.58)	(-1.21)		

* Statistically significant at the 10% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 1% level.

Table 6. Pricing hedge fund returns using the seemingly-unrelated regression approach

This table repeats the analyses in Table 4 using a seemingly unrelated regression (SUR) approach. Regression analyses employ the Fama and French (2018) six-factor model to risk-adjust hedge fund portfolio excess returns for the four fund categories as follows:

$$R_t^{AIML} = a_1 + b_1 MKT_t^{EX} + s_1 SMB_t + h_1 HML_t + r_1 RMW_t + c_1 CMA_t + m_1 UMD_t + u_{1,t},$$
$$R_t^{SYS} = a_2 + b_2 MKT_t^{EX} + s_2 SMB_t + h_2 HML_2 + r_2 RMW_t + c_2 CMA_t + m_2 UMD_t + u_{2,t},$$
$$R_t^{COM} = a_3 + b_3 MKT_t^{EX} + s_3 SMB_t + h_3 HML_t + r_3 RMW_t + c_3 CMA_t + m_3 UMD_t + u_{3,t},$$
$$R_t^{DIS} = a_4 + b_4 MKT_t^{EX} + s_4 SMB_t + h_4 HML_t + r_4 RMW_t + c_4 CMA_t + m_4 UMD_t + u_{4,t},$$

where $R_{i,t}^{e}$ is the respective hedge fund portfolio excess return over the one-month U.S. Treasury bill rate, MKT_t^{EX} is the value-weight (VW) market portfolio return minus the risk-free rate at time *t*, SMB_t (small minus big) is the size factor, HML_t (high minus low book-to-market equity) is the value factor, RMW_t (robust minus weak) is the profitability factor, CMA_t (conservative minus aggressive) is an investment factor, and UMD_t (winners minus minus losers) is the momentum factor. SUR takes into account contemporaneous correlation between the returns of the four different hedge funds categories. The sample period is from September 2006 to January 2021 (or 173 months). The *t*-statistics accounting for contemporaneous correlation are show in parentheses.

	Alpha	MKT	SMB	HML	RMW	CMA	UMD	Adj R-squared
AIML	0.79***	0.16***	0.12	-0.05	-0.02	-0.00	0.03	0.14
	(4.50)	(3.67)	(1.61)	(-0.62)	(-0.22)	(-0.02)	(0.39)	
Systematic	0.03	0.49***	0.02	-0.04	-0.03	-0.04	0.05***	0.81
	(0.39)	(23.48)	(0.47)	(-0.99)	(-0.63)	(-0.68)	(2.65)	
Combined	0.16**	0.54***	0.16***	-0.05	-0.05	-0.02	-0.06***	0.91
	(2.29)	(31.56)	(5.37)	(-1.44)	(-1.20)	(-0.36)	(3.67)	
Discretionary	0.28***	0.52***	0.27***	-0.05*	-0.11***	-0.07	-0.04**	0.93
	(4.50)	(33.74)	(9.82)	(-1.72)	(-2.70)	(-1.53)	(-2.48)	

* Statistically significant at the 10% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 1% level.

Appendix

Table A.1. Correlation matrix for hedge funds categories

This table shows the correlation matrix of four hedge funds categories sorted by human involvement. Discretionary hedge funds exhibit the highest level of human involvement, whereas AIML hedge funds have the lowest level of human involvement.

	AIML	Systematic	Combined	Discretionary
AIML	1			
	(--)			
Systematic	0.34***	1		
	(4.75)	(--)		
Combined	0.43***	0.85***	1	
	(6.26)	(21.50)	(--)	
Discretionary	0.42***	0.84***	0.97***	1
	(6.06)	(20.54)	(57.11)	(--)