When Machine Comes to Town: Fund Analysts' Performance with Artificial Intelligence[1]

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Abstract: How does the introduction of artificial intelligence (AI) technology affect the performance of mutual fund analysts? Using a unique setting in which AI was introduced to generate ratings for previously uncovered mutual funds in a large financial research company, we find that the analyst ratings' predictive power for future fund performance increases, suggesting higher rating quality. Further difference-in-differences analyses suggest two possible mechanisms through which AI adoption involving a separate set of funds affects the quality of human ratings: the reduction of analyst favoritism towards socially connected fund managers, and the availability of ratings for a large set of previously uncovered benchmark funds. The effects of AI adoption on fund analysts are more pronounced for analysts with stronger social ties with fund managers and higher past performance. This paper contributes to the growing literature on the interaction between AI and humans and provides unique insights on the mechanisms through which AI affects human performance.

Keywords: artificial intelligence, machine learning, mutual fund, analyst performance, social connection, benchmark information

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1. Introduction

The rise of artificial intelligence (AI hereafter) has significantly altered the landscape of the modern business world. In contrast to previous technological reforms, AI is uniquely able to continuously adapt and self-learn. As a result, AI can perform complex cognitive tasks that once required human judgment (Brynjolfsson and McAfee 2014, Brynjolfsson and Mitchell 2017, Kleinberg et al. 2018). The financial industry consistently ranks high in terms of investment in AI-based solutions. Betting on AI's ability to efficiently process and analyse a vast amount of data, the industry has integrated AI into areas such as trading, financial research, and risk analysis. This has led to public concerns about whether machines will substitute for financial workers and trigger large scale lay-offs (Acemoglu and Restrepo, 2020; Agrawal, Gans, and Goldfarb, 2019). While the media has often portrayed a dystopian future related to AI, scholars and practitioners are increasingly focusing on AI's potential to augment workers' productivity, and they link such augmentation strategies to superior performance (Daugherty and Wilson, 2018; Davenport and Kirby, 2016; Raisch and Krakowski, 2021). Instead of asserting that AI will completely replace tasks or jobs, we see opportunities for AI use that complements and enhances human performance. In the financial industry, decisions are often made with incomplete information under uncertain conditions, so firms must leverage the domain expertise of financial professionals to make contextualized decisions. We therefore believe that the human experts in the financial industry will not be completely substituted, and that their productivity will be augmented by AI solutions.

In this paper, we study the impact of AI adoption on human workers in the economically significant mutual fund industry. We leverage a unique setting in which Morningstar Inc. (Morningstar hereafter), the biggest independent financial research firm in the United States, has introduced a machine learning algorithm in order to scale up production. Morningstar has deployed the algorithm to produce mutual fund ratings for all of its previously uncovered mutual funds. Our results suggest that when AI was adopted to perform similar tasks as human analysts, the human analysts changed their rating behaviors such that their own ratings became higher in quality. Further difference-in-differences analyses suggest two possible channels through which such improvement is achieved: a disciplinary channel where AI curbs analysts' favoritism in evaluating mutual fund managers who are socially connected with them, and an information channel where AI provides ratings for a large number of previously uncovered benchmark funds. Our findings provide important insights on the potential benefits of collaboration between AI and human beings, and on the channels through which such benefits are realized.

Morningstar is the largest independent financial research company in the United States, and evaluating mutual fund quality is one of its main services. Since 1999, the financial analysts at Morningstar have conducted independent research and provided ratings (human ratings hereafter) for around 4,000 mutual funds, to help investors choose among the funds. In 2015, to expand its coverage, Morningstar developed a machine learning algorithm that mimics the decision-making process of the analysts based on their past decisions and the data used to support them. Morningstar then applied the algorithm to the universe of funds NOT covered by human analysts and published the results as the Morningstar Quantitative Ratings (machine ratings hereafter). Today, working in parallel to the algorithm, human analysts continue to rate selected funds on their coverage list following the existing methodology. The machine ratings have been available to all Morningstar subscribers since June 2017. The introduction of machine ratings has significantly enhanced the breadth of fund coverage and the frequency of rating updates. As of February 2021, the fund analysts cover 3,227 funds and 563 ETFs globally, while the machines cover 34,002 funds and 3,950 ETFs, corresponding to a tenfold increase in coverage.

It is important to understand the mutual fund evaluation process and the implications of AI adoption in that industry. The mutual fund industry in the United States is economically important, with nearly 8,000 unique funds managing USD 17.76 trillion of total financial assets by the end of June 2022 (Federal Reserve Bank of St. Louis, 2022)—equal to more than 40% of the global mutual fund market. The industry is also important for U.S. households, as 46.2% of them hold investments in mutual funds. Due to the vast number of available funds, fund investors who are making investment decisions rely heavily on the recommendations of financial research experts, such as the fund ratings produced by the Morningstar fund analysts. Previous studies show that investors react to the Morningstar mutual fund ratings such that the higher-rated funds experience significantly higher net cash inflow than the lower-rated ones (Sirri and Tufano, 1998; Goetzmann and Peles 1997). A study in the *Boston Globe* and the *Wall Street Journal* shows that 97% of the money flowing into no-load equity funds between January and August 1995 was invested in funds with four- or five-star Morningstar ratings (Blake and Morey, 2000). Thus, the quality of Morningstar ratings has an important impact on investment efficiency in the mutual fund industry.

Our goal is to explore the effects of AI adoption on human analysts' performance when both the machine and human beings are rating funds. We find that after the machine ratings became available, the overall human ratings have higher predictive power for future fund returns both at the short-term and long-term horizons, suggesting higher ratings quality. Such improvement is driven mainly by the components of the overall rating that focus explicitly on the fund's managers (the People pillar) and human resources (the Parent pillar) and are therefore more susceptible to human analysts' subjectivity. We also find that the net cash inflows into the funds become more sensitive to the overall ratings and the People pillar ratings after AI adoption, suggesting that the market perceives an improvement in these ratings' quality.

Having shown that AI adoption improves the quality of human fund ratings, we conduct additional analyses to explore the channels through which this may have occurred. First, we hypothesize that AI adoption influences analyst ratings via a *disciplinary channel*. To produce the fund ratings, Morningstar's mutual fund analysts need to evaluate the management quality of the fund managers. These evaluations typically involve social interactions, such as phone exchanges and face-to-face meetings, between the analysts and the fund managers. Thus, giving low ratings to the fund managers is likely to introduce tension between the parties, especially when the fund managers are socially connected with the fund analysts. Prior studies find that various financial market participants, including equity research analysts, exhibit favoritism towards socially connected individuals and are more likely to recommend stocks or give optimistic earnings forecasts to the connected firms. Such favoritism can also be found in other professions, including executives, board members, and even judges (Westphal, 1999; Bradley, Gokkaya, and Liu, 2020; Gu et al., 2019).

To identify social connections, we obtain a proprietary dataset of the educational backgrounds of fund analysts and fund managers from covered funds; we consider pairs who attended the same institution to be socially connected. Consistent with prior literature, we find that the mutual fund analysts in Morningstar do show favoritism towards socially connected fund managers, giving higher ratings to those who attended the same educational institutions as they. However, we expect that when AI is introduced to perform similar tasks as the human analysts, this favoritism will be curbed through the *disciplinary channel*. In this channel, analysts will be incentivised to exert more effort and produce higher-quality ratings due to career concerns about being replaced by AI (Acemoglu and Restrepo, 2018; 2020). In addition, since investors will have access to the machine ratings for comparable benchmark funds and fund managers, any biases in the human ratings will be more visible and subject to higher scrutiny. Both of these factors should discipline analysts to provide more objective and fair ratings.

Consistent with the existence of a disciplinary channel, we find that after analysts begin receiving machine ratings internally in February 2015, they reduce the People pillar ratings (i.e., manager ratings) and the overall firm ratings of connected fund managers while increasing the ratings of unconnected managers. After the change, the People pillar ratings and the overall ratings better predict fund performance over the next one year and next three years. The net cash inflows into the funds also become more sensitive to the ratings, suggesting that investors perceive the human ratings as being of higher quality after the AI introduction.

Second, we hypothesize that AI adoption can influence analyst ratings via a *learning channel*. Prior research shows that financial research analysts pay attention to, and learn from, peers' opinions (Graham, 1999; Trueman, 1994; Welch, 2000). Also, having access to the information of peer groups or benchmark groups can help decision makers make better decisions via learning (Kumar, Rantala, and Xu, 2022). After AI began generating ratings for the previously uncovered funds in Morningstar, the analysts could compare their evaluations with those of the benchmark funds and reflect on their own rating practices. Our interviews with several financial analysts from Morningstar confirmed that they refer to the machine ratings of benchmark funds and reflect on their own rating routines. Consistent with the learning channel, we show that the quality of human ratings improves more for analysts who follow funds for which there is a larger increase in benchmark fund coverage.

We then explore the heterogeneity of the effects of AI adoption on fund analyst performance depending on analyst tenure and quality. We find that more experienced analysts and analysts with better past performance make larger adjustments to their ratings and experience greater improvements in rating quality following AI adoption.

Our first sets of results focus on the quality of fund analysts' ratings, but fund analysts also produce reports on the mutual funds they cover, and an understanding how AI adoption affects the quality of these reports is important. We therefore complement our main analyses with textual analyses of fund analyst reports. We find that, consistent with the disciplinary channel, analysts who are socially connected with the fund managers provide less optimistic and less subjective analyst reports following AI adoption. Such results further support the notion that AI can discipline fund analysts to overcome their favoritism towards connected funds and improve the objectivity of their evaluations.

Our paper contributes to several streams of literature. First, we contribute to the literature on the interactions between artificial intelligence and human beings. Empirical studies find mixed results on the effect of AI adoption on human workers' performance (Allen and Choudhury, 2022; Agrawal, Gans, and Goldfarb, 2019; Scholl and Hanson, 2020; Tong et al., 2021). Our results shed light on the potential benefits of human–machine collaboration and provide important insights for companies and organizations who are considering integrating artificial intelligence into their workflow. In addition, we identify human characteristics—including work experience and past performance—that can affect the benefits linked to AI adoption.

Second, we contribute to the literature on mutual fund analysts. Currently, there is little research on decision making by fund analysts, despite their being among the most important players in the economically significant mutual fund industry. There is a larger literature on equity research analysts, and the jobs of fund analysts and equity research analysts are similar in some ways. However, the two types of analysts have different specialties and respond to different incentives during the evaluation process. One key difference is that fund analysts need to explicitly evaluate the management team of a mutual fund. Our unique dataset of fund analysts' backgrounds and characteristics enables us to investigate factors affecting their incentives. A recent working paper by Cheng, Lu, and Zhang (2021) is related to our study, as it examines whether the quantitative ratings in Morningstar perform better than traditional analyst ratings. To assess this, the authors run a horse race between the analyst ratings and machine ratings by constructing synthetic machine ratings for funds currently covered by human analysts. Our paper differs from theirs in that we focus on whether and how fund analysts' work quality is affected and augmented by AI adoption. We also further explore how fund analysts react to AI and how their varied incentives and characteristics affect the outcomes of AI adoption. Understanding the behavioral changes in response to AI is particularly important in contexts where humans and AI complement each other. In such contexts (including the mutual fund research industry), the best solution is likely neither human-only nor AI-only but rather a collaborative system that keeps humans in the decision-making loop. Hence, to design better human-augmenting solutions in the future, on must first understand the interactions between humans and machines.

Finally, we add to the literature on how analysts learn from their peers. Prior studies show that analysts learn from peers and tend to issue recommendations similar to theirs (Kumar et al., 2022). In our case, the peer is AI. Since the development of the machine algorithm was based on the rating practices of many different analysts, the machine ratings are less likely to be affected by the biases of a particular fund analyst. Also, AI utilizes more information than humans can collect and process. Thus, AI should be able to provide high quality benchmarking information, which fund analysts could learn from and use to improve their own rating quality. Our findings confirm this prediction and thus have important implications for the application of AI in other settings.

2. Institutional Background

2.1. Morningstar Human Ratings

Morningstar, headquartered in Chicago, is the largest independent financial research firm in the United States. As one of its core businesses, Morningstar started rating mutual funds globally in 1986. At any point in time, around 100 unique fund analysts are working at Morningstar, covering 4,000 different mutual funds on average. The fund analysts conduct independent research using public sources and private communications with fund insiders (including interviews with fund managers) before assigning their ratings—which we refer to as human ratings—to the funds.[2] As a result of this research process, the human ratings rely heavily on the fund analysts' investigation and personal judgment. In addition to ratings, the fund analysts also produce analyst reports for the covered funds.

Over time, the analysts' rating methodology has evolved. The most recent Morningstar human rating system was introduced in 2011. It includes a forward-looking overall rating that incorporates fund analysts' belief on the fund's ability to outperform its peer group or relevant benchmark group in the future, as well as five pillar ratings—People, Parent, Process, Performance, and Price—that capture different aspects of the quality of a mutual fund. The overall rating is on a scale of five: gold, silver, bronze, neutral, or negative. A gold rating means the analyst expects the fund to outperform its relevant benchmark fund; it requires distinguished ratings across all five pillars. At the other extreme, funds with negative ratings possess at least one flaw (e.g., high fees or an unstable management team) that the analyst believes will significantly hamper their future performance.

The fund analysts start by assigning a rating for each of the five pillars. Each pillar rating during our sample period is on a scale of three: positive, neutral, or negative.[3] The People pillar pertains to the talent, tenure, and resources of the fund managers. The Parent pillar is specific to the stewardship quality of the fund resources. The Process pillar evaluates the fund manager's overall investment style. The Performance pillar involves the fund's ability to generate long-term returns (in contrast to its historical performance). Lastly, the Price pillar considers the fund's expenses and fees.

[2] See "Morningstar Analyst Rating for Funds Methodology Document", November 15, 2011.

[3] Morningstar changed the rating scales of People, Parent, and Process pillars starting from October 2019. To maintain consistencies in the rating scales, we end our sample in October 2019.

After the pillar ratings are available, the overall ratings are calculated based on the following methodology: First, the funds are classified into different categories following a proprietary Morningstar fund classification system. Next, the analysts calculate the distribution of performance for each investment category and the weighted sum of the pillar scores scaled by the width of the distribution and subtract its fee. Finally, the normalized scores are sorted into "medallist-eligible" and "medallist-ineligible" groups, based on the analyst's prediction on whether or not the fund will outperform its benchmark and category average. The top 15% of the medallist-eligible group are given a gold rating, the next 35% are silver, and the bottom 50% are bronze. Of the medallist-ineligible funds, the top 70% are rated neutral and the bottom 30% are negative.

Given the rating methodology of human fund analysts, the performance of analysts depends on whether their mutual fund ratings and recommendations successfully identify funds that outperform benchmark funds.

2.2 Morningstar Quantitative Ratings

In order to expand its fund coverage, Morningstar introduced the Morningstar Quantitative Rating (machine rating) following research and development that dated to 2012. After several rounds of testing, the machine ratings have been internally circulated since February 2015 and were officially published and made available to all subscribers in February 2017. A detailed timeline of the rollout is presented in Appendix II. The machine ratings were developed with the goal of mimicking the rating assignment behaviors of fund analysts. The machine rating system consists of an overall rating and three pillar ratings (Parent, People, and Process) for each fund. The pillar ratings aim to measure the same attributes as under the human rating evaluation process.

The machine-learning algorithm estimates the pillar ratings for each fund, then aggregates them to get the overall rating. Specifically, the algorithm employs "random forest" models, which fit a relationship between a fund's pillar ratings and its evaluation attributes. For each pillar, two random forest models are estimated: one to determine the probability distribution of a fund being rated positive, the other to determine the probability distribution of a fund being rated negative. In total, six individual random forest models are used to estimate the three pillar ratings, and the probabilities produced by the models are aggregated to get the overall rating. After the three pillar ratings are available, the same processes are implemented to aggregate them and to sort firms into different ratings groups.

At Morningstar, the algorithm has significantly expanded the breadth of coverage of mutual funds. As of February 2021, fund analysts cover 3,227 funds and 563 ETFs globally, whereas the machines cover 34,002 funds and 3,950 ETFs, corresponding to a tenfold increase in coverage. In addition, the quality of machine ratings seems promising: recent Morningstar research indicates that the machine ratings have high predictive power in picking overperforming and underperforming funds over both short-term and long-term horizons (Agarwal, 2019).[4]

3. Hypothesis Development

3.1 AI Adoption and Analyst Performance

A priori, it is unclear how the adoption of AI will affect fund analysts' performance. Although lower-skilled workers are known to be vulnerable to automated technologies such as machinery, robots, and computer systems, high-skilled workers have traditionally been considered automation-proof because their jobs require complex cognitive skills (Acemoglu and Restrepo,

[4] Morningstar changed the rating scales of the People, Parent and Process pillars starting in October 2019. To maintain consistency in the rating scales, we end our sample at October 2019.

2020; Autor, 2015; Autor et al., 2018; Michaels, Natraj, and Van Reenen, 2014). However, unlike prior technology advancements, AI is designed to imitate intelligent human behaviour and is able self-adapt and self-learn (hence the name "machine learning"). As a result, AI has been applied to tasks that were once only performed by high-skilled human workers, including financial workers such as paralegals, credit raters, and financial planners (Cheishvili, 2021; Sahota, 2019). This has put the careers of these workers at risk (Frey and Osborne, 2017). In the Morningstar setting, AI performs similar tasks as the fund analysts at a lower cost per rating, and can provide more frequent rating updates for a significantly larger amount of mutual funds. Thus, concerns about being replaced by AI may incentivize human analysts to exert more effort and reflect on their rating methodologies, leading to improved ratings performance. However, it is also possible that fund analysts will not be affected by the introduction of AI, for two reasons. First, at Morningstar, AI only covers funds that are currently not covered by human analysts, so there is no *direct* competition between human and machine. Second, analysts may exhibit algorithm aversion, according to the literature on noncompliance behaviors (Dietvorst et al., 2015). Studies find that people tend to discount or completely ignore algorithmic predictions regardless of the prediction quality (Dietvorst et al., 2015; Christin, 2017; Glaeser et al., 2021). Since experts are more prone to algorithmic aversion (Allen and Choudhury, 2022), analysts with strong expertise and domain experience might stick to their working routines and ignore the introduction of AI. Third, as prior literature suggests, analysts have unique advantages over machines in that they utilize both public and private information in their jobs, with the private information coming from their communications with managers, social networks, and past experience (Chen and Jiang, 2006; Bradshaw et al., 2021). No matter how advanced an algorithm is, it is unlikely to collect such private information. Thus, analysts might not be affected by the AI adoption or change their behaviors due to AI-related career concerns.

Based on the above discussion, we state the first hypothesis in the null form:

H1: On average, there are no changes in fund analysts' rating behaviours and rating quality after the adoption of AI.

If we indeed find a change in fund analysts' rating behaviors and rating quality, we propose two potential channels through which it could happen: the disciplinary channel and the learning channel. We elaborate on these two channels in the following sections.

3.2 The Disciplinary Channel and Rating Quality

According to the rating methodology, fund analysts in Morningstar need to provide ratings for each of the five pillars (People, Parent, Process, Price, and Performance) before they can generate an overall rating for a mutual fund. Although there is a strict rule on the percentages of funds that can be given gold, silver, or bronze overall ratings, analysts have more discretion in assigning the pillar ratings, as there is no quota for how many funds can obtain positive ratings for each pillar. Of the pillars, the People pillar, in which the analysts evaluate the quality of fund managers, may be the most subjective. Fund managers are evaluated along various dimensions, including their experience, ability, temperament, team stability, and communication style. To rate the managers, the fund analysts often need to interact with them during phone or internet exchanges and face-to-face meetings. As a result, analysts might tend to give high ratings to fund managers in order to maintain good relationships with them. Another possibility is that, via these interactions, the fund analysts gather private information about a manager's quality that goes beyond the performance of her fund, in which case they might give her a high rating even if her fund is performing poorly (or vice versa). We expect that any favoritism towards fund managers will be even larger when the managers are socially connected with the fund analysts, such as, for example, when they have attended the same educational institution. Prior studies find that even sophisticated professionals, including executives, board members, equity research analysts, and judges, exhibit favoritism towards socially connected individuals. These professionals are more likely to recommend stocks or give more optimistic earnings forecasts to the connected firms, or to render more favorable judgments (Westphal, 1999; Bradley, Gokkaya, and Liu, 2020; Gu et al., 2019). As a result, we expect that analysts who are connected to fund managers will likely rate those managers higher in the People pillar, even if such ratings are incompatible with the managers' actual performance.

When AI is introduced to perform similar tasks as the human analysts, we expect that the analysts' favoritism towards socially connected managers will be curbed through the *disciplinary channel*, for at least two reasons. First, the analysts might be disciplined to exert more efforts and produce higher-quality ratings due to career concerns about being replaced by the AI (Acemoglu and Restrepo, 2018 and 2020). Second, since investors have access to the machine's overall ratings and People pillar ratings for comparable benchmark funds and fund managers, any biases in the human ratings will be more visible and subject to higher scrutiny. Thus, fund analysts will be disciplined to provide more objective and fair ratings. We thus make the second hypothesis:

H2: Fund analysts will lower the overall ratings and pillar ratings, especially the People pillar ratings, for socially connected fund managers after the adoption of AI.

3.3 The Learning Channel and Rating Quality

Another important implication of the availability of machine ratings for previously uncovered funds is that it significantly increases the information about benchmarking funds, both for investors and fund analysts. Due to the limited number of Morningstar fund analysts (around 100 at any point in time) and their limited attention, only a small number of funds were traditionally covered. As a result, analysts are often highly specialised, covering selected fund families and investment styles. As of February 2021, the Morningstar fund analysts cover 3,227 funds and 563 ETFs globally. Following the adoption of the AI technology to generate ratings, machines cover 34,002 funds and 3,950 ETFs, corresponding to a tenfold increase in coverage. As a result, there has been a sharp increase in the amount of information about benchmarking funds that the analysts can refer to when rating their mutual funds. Prior studies find that analysts utilize peer information when making recommendations and that having access to such information can lead to higher forecast accuracy (Graham, 1999; Trueman, 1994; Welch, 2000; Kumar, Rantala and Xu, 2021). Moreover, the Morningstar analyst ratings are relative in nature, meaning that funds with high ratings should outperform their peers. Thus, increased information on peer funds is beneficial to analysts. At Morningstar, an added benefit of the AI is that it was developed based on the rating decisions of numerous analysts, so it is less subject to the biases or inefficiencies of a single analyst.

Consequently, we expect that fund analysts can learn from the machine ratings of the benchmark funds, leading to better rating quality. We expect that this effect will be more pronounced when the increase in the availability of information on benchmarking funds is larger. We make our third hypothesis as follows:

H3: Fund analysts covering funds with a larger increase in available benchmarking funds information will experience a higher increase in ratings quality.

4. Methodology

To test the effect of the adoption of AI on analysts' rating behavior and quality, we first adopt a pre–post analysis comparing the level and performance of human ratings before and after the AI adoption. There are several important milestones in the AI implementation process (shown in detail in Appendix II), including 1) the availability of snapshots of machine ratings to the fund analysts in February 2015, 2) the soft launch of machine ratings in the US regions in June

2016, and 3) the official launch of machine ratings in June 2017. Based on our interview with the analysts in Morningstar, we consider the periods after the official launch of the Morningstar machine ratings in June 2017 as the post-treatment periods. During these periods, both Morningstar analysts and Morningstar subscribers have access to the machine ratings.

Across different specifications, we control for the fund–share class fixed effects, as the ratings are given to a specific share class under each fund. The use of these fixed effects allows us to understand the effects of AI adoption while controlling for a large set of unobservable factors that could affect the quality of the funds being rated. In untabulated robustness tests, our results are also robust to controlling for other fixed effects. These include Morningstar category fixed effects, which capture funds' investment styles and regions; and analyst fixed effects, which capture each analyst's ratings and rating quality.

Next, we use difference-in-differences analyses to test the two mechanisms through which AI adoption could affect analysts' performance: the disciplinary channel and the learning channel. The disciplinary channel states that the availability of machine ratings will cause the analysts to reflect on their rating practices, especially when the analysts are socially connected to the fund managers they cover. To identify social connections, we create a unique dataset of the school networks of fund managers and Morningstar fund analysts. In our sample, for every fund-year-month observation, if one of the fund managers in the management team attended the same educational institution as the fund analyst covering the fund, we consider the fund management and the analyst to be socially connected.

The second mechanism is the learning channel. We expect that the analysts covering funds for which there was a larger percentage increase in benchmark funds will benefit more from the AI adoption and therefore produce better ratings. We define the benchmark funds of a focal fund as funds belonging to the same Morningstar category. The Morningstar category is a proprietary classification method adopted by Morningstar to classify funds based on their investment styles, securities, and regions. In total there are 111 unique Morningstar categories. Examples include "US Fund Foreign Small/Mid Blend," "US Fund Muni National Long," and "US Fund Large Growth." For a given fund, we measure the increase in coverage of benchmark funds as the percentage of funds in the same Morningstar category as the focal fund that are covered by machine ratings every year.

Lastly, we investigate how analyst tenure and analyst ability moderate the effects of AI adoption. Prior research suggests that people are averse to artificial intelligence, and that the aversion is stronger among more experienced professionals, since they have more confidence in their own judgment (Glikson and Woolley 2020, Longoni et al. 2019, Möhlmann and Zalmanson 2017). Analysts' abilities could also affect how much they benefit from the machine ratings, since assessing the quality of the new information may require additional effort and training (Allen and Choudhury, 2022). We measure analysts' experience as the number of years they have worked for Morningstar. We measure analysts' ability as the predictive power of their overall ratings for funds' future 12-month cumulative returns.

5. Data and Sample

For our analyses, we obtain data from both public and proprietary sources.

Morningstar ratings

We obtain Morningstar ratings from Morningstar Direct, an interface for all Morningstar subscribers. We obtain the monthly human ratings of the open-end US mutual funds for the period of September 2011 to October 2019. We obtain the monthly machine ratings that are available publicly from June 2017 to October 2019. We end our sample in October 2019 due to a methodology change that affected the calculation of machine and human ratings. Before October 2019, human- and machine-rated funds were separated when calculating ratings distribution within the same fund category. In November 2019, however, Morningstar began pooling all the funds, regardless of the ratings source, when it derived the statistical distribution to determine the overall fund ratings. The methodology change affected the level of human ratings in a manner outside the fund analysts' control. We also obtain certain information on the mutual funds from Morningstar Direct, including their size, investment strategy, and Morningstar category.

Mutual Fund Data

We supplement the mutual fund data using the mutual fund database from CRSP, which provides data on monthly fund returns, fund flows, expense ratios, and fund fees, for each share class.[5] For our analyses, we follow prior literature (Rea and Reid, 1998; Blake and Morey, 2000) and use the load-adjusted excess returns to account for sale charges.[6] In untabulated results, our findings are robust when we use the alphas from a four-factor model as the return measures.

Fund Analysts and Fund Manager Characteristics

We obtain a proprietary dataset of the identities and characteristics of the Morningstar fund analysts, including their education level, work experience, and gender, directly from the Morningstar research team. There are 300 unique analysts who rated one or more funds during the years 2011 to 2019. The number of working fund analysts each year ranges between 85 and 129.

We also manually collect the fund managers' identities and information about their educational background, age, gender, and work experience from the homepage of mutual funds on

[5] There could be multiple share classes under a same fund. Holders of different share classes have different rights, and could be subject to different fees. For our analysis, we use the share class-level observation as the ratings are given at the share class-level.

[6] The load adjustment process is as follows: Assume L is the load adjustment. If there is no load, then L=1. If there is a load, L is less than one. The load-adjusted return will be the raw return multiplied by L. For a fund with a front-end load of 5%, L = 0.95. The front-end load is assumed to be the maximum possible load, and the deferred or back-end load is reduced as the holding period is increased. Alternatively, we use a simple version of non-load-adjusted excess return, which is raw return minus risk-free returns (30-day T-Bill returns), as the return measure.

Morningstar. In total, we have information for 1,147 unique fund managers managing 11,136 different funds throughout our sample period. Each manager on average manages 21 different funds (share class) every year.

Our final sample consists of 187,079 fund share class-month level observations from 11,136 unique funds, during the periods of January 2011 to October 2019.

6. Results

6.1 Summary Statistics

Table 1 presents the summary statistics of important variables used in our study. Panel A presents the descriptive statistics of the Morningstar ratings before and after AI adoption in June 2017. The mean (median) overall rating for the full sample (January 2011 to October 2019) is 3.067 (3.000) out of 5 points. The mean overall rating was 3.161 before the AI adoption and falls to 2.959 afterwards, a relative decline of 6.39%. In terms of the pillar ratings, the People pillar has the highest mean both before and after AI adoption: 2.736 out of 3 points during the pre period, and 2.704 afterwards. Similarly, the People pillar ratings has experienced a relative decrease of 1.17% after AI adoption.

Table 1 Panel B presents the summary statistics of other important fund-level variables. On average, the fund managers are 48 years old with six years of working experience in the focal fund. Nearly 90% are male. The fund analysts, in contrast, have 10.5 years of working experience on average, and their gender composition is more balanced: 60% male and 40% female. Of the fund-month observations, 1.6% involve socially connected fund managers and fund analysts. In total, there are 618 unique analyst–manager pairs that have attended the same educational institution.

6.2 Determinants of Human Ratings Levels

Table 2 presents the regression results of the determinants of and the trends in the levels of Morningstar ratings after the AI adoption in June 2017. The dependant variables are the overall ratings and the five pillar ratings rated by human analysts. Since the ratings are given to each individual share class under a fund, we include the fund–share class fixed effects and year fixed effects in all regressions to capture the unobservable time-invariant and time-varying characteristics of each share class of a fund. We find that fund ages and fund sizes are important predictors of the overall ratings, with younger funds with larger funds tending to have higher ratings. We also find that funds get higher overall ratings when they are covered by more junior analysts and male analysts. Also, the People pillar ratings are positively associated with analysts' tenure. One explanation for this finding is that there is a matching between more senior analysts and outperforming fund managers. Alternatively, the finding might suggest that senior analysts have developed more solid relationships with the fund managers and are more optimistic when rating them.

Although we do not have any specific hypothesis related to the changes in the ratings levels for the full sample, we also include an indicator, $POST$, that specifies the periods after the machine ratings became available in Morningstar. This variable may help us to better understand the trends in the overall ratings. On average, the Parent pillar and the Process pillar ratings become higher after AI adoption, whereas the Price pillar rating becomes lower.

6.3 Human Ratings Quality After AI Adoption

Table 3 presents the regression results of the quality of human ratings after the AI adoption. We examine the rating quality in both the short-term and long-term horizons, and we consider a rating to be of higher quality if it can better predict future fund returns. In Panel A of Table 3, the dependent variables are the future three-month, one-year, and three-year load-adjusted returns. In column (1), we find that, by itself, the coefficient of the overall rating, $MS\_Overall$, is insignificant, suggesting that, on average, the funds with higher overall ratings do not show significantly higher returns. However, the interaction term $MS\_Overall \times POST$ is positive and significant, suggesting that the predictive power of the overall ratings improves significantly after the AI adoption. A one-scale increase in the overall rating is associated with a 68.8 basis points higher future one-year return in the post-AI adoption period, suggesting that the ratings better identify high-performing funds. In columns (2) to (4), we find that the predictive power of the People, Parent, and Price pillar ratings for the future one-year return also increase significantly post AI. In Panel B, we present the predictive power of the human ratings for future three-year returns. We find improvements in the predictive power of the overall ratings and pillar ratings for future three-year returns.[7] The results suggest that, on average, the quality of human analysts' ratings becomes higher after AI adoption.

In Table 4, we examine the net cash inflows into the mutual funds in response to human ratings. We calculate the net cash inflows into the mutual funds as the dollar amount of the difference between the total net asset value of a fund between the future month and the current month, minus appreciation.[8] In columns (1), (2), (4), and (6), we find that the net cash inflows are higher for funds with higher overall ratings and higher People, Price and Performance pillar ratings in the post-AI adoption period, relative to the pre-AI period. Thus, investors seem to be aware of the improved quality of the human ratings. The increase in the response of the net cash inflow is the largest for the People pillar, where every one-scale increase in rating is associated with a net cash inflow increase of \$1.103 million. In untabulated results, we show that our findings are robust after controlling for category fixed effects, fund–share class fixed effects, and analyst fixed effects. The results so far suggest that after AI-generated machine

[7] In untabulated results, we test the parallel trend assumption and we do not find significant differences between the rating quality in predicting future returns for the overall ratings and the pillar ratings during the pre period. The predictive power became significant for the overall (People pillar) ratings since the year 2018 (2017).

[8] $Net\ Cash\ Inflow_{m+1} = Total\ Net\ Asset\ Value_{m+1} - Total\ Net\ Asset\ Value_{m}(1 - Ret_{\ m})$

ratings become available, the quality of the human-generated overall ratings and pillar ratings improves.

6.4 Mechanisms of AI's Influence on Human Analysts

To understand the underlying mechanisms of the improvement in human rating quality, we empirically test the two proposed channels: disciplinary and learning.

6.4.1 The Disciplinary Channel

Table 5 presents the difference-in-differences regressions of the effect of the disciplinary channel. The dependent variables are the levels of the overall ratings and each of the five pillar ratings. The key independent variable, $CONNECTED$, is an indicator that equals one when the fund analyst attended the same educational institution as a fund manager, and zero otherwise. We find that the coefficients of $CONNECTED$ are positive and significant for the People pillar ratings, the Parent pillar ratings, and the overall ratings. This suggests that, before AI adoption, connected managers tend to receive higher ratings in dimensions relating to management quality and style, which in turn contributes to a higher overall rating. Being connected to the fund analyst is associated with a 1.84% (3.10%) higher People (Parent) pillar rating and a 4.89% higher overall rating, relative to the sample mean. Such results are not surprising, because the People and Parent pillars focus, respectively, on the managers' talents and the funds' human resource policies, both of which entail more subjective evaluations than other pillars. Analysts also have the most discretion in rating these two pillars, due to their research and interactions with the management team. As a result, analysts are more likely to express their favoritism for connected managers in these pillars.

In contrast, the coefficients of the interaction term $CONNECTED \times POST$ are negative and significant for the People and Parent pillar ratings. The reduction is significant: following the introduction of AI, funds with socially connected managers experience a 7.56% decline in the overall rating and a 3.27% (5.24%) relative decline in the People (Parent) pillar ratings. This evidence supports the notion that the AI adoption potentially disciplines the fund analysts and mitigates the risk that they engage in favoritism-related overoptimism in their ratings. [9]

To visualize the disciplinary effect, we plot the annual mean of the overall ratings (Figure 1) and the People pillar ratings (Figure 2) for the periods between 2012 and 2019 separately for funds with connected managers and funds with unconnected managers. In Figure 1, we find that the mean overall rating is higher for connected funds than for unconnected funds, but the differences are declining over time. In Figure 2, we find that before 2015, the People pillar ratings were higher for connected funds than for unconnected funds. The evidence seems to suggest that, pre 2015, analysts favor funds with socially connected managers and bias against funds with unconnected managers. However, the mean People pillar rating for connected funds decreases after 2015 and is further reduced in 2017. These timings coincide with the first internal circulation of the machine ratings in 2015 and the official dissemination of the machine ratings in 2017 (with the official dissemination having a larger effect). Overall, the results suggest that AI adoption may discipline analysts' favoritism towards socially connected fund managers, leading them to downwardly adjust the overall ratings and manager-associated ratings.

6.4.2 The Learning Channel

Next, we test the learning channel by examining the effects of the increased coverage of benchmark funds on the quality of human ratings. Based on our interview with the Morningstar mutual fund research team, the analysts had easy access to machine ratings starting in June 2017. Thus, we construct the continuous treatment variable $CoverageIncrease$. Before the AI adoption in June 2017, this variable equals zero. From June 2017 onward, it equals a

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[9] In untabulated results, we test the parallel trend assumption and we do not find significant differences in the levels of People pillar ratings between socially connected and non-connected analysts during the years 2011 to 2015. The differences became significant since the year 2016, probably due to the fact that the analysts were already aware of the machine algorithm after the internal circulation of machine ratings in February 2015.

continuous value that corresponds to the increase in the percentage of funds in the focal fund's Morningstar category that are machine rated.

Table 6 presents the results of the effects of fund coverage increases on the quality of human ratings. The dependent variables are the one-year-ahead and three-year-ahead load-adjusted returns of the mutual funds in Panels A and B. We find that the interaction term $MS\ Overall \times CoverageIncrease$ is positive and significant in both regressions, indicating that, as the coverage of benchmark funds increases, the overall human ratings become more informative about future returns for funds. Every one-percentage-point increase in the coverage of benchmark funds in the same category as the focal firm is associated with a 0.77 (1.87) basis points increase in the future one-year (three-year) load-adjusted returns in response to a one-scale increase in the overall rating. In terms of the pillar ratings, we find that the coverage increase in benchmarking funds is positively associated with the ratings' ability to predict returns over a longer horizon (three-year-ahead future returns). In Table 7, we also find that future net cash inflows into the funds are more sensitive to the overall ratings when the increase in the coverage of benchmark funds is larger. This indicates that investors have more confidence in the ratings, possibly because they are aware of the higher-quality ratings and reports that analysts produce from the expanded, machine-generated information sets. Such results support the learning channel, where analysts improve their ratings quality by utilizing and expanding on the information from the machines' increased coverage of peer funds.

6.5 Moderation Effects of Analysts Tenure and Talent

Prior research shows that the impact of new technology and artificial intelligence is heterogeneous for individuals, especially those who differ in their work tenure and ability level. Research shows that "algorithmic aversion" is more intense among experts (Allen and Choudhury 2022), who, being confident in their ability to assess and resolve complex problems, are more reluctant to accept AI-generated suggestions. Thus, shorter-tenured analysts might be more affected by an AI adoption. On the other hand, more experienced analysts might have developed more solid relationships with fund managers and thus been more prone to give high ratings, pre AI, to the socially connected ones. We can see evidence of such an effect in Table 2, where the coefficients on the variable $AnalystTenure$ are positively and significantly associated with People pillar ratings level. Thus, it is possible that more experienced analysts will be more affected by the disciplinary channel, as AI adoption will reduce their favoritism towards connected fund managers.

In Table 8, we examine the effects of the disciplinary channel and learning channel for the subsample of experienced and junior analysts. Experienced (junior) analysts are analysts with above-median (below-median) work experience at Morningstar. In all the specifications, we control for fund fixed effects to account for the impacts of time-invariant fund characteristics that can affect the difficulty in rating the fund. In columns (1) and (2) of Table 8, we find that, post AI, junior analysts reduce their overall ratings more than experienced analysts. In columns (3) and (4), however, we find that experienced analysts reduce the connected funds' People pillar ratings more than junior analysts. Thus, while junior analysts become more conservative in rating funds overall, experienced analysts are more likely to reduce their People pillar ratings for connected managers. Such results support the argument that experienced analysts display more favoritism to connected fund managers ex ante and thus adjust their rating behaviors more ex post. Lastly, in columns (5) and (6) of Table 8, we find that the effect of the learning channel is more pronounced for the subsample of experienced analysts. Relative to junior analysts' ratings, their ratings better predict future fund returns as more machine ratings of benchmark funds become available.

In addition to experience, analysts' quality can also affect their response to AI adoption. Allen and Choudhury (2022) suggest that the decision makers' inability to assess the quality of the algorithmic output contributes to their algorithmic aversion. Thus, analysts who are high performers may be more likely to benefit from the AI adoption. We measure each analyst's quality by their ratings' ability to predict future fund returns. We estimate a 60-month rolling window regression of future 12-month cumulative fund returns on the overall ratings and a list of control variables, then obtain the coefficients of the overall rating variables. We classify analysts as high (low) performers if the size of the coefficient is in the top (bottom) quintile in a given year.

In Table 9, we replicate the results of Table 8 for the subsamples of high and low past performers. The results show that high performers are more likely to downwardly adjust the overall and People pillar ratings for connected funds, and that high performers' ratings improve more following the increase in the coverage of benchmark funds. In total, we find that the AI adoption has more impact, via both channels, on more experienced and more high-performing analysts.

6.6 Textual Analysis of Fund Analysts' Reports

So far, our results are based on the levels and quality of the ratings produced by the mutual fund analysts. However, another critical product of fund analysts is analyst reports, and it is equally important to understand how AI adoption affects these reports. We thus complement our main analyses by examining how the characteristics of analyst reports change following the AI adoption. We collected a sample of 10,237 fund analyst reports covering 2,931unique funds during our sample periods. We expect that, based on the prediction of the disciplinary channel, analysts will reduce their favoritism towards socially connected managers post AI. As a result, the tone of the analyst reports for connected fund managers should become less positive, and the level of subjectivity should be reduced, i.e., the reports will become more objective. Based on the previous results for the disciplinary channel, we also expect that such effects will be stronger for more experienced analysts.

Table 10 presents the results on the changes in analyst report attributes after the AI adoption. We examine two characteristics of the textual contents of the analyst reports: the polarity score, calculated as the difference between the positive score and negative score, representing the net positivity of the tone; and the subjectivity score, representing the level of subjectivity of the texts.[10] Consistent with our predictions, we find that, post AI, the reports' tone becomes more negative when the fund analysts and fund managers are socially connected. The reports also become more objective in describing connected managers. In addition, we find that these adjustments to the reports are only significant for the longer-tenured analysts. Together, these results provide additional evidence of the existence of a disciplinary effect in which AI adoption curbs favoritism towards socially connected managers.

7. Conclusion

In light of the growing popularity of artificial intelligence in the financial industry, we study the effect of AI adoption on mutual fund analysts using the unique setting of the introduction of machine algorithms to rate mutual funds in Morningstar. We find that following the availability of algorithm-generated machine ratings, the quality of the mutual fund ratings by human analysts improves: their predictive power of future fund performance is higher, and they attract a larger amount of cash inflow into the mutual funds. We propose, and provide supporting evidence on, two possible channels through which the machine ratings help improve the human ratings: a disciplinary channel, where the AI adoption helps curb analysts' favoritism towards socially connected fund managers; and a learning channel, where AI

[10] We calculate the polarity score and the subjectivity score based on Natural Language Processing (NLP) technique. The polarity scores range from -1 to 1, where -1 (1) indicates that the sentiment of the text is highly negative (positive). The subjectivity scores range from 0 to 1, where a higher value indicates that the text reflects more personal opinion rather than factual information.

provides information on a large number of benchmark funds that were not previously covered. We also find that more experienced and more talented analysts benefit more from the AI adoption.

Our study contributes to the literature on the impact of new technologies in the financial industry. We find that the introduction of AI improves the investment efficiency in the U.S. mutual fund industry indirectly by improving the quality of mutual fund ratings. Given that the mutual fund industry is large and important for the US economy, our findings are valuable to financial market participants such as regulators, investors, and mutual fund managers.

Our findings also offer insights into the effects of AI adoption on skilled workers' productivity. Recently there have been heated debates on whether artificial intelligence will eventually replace human workers. Our exploration of the interactions between humans and machines suggests that the introduction of artificial intelligence presents both the incentives and opportunities for humans to improve their own productivity and performance. These findings will be valuable for potential adopters of artificial intelligence and new technologies as they explore models that are suitable for their tasks.

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Appendix I. Variable Definitions

Panel A. Morningstar Ratings

Variable	Definition
MS_Overall	The monthly Morningstar overall rating. Source: Morningstar Direct
MS_People	The monthly Morningstar people pillar ratings. Source: Morningstar Direct
MS_Parent	The monthly Morningstar parent pillar ratings. Source: Morningstar Direct
MS_Price	The monthly Morningstar price pillar ratings. Source: Morningstar Direct
MS_Process	The monthly Morningstar process pillar ratings. Source: Morningstar Direct
MS_Performance	The monthly Morningstar performance pillar ratings. Source: Morningstar Direct

Panel B. Other Fund-Level Variables

Variable	Definition
AnalystGender	Equals 1 if the fund analyst is a male, 0 if the fund analyst is a female. Source: Morningstar Research Team.
AnalystTenure	The number of years the fund analyst has worked at Morningstar. Source: Morningstar Research Team.
AvgManagerTenure	The average number of years the fund managers have worked in the fund. Source: Morningstar Direct
Connected	Equals 1 if the fund manager and the fund analyst attended the same educational institution, 0 otherwise.
CoverageIncrease	The percentage of funds with available machine ratings in a Morningstar category.
Exp_ratio	The ratio of total investment that shareholders pay for the fund's operating expenses. Source: CRSP Mutual Fund
$FRET_{1Y}$	The future 12 months' cumulative fund's load-adjusted returns in excess of the 30-day T-Bill rates.
$FRET_{3Y}$	The future 3 years' cumulative fund's load-adjusted returns in excess of the 30-day T-Bill rates.
FundAge	The natural log of one plus the years since the fund's inception date
FundSize	The natural log of the fund's total net assets at the end of each month. Source: CRSP Mutual Fund
FutFundFlow	The natural log of net dollar amount of cash inflow into the funds in the following month, minus appreciation.
LagFundFlow	The percentage growth of fund net asset value from month t-2 to t-1. Source: CRSP Mutual Fund
LagRet	The lagged monthly raw fund returns. Source: CRSP Mutual Fund
ManagerAge	The average manager ages in a fund's management team. Source: Morningstar Direct
Percentagemale	The percentage of male managers in the fund's management team. Source: Morningstar Direct
Polarity	The polarity score (positive score minus negative score) of the texts of the fund analysts' reports. Source: Morningstar Direct
Subjectivity	The subjectivity score of the texts of the fund analysts' reports. Source: Morningstar Direct

Appendix II. Morningstar Machine Rating Introduction Timeline

Time	Progress
Feb-2013	First prototype of machine ratings is displayed at manager research team meeting.
Jul-2013	Back testing efforts begin.
Jan-2015	Updated model is deployed to live environment.
Feb-2015	Manager research analysts begin receiving monthly snapshots.
Dec-2015	Final signoff to launch in 2016
Jun-2016	Morningstar Quantitative ratings are soft-launched in Morningstar Direct for US subscribers only.
Jun-2017	**The quantitative ratings become live in Morningstar products and on Morningstar quote pages.**
Jun-2018	Quantitative ratings become available for institutional use in Asia (ex-Japan and ex-India), the EU, and the UK.
Jun-2018	Quantitative ratings are launched for all Direct subscribers in Canada.
Oct-2019	Analyst Rating/MQR 2.0 is launched.

Appendix III. Morningstar Rating Scale Conversion

Overall Rating	Score
Gold	5
Silver	4
Bronze	3
Neutral	2
Negative	1
Under review	Excluded
Not Rateable	Excluded

Pillar Rating	Score
Positive	3
Neutral	2
Negative	1

Table 1 Summary Statistics

This table presents the summary statistics of the variables used in the analyses. Panel A presents the summary statistics of the human ratings, and Panel B presents the summary statistics of other fund-level variables. More detailed descriptions of the variables can be found in Appendix I.

Panel A. Morningstar Mutual Fund Human Ratings
Full Sample (January 2011 to October 2019)

Variables	Obs.	Mean	S.D.	p25	p50	p75
MS_Overall	187,079	3.067	1.007	2.000	3.000	4.000
MS_People	187,079	2.721	0.463	2.000	3.000	3.000
MS_Parent	187,079	2.480	0.535	2.000	2.000	3.000
MS_Price	187,079	2.492	0.703	2.000	3.000	3.000
MS_Process	187,079	2.590	0.513	2.000	3.000	3.000
MS_Performance	187,079	2.515	0.575	2.000	3.000	3.000

	Pre-AI Adoption (Jan 2011 to May 2017)			**Post-AI Adoption (June 2017 to Oct 2019)**		
Variables	Obs.	Mean	S.D.	Obs.	Mean	S.D.
MS_Overall	100,050	3.161	1.030	87,029	2.959	0.969
MS_People	100,050	2.736	0.465	87,029	2.704	0.460
MS_Parent	100,050	2.461	0.539	87,029	2.502	0.529
MS_Price	100,050	2.547	0.674	87,029	2.428	0.730
MS_Process	100,050	2.640	0.505	87,029	2.532	0.516
MS_Performance	100,050	2.508	0.604	87,029	2.524	0.541

Panel B. Other Fund-level Variables (January 2011 to October 2019)

Variables	Obs.	Mean	S.D.	p25	p50	p75
AnalystGender	187,079	0.603	0.489	0.000	1.000	1.000
AnalystTenure	187,079	10.503	7.875	4.000	9.000	16.000
AvgManagerTenure	187,079	25.180	6.301	20.923	25.000	29.667
Connected	187,079	0.016	0.124	0.000	0.000	0.000
CoverageIncrease	187,079	0.199	0.146	0.104	0.176	0.281
Exp_ratio	187,079	0.964	0.548	0.580	0.910	1.310
FundSize	187,079	3.865	2.832	2.067	4.113	5.919
FutRet_1Y(%)	187,079	5.697	10.089	-0.031	4.734	11.146
FutRet_3Y(%)	187,079	21.304	20.670	7.650	17.370	31.570
LagFundFlow	187,079	0.029	0.270	-0.016	0.000	0.030
FutFundFlow	187,079	0.026	0.252	-0.016	0.000	0.030
LagRet	187,079	0.005	0.029	-0.006	0.005	0.019
ManagerAge	187,079	48.009	8.788	42.000	47.667	52.000
PercentageMale	187,079	0.899	0.172	0.833	1.000	1.000
Subjectivity	10,237	0.407	0.033	0.384	0.409	0.429
Polarity	10,237	0.089	0.035	0.065	0.089	0.110

Table 2. Human Ratings Levels After AI Adoption

This table presents the results of the changes in mutual fund human ratings after the AI adoption. $MS\_Overall$ is the overall Morningstar rating for the fund, MS_People, MS_Parent, MS_Price, $MS\_Process$, and $MS\_Performance$ are the people, parent, price, process, and performance pillar ratings, respectively. $POST$ is an indicator variable that equals 1 for the period after June 2017, 0 otherwise. $LagRet$ is last month's fund return. $FundSize$ is the natural log of last month's fund net asset value. Exp_ratio is the fund's expense ratio. $LagFundFlow$ is the changes in fund net asset values from the past month. $AvgManagerTenure$ is the mean years of experience of all the fund managers in the management team for a given fund. $PercentageMale$ is the percentage of male managers in the management team for a given fund. $AnalystTenure$ is the number of years the fund analyst has worked at Morningstar. $AnalystGender$ is an indicator variable that equals 1 if the analyst is a male, 0 if the analyst is a female. T-statistics are presented in parentheses. *** indicates that the estimated coefficient is significantly different from zero at the 1% level, ** at the 5% level, and * at the 10% level. The standard errors are clustered at the Morningstar category level.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	MS_Overall	MS_People	MS_Parent	MS_Price	MS_Process	MS_Performance
POST	-0.012	-0.006	0.016***	-0.028***	0.018*	-0.006
	(-1.14)	(-0.92)	(2.83)	(-2.97)	(1.88)	(-0.81)
LagRet	-0.030	0.029	-0.043*	-0.002	0.003	-0.076*
	(-0.80)	(1.32)	(-1.72)	(-0.05)	(0.11)	(-1.92)
FundAge	-0.114**	0.004	-0.028	0.030	-0.025	-0.038
	(-2.58)	(0.21)	(-1.04)	(1.11)	(-0.99)	(-1.03)
FundSize	0.044**	0.005	0.018*	0.016*	-0.007	0.036***
	(2.32)	(0.69)	(1.96)	(1.69)	(-0.62)	(2.91)
Exp_ratio	0.135	-0.030	-0.071	-0.452***	0.319***	0.228***
	(1.51)	(-0.69)	(-1.34)	(-5.07)	(2.94)	(3.39)
LagFundFlow	0.016	0.004	0.029*	0.009	0.028**	0.016
	(1.07)	(0.40)	(1.96)	(0.68)	(2.10)	(1.06)
AvgManagerTenure	-0.136	0.189	-0.336	-0.116	-0.135	-0.112
	(-0.36)	(0.82)	(-1.39)	(-0.74)	(-1.12)	(-0.39)
PercentageMale	0.004	0.014	-0.041***	0.021***	0.022**	-0.002
	(0.22)	(1.52)	(-4.67)	(2.67)	(2.12)	(-0.16)
ManagerAge	0.011	0.005*	0.013***	-0.002	0.001	0.008
	(1.31)	(1.97)	(2.96)	(-0.81)	(0.19)	(1.31)
AnalystTenure	0.000	-0.000	0.000	0.000	-0.000	-0.000
	(0.12)	(-0.03)	(1.38)	(1.12)	(-0.18)	(-0.63)
AnalystGender	0.002	-0.003	-0.003	0.000	0.003	0.000
	(0.60)	(-1.09)	(-0.98)	(0.13)	(0.93)	(0.13)
Constants	Y	Y	Y	Y	Y	Y
Fund-ShareClass FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	187,079	187,079	187,079	187,079	187,079	187,079
R-squared	0.890	0.809	0.818	0.857	0.789	0.746
Adj.R-squared	0.887	0.803	0.813	0.853	0.783	0.738

Table 3. Human Ratings Quality After AI Adoption

This table presents the results of the regressions of future fund performance on human ratings. $FRET_{1Y}$ ($FRET_{3Y}$) is the future one-year (three-year) cumulative returns of the funds. $MS\_Overall$ is the overall Morningstar rating for the fund, MS_People, MS_Parent, MS_Price, $MS\_Process$, and $MS\_Performance$ are the people, parent, price, process, and performance pillar ratings, respectively. $POST$ is an indicator variable that equals 1 for the period after June 2017, 0 otherwise. $LagRet$ is last month's fund return. $FundSize$ is the natural log of last month's fund net asset value. Exp_ratio is the fund's expense ratio. $LagFundFlow$ is the changes in fund net asset values from the past month. $AvgManagerTenure$ is the mean years of experience of all the fund managers in the management team for a given fund. $PercentageMale$ is the percentage of male managers in the management team for a given fund. $AnalystTenure$ is the number of years the fund analyst has worked at Morningstar. $AnalystGender$ is an indicator variable that equals 1 if the analyst is a male, 0 if the analyst is a female. T-statistics are presented in parentheses. *** indicates that the estimated coefficient is significantly different from zero at the 1% level, ** at the 5% level, and * at the 10% level. The standard errors are clustered at the Morningstar category level.

Panel A. One-Year-Ahead Return

VARIABLES	(1) $FRET_{1Y}$	(2) $FRET_{1Y}$	(3) $FRET_{1Y}$	(4) $FRET_{1Y}$	(5) $FRET_{1Y}$	(6) $FRET_{1Y}$
MS_Overall×POST	0.688**					
	(2.51)					
MS_Overall	-0.133					
	(-0.33)					
MS_People×POST		0.127*				
		(1.99)				
MS_People		0.071				
		(0.99)				
MS_Parent×POST			1.945***			
			(3.55)			
MS_Parent			-0.495			
			(-0.84)			
MS_Price×POST				1.057**		
				(2.07)		
MS_Price				-0.626		
				(-1.12)		
MS_Process×POST					0.087	
					(0.11)	
MS_Process					0.361	
					(0.84)	
MS_Performance×POST						0.256
						(0.49)
MS_Performance						-0.536
						(-1.19)
POST	-2.441	-7.438*	-9.663***	-0.133	-6.465**	-2.885
	(-1.46)	(-1.85)	(-3.32)	(-0.06)	(-2.25)	(-1.06)
Constant	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Fund-ShareClass FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	187,079	187,079	187,079	187,079	187,079	187,079
R-squared	0.411	0.410	0.411	0.411	0.410	0.410
Adj. R-squared	0.379	0.379	0.380	0.379	0.379	0.379

Table 3. (Continued)

Panel B. Three-Year-Ahead Return

VARIABLES	(1) $FRET_{3Y}$	(2) $FRET_{3Y}$	(3) $FRET_{3Y}$	(4) $FRET_{3Y}$	(5) $FRET_{3Y}$	(6) $FRET_{3Y}$
MS_Overall×POST	1.948***					
	(4.01)					
MS_Overall	1.356*					
	(1.68)					
MS_People×POST		4.034***				
		(2.85)				
MS_People		-1.566				
		(-1.35)				
MS_Parent×POST			3.660***			
			(3.83)			
MS_Parent			-1.121			
			(-1.00)			
MS_Price×POST				3.660***		
				(3.83)		
MS_Price				0.250		
				(0.32)		
MS_Process×POST					3.786***	
					(3.72)	
MS_Process					0.129	
					(0.15)	
MS_Performance×POST						2.618**
						(2.47)
MS_Performance						0.909
						(1.01)
POST	-2.441	-7.438*	-9.663***	-0.133	-6.465**	-2.885
	(-1.46)	(-1.85)	(-3.32)	(-0.06)	(-2.25)	(-1.06)
Constant	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Fund-ShareClass FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	187,079	187,079	187,079	187,079	187,079	187,079
R-squared	0.778	0.777	0.779	0.777	0.777	0.777
Adj. R-squared	0.767	0.765	0.767	0.765	0.765	0.765

Table 4. Net Cash Inflows and Human Ratings After AI Adoption

This table presents the results of regressions of future fund performance and Human Ratings. Panel A presents the results of overall ratings and Panel B presents the results of the pillar ratings. $FutFundFlow$ is the natural log of net cash inflow into the funds in the following month. $MS\_Overall$ is the overall Morningstar rating for the fund, MS_People, MS_Parent, MS_Price, $MS\_Process$, and $MS\_Performance$ are the people, parent, price, process, and performance pillar ratings, respectively. $POST$ is an indicator variable that equals 1 for the period after June 2017, 0 otherwise. $LagRet$ is last month's fund return. $FundSize$ is the natural log of last month's fund net asset value. Exp_ratio is the fund's expense ratio. $LagFundFlow$ is the changes in fund net asset values from the past month. $AvgManagerTenure$ is the mean years of experience of all the fund managers in the management team for a given fund. $PercentageMale$ is the percentage of male managers in the management team for a given fund. $AnalystTenure$ is the number of years the fund analyst has worked at Morningstar. $AnalystGender$ is an indicator variable that equals 1 if the analyst is a male, 0 if the analyst is a female. T-statistics are presented in parentheses. *** indicates that the estimated coefficient is significantly different from zero at the 1% level, ** at the 5% level, and * at the 10% level. The standard errors are clustered at the Morningstar category level.

VARIABLES	(1) FutFundFlow	(2) FutFundFlow	(3) FutFundFlow	(4) FutFundFlow	(5) FutFundFlow	(6) FutFundFlow
MS_Overall×POST	0.028**					
	(2.32)					
MS_ Overall	0.036**					
	(2.31)					
MS_People×POST		0.096***				
		(3.72)				
MS_People		-0.034				
		(-1.20)				
MS_Parent×POST			0.035			
			(1.33)			
MS_Parent			0.004			
			(0.14)			
MS_Price×POST				0.046*		
				(1.80)		
MS_Price				0.027		
				(1.28)		
MS_Process×POST					-0.000	
					(-0.01)	
MS_Process					-0.012	
					(-0.47)	
MS_Performance×POST						0.026*
						(1.67)
MS_Performance						0.034**
						(2.35)
POST	0.178***	0.004	0.182**	0.148*	0.270***	0.203***
	(3.47)	(0.06)	(2.51)	(1.98)	(3.57)	(4.22)
LagRet	-2.989***	-2.993***	-2.987***	-2.989***	-2.988***	-2.987***
	(-22.23)	(-22.20)	(-22.20)	(-22.25)	(-22.31)	(-22.29)
FundAge	-0.114***	-0.120***	-0.116***	-0.117***	-0.120***	-0.118***
	(-4.17)	(-4.41)	(-4.35)	(-4.24)	(-4.40)	(-4.30)
FundSize	0.301***	0.303***	0.301***	0.301***	0.302***	0.301***
	(25.53)	(24.79)	(24.95)	(24.71)	(25.05)	(25.24)
Exp_ratio	-0.155**	-0.150**	-0.157**	-0.139**	-0.157**	-0.161**
	(-2.48)	(-2.46)	(-2.54)	(-2.35)	(-2.58)	(-2.60)
AvgManagerTenure	0.805***	0.805***	0.805***	0.805***	0.805***	0.805***
	(28.74)	(28.71)	(28.75)	(28.68)	(28.71)	(28.72)
PercentageMale	0.180	0.175	0.185	0.179	0.170	0.178
	(1.19)	(1.07)	(1.16)	(1.04)	(1.02)	(1.12)

Table 4. (Continued)

VARIABLES	(1) FutFundFlow	(2) FutFundFlow	(3) FutFundFlow	(4) FutFundFlow	(5) FutFundFlow	(6) FutFundFlow
ManagerAge	-0.013**	-0.003	-0.015**	-0.013**	-0.012**	-0.013**
	(-2.27)	(-0.63)	(-2.54)	(-2.18)	(-2.09)	(-2.20)
AnalystTenure	0.010	0.005	0.011	0.010	0.010	0.010
	(1.21)	(0.30)	(1.24)	(1.17)	(1.19)	(1.19)
AnalystGender	0.028**	-0.036**	0.004	0.148*	0.270***	0.203***
	(2.32)	(-2.28)	(0.06)	(1.98)	(3.57)	(4.22)
Constants	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	187,079	187,079	187,079	187,079	187,079	187,079
R-squared	0.777	0.575	0.758	0.759	0.759	0.758
Adj. R-squared	0.770	0.575	0.757	0.758	0.758	0.758

Table 5. Socially Connected Analysts and Human Ratings Post AI Adoption

This table presents the results of the relations between human ratings given by connected analysts after the AI adoption. Panel A presents the results of overall ratings, and Panel B presents the results of the pillar ratings. $MS\_Overall$ is the overall Morningstar rating for the fund, MS_People, MS_Parent, MS_Price, $MS\_Process$, and $MS\_Performance$ are the people, parent, price, process, and performance pillar ratings, respectively. $CONNECTED$ is the number of managers that are alumni of the same institution as the analyst. $POST$ is an indicator variable that equals 1 for the period after June 2017, 0 otherwise. $LagRet$ is last month's fund return. $FundSize$ is the natural log of last month's fund net asset value. Exp_ratio is the fund's expense ratio. $LagFundFlow$ is the changes in fund net asset values from the past month. $AvgManagerTenure$ is the mean years of experience of all the fund managers in the management team for a given fund. $PercentageMale$ is the percentage of male managers in the management team for a given fund. $AnalystTenure$ is the number of years the fund analyst has worked at Morningstar. $AnalystGender$ is an indicator variable that equals 1 if the analyst is a male, 0 if the analyst is a female. T-statistics are presented in parentheses. *** indicates that the estimated coefficient is significantly different from zero at the 1% level, ** at the 5% level, and * at the 10% level. The standard errors are clustered at the Morningstar category level.

Panel A. Post AI Adoption

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	MS_Overall	MS_People	MS_Parent	MS_Price	MS_Process	MS_Performance
CONNECTED×POST	-0.232**	-0.089**	-0.130*	0.001	-0.049	-0.086
	(-2.22)	(-2.72)	(-2.03)	(0.01)	(-0.82)	(-1.27)
CONNECTED	0.150**	0.050*	0.077*	-0.016	0.012	0.040
	(2.24)	(1.82)	(1.93)	(-0.31)	(0.28)	(0.74)
POST	-0.002	0.026**	0.004	0.011	-0.027**	-0.023*
	(-0.18)	(2.48)	(0.22)	(1.19)	(-2.26)	(-1.86)
LagRet	-0.024	0.011	-0.043*	-0.004	0.024	-0.059
	(-0.63)	(0.57)	(-1.77)	(-0.12)	(1.11)	(-1.54)
FundAge	-0.118**	0.005	-0.034	0.029	-0.029	-0.039
	(-2.61)	(0.25)	(-1.23)	(1.10)	(-1.14)	(-1.03)
FundSize	0.033**	0.003	0.016**	0.011	-0.003	0.026***
	(2.38)	(0.56)	(2.29)	(1.58)	(-0.34)	(2.83)
Exp_ratio	0.091	-0.035	-0.054	-0.379***	0.247**	0.181***
	(1.10)	(-0.86)	(-1.13)	(-4.67)	(2.33)	(2.63)
LagFundFlow	-0.002	0.003	0.005	-0.002	0.006	-0.001
	(-0.52)	(1.11)	(1.24)	(-0.44)	(1.54)	(-0.13)
AvgManagerTenure	-0.141	0.189	-0.338	-0.116	-0.138	-0.112
	(-0.37)	(0.82)	(-1.39)	(-0.73)	(-1.14)	(-0.39)
PercentageMale	0.005	0.014	-0.040***	0.021***	0.022**	-0.002
	(0.27)	(1.51)	(-4.64)	(2.69)	(2.21)	(-0.16)
ManagerAge	0.010	0.005*	0.013***	-0.002	0.000	0.008
	(1.25)	(1.95)	(2.94)	(-0.75)	(0.07)	(1.31)
AnalystTenure	0.000	0.026**	0.004	0.011	-0.027**	-0.023*
	(0.54)	(2.48)	(0.22)	(1.19)	(-2.26)	(-1.86)
AnalystGender	0.002	0.011	-0.043*	-0.004	0.024	-0.059
	(0.52)	(0.57)	(-1.77)	(-0.12)	(1.11)	(-1.54)
Constants	Y	Y	Y	Y	Y	Y
Fund-ShareClass FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	187,079	187,079	187,079	187,079	187,079	187,079
R-squared	0.650	0.541	0.650	0.545	0.532	0.455
Adj.R-squared	0.647	0.536	0.647	0.541	0.527	0.450

Figure 1. Time Series of Overall Ratings

This figure presents the time series of the average monthly Morningstar overall ratings by fund analysts from January 2011 to October 2019, separately for funds with and without managers connected with the fund analyst that covers the fund.

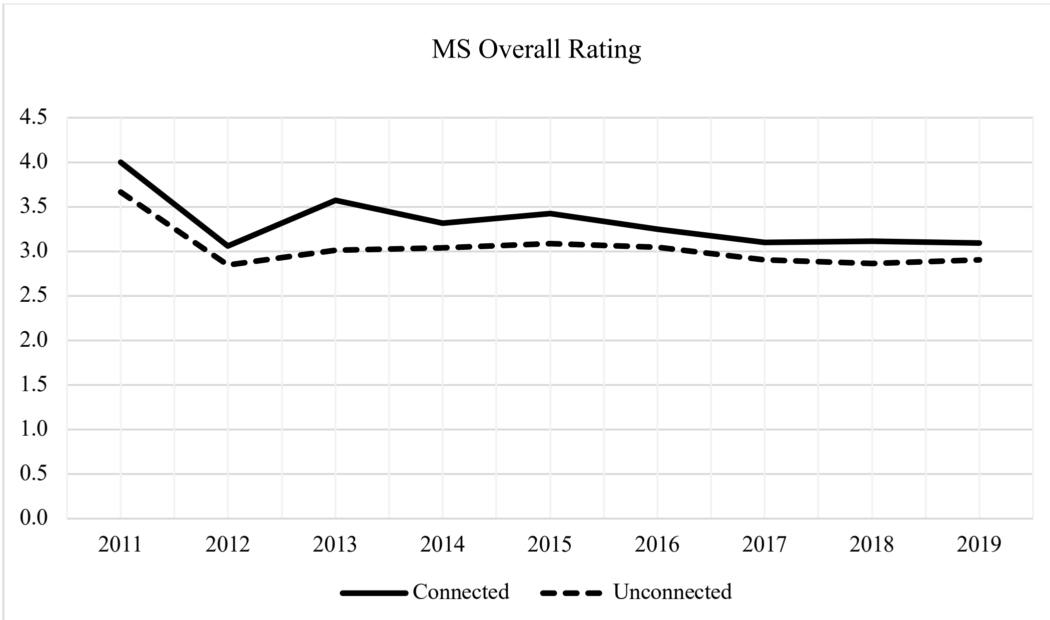

Figure 2. Time Series of People Pillar Ratings

This figure presents the time series of the average monthly Morningstar people pillar Ratings by fund analysts from January 2011 to October 2019, separately for funds with and without managers connected with the fund analyst that covers the fund.

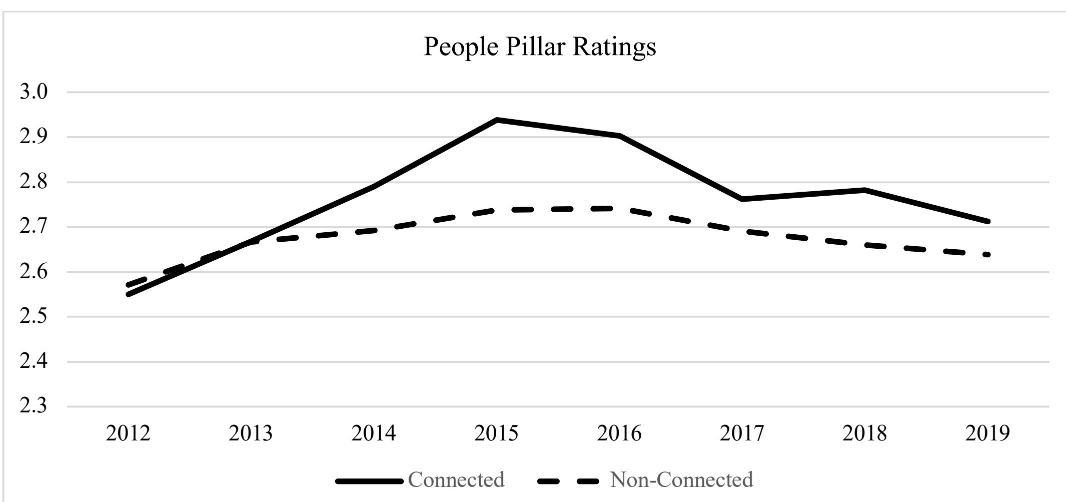

Table 6. Rating Quality and Benchmark Funds Coverage Increase

This table presents the results of the relations between human ratings and the increase in coverage of benchmark funds after the AI adoption. $FRET_{1Y}$ ($FRET_{3Y}$) is the future one-year (three-year) cumulative returns of the funds. $MS\_Overall$ is the overall Morningstar rating for the fund, MS_People, MS_Parent, MS_Price, $MS\_Process$, and $MS\_Performance$ are the people, parent, price, process, and performance pillar ratings, respectively. $CoverageIncrease$ is the percentage of benchmark funds with Morningstar ratings in the same Morningstar category as the focal fund. $POST$ is an indicator variable that equals 1 for the period after June 2017, 0 otherwise. $LagRet$ is last month's fund return. $FundSize$ is the natural log of last month's fund net asset value. Exp_ratio is the fund's expense ratio. $LagFundFlow$ is the changes in fund net asset values from the past month. $AvgManagerTenure$ is the mean years of experience of all the fund managers in the management team for a given fund. $PercentageMale$ is the percentage of male managers in the management team for a given fund. $AnalystTenure$ is the number of years the fund analyst has worked at Morningstar. $AnalystGender$ is an indicator variable that equals 1 if the analyst is a male, 0 if the analyst is a female. T-statistics are presented in parentheses. *** indicates that the estimated coefficient is significantly different from zero at the 1% level, ** at the 5% level, and * at the 10% level. The standard errors are clustered at the Morningstar category level.

VARIABLES	(1) $FRET_{1Y}$	(2) $FRET_{1Y}$	(3) $FRET_{1Y}$	(4) $FRET_{1Y}$	(5) $FRET_{1Y}$	(6) $FRET_{1Y}$
MS_Overall×CoverageIncrease	0.765***					
	(4.12)					
MS_Overall	0.603					
	(1.40)					
MS_People× CoverageIncrease		0.771				
		(1.59)				
MS_People		0.559				
		(0.81)				
MS_Parent× CoverageIncrease			1.676***			
			(3.75)			
MS_Parent			0.839			
			(1.04)			
MS_Price×CoverageIncrease				0.871**		
				(2.21)		
MS_Price				0.491		
				(1.01)		
MS_Process× CoverageIncrease					0.637	
					(1.31)	
MS_Process					0.535	
					(0.73)	
MS_Performance×CoverageIncrease						0.394
						(0.97)
MS_Performance						-0.228
						(-0.36)
CoverageIncrease	-3.314*	-2.128	-4.582**	-2.414	-1.673	-1.160
	(-1.98)	(-1.29)	(-2.51)	(-1.26)	(-1.00)	(-0.71)
Constants	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Fund-ShareClass FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	187,079	187,079	187,079	187,079	187,079	187,079
R-squared	0.373	0.372	0.373	0.372	0.372	0.372
Adj. R-squared	0.340	0.338	0.340	0.339	0.338	0.338

Table 6. Continued

VARIABLES	(1) $FRET_{3Y}$	(2) $FRET_{3Y}$	(3) $FRET_{3Y}$	(4) $FRET_{3Y}$	(5) $FRET_{3Y}$	(6) $FRET_{3Y}$
MS_Overall×CoverageIncrease	1.866***					
	(4.33)					
MS_Overall	2.889***					
	(3.67)					
MS_People× CoverageIncrease		3.313***				
		(2.99)				
MS_People		1.371				
		(1.02)				
MS_Parent× CoverageIncrease			4.919***			
			(5.79)			
MS_Parent			3.089***			
			(3.07)			
MS_Price×CoverageIncrease				1.705**		
				(2.27)		
MS_Price				1.492*		
				(1.88)		
MS_Process× CoverageIncrease					2.901***	
					(3.44)	
MS_Process					2.899***	
					(3.28)	
MS_Performance×CoverageIncrease						2.237**
						(2.57)
MS_Performance						2.868***
						(2.70)
CoverageIncrease	-8.427	-10.223*	-14.256**	-5.595	-8.561**	-7.454
	(-1.56)	(-1.80)	(-2.63)	(-1.01)	(-2.01)	(-1.55)
Constants	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Fund-ShareClass FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	187,079	187,079	187,079	187,079	187,079	187,079
R-squared	0.777	0.775	0.778	0.775	0.776	0.776
Adj. R-squared	0.766	0.763	0.766	0.763	0.764	0.764

Table 7. Net Cash Inflows and Benchmark Funds Coverage Increase

This table presents the results of the relations between future net cash inflows and the increase in coverage of benchmark funds after the AI adoption. $FutFundFlow$ is the natural log of net cash inflow into the funds in the following month. $CoverageIncrease$ is the percentage of benchmark funds with Morningstar ratings in the same Morningstar category with the focal fund. $MS\_Overall$ is the overall Morningstar rating for the fund. $POST$ is an indicator variable that equals 1 for the period after June 2017, 0 otherwise. $LagRet$ is last month's fund return. $FundSize$ is the natural log of last month's fund net asset value. Exp_ratio is the fund's expense ratio. $LagFundFlow$ is the changes in fund net asset values from the past month. $AvgManagerTenure$ is the mean years of experience of all the fund managers in the management team for a given fund. $PercentageMale$ is the percentage of male managers in the management team for a given fund. $AnalystTenure$ is the number of years the fund analyst has worked at Morningstar. $AnalystGender$ is an indicator variable that equals 1 if the analyst is a male, 0 if the analyst is a female. T-statistics are presented in parentheses. *** indicates that the estimated coefficient is significantly different from zero at the 1% level, ** at the 5% level, and * at the 10% level. The standard errors are clustered at the Morningstar category level.

	(1)	(2)
VARIABLES	FutFundFlow	FutFundFlow
MS_Overall×CoverageIncrease	0.038**	0.065***
	(2.26)	(4.21)
MS_Overall	-0.018	0.031***
	(-1.51)	(3.46)
CoverageIncrease	0.074	-0.141
	(0.87)	(-1.59)
LagRet	-2.443***	-2.838***
	(-16.99)	(-22.52)
FundAge	-0.195***	-0.118***
	(-12.78)	(-4.30)
FundSize	0.420***	0.302***
	(59.46)	(25.80)
Exp_ratio	-0.300***	-0.156**
	(-10.56)	(-2.45)
AvgManagerTenure	0.828***	0.804***
	(29.39)	(28.62)
PercentageMale	-0.115	0.170
	(-1.13)	(1.13)
ManagerAge	-0.003	-0.014**
	(-0.66)	(-2.34)
AnalystTenure	0.002	0.001
	(1.25)	(0.95)
AnalystGender	0.006	0.010
	(0.32)	(1.20)
Constants	Y	Y
Year FE	Y	Y
Fund-ShareClass FE	N	Y
Observations	187,079	187,079
R-squared	0.583	0.552
Adj.R-squared	0.582	0.552

Table 8. Analyst Tenure and the Effects of AI Adoption

This table presents the tests of the effects of AI adoption on the levels and the quality of the Morningstar overall rating and people pillar rating for the subsample of experienced and junior analysts. $CONNECTED$ is the number of managers that are alumni of the same institution as the analyst. $MS\_Overall$ is the overall Morningstar rating for the fund, MS_People, MS_Parent, MS_Price, $MS\_Process$, and $MS\_Performance$ are the people, parent, price, process, and performance pillar ratings, respectively. $POST$ is an indicator variable that equals 1 for the period after June 2017, 0 otherwise. $CoverageIncrease$ is the percentage of benchmark funds with Morningstar ratings in the same Morningstar category with the focal fund. $LagRet$ is last month's fund return. $FundSize$ is the natural log of last month's fund net asset value. Exp_ratio is the fund's expense ratio. $LagFundFlow$ is the changes in fund net asset values from the past month. $AvgManagerTenure$ is the mean years of experience of all the fund managers in the management team for a given fund. $PercentageMale$ is the percentage of male managers in the management team for a given fund. $AnalystTenure$ is the number of years the fund analyst has worked at Morningstar. $AnalystGender$ is an indicator variable that equals 1 if the analyst is a male, 0 if the analyst is a female. T-statistics are presented in parentheses. The differences between the interaction terms between experienced and junior analysts are presented with the significance levels of the chi-squared tests denoted in stars. *** indicates that the estimated coefficient is significantly different from zero at the 1% level, ** at the 5% level, and * at the 10% level. The standard errors are clustered at the Morningstar category level.

	Experienced Analyst	Junior Analyst	Experienced Analyst	Junior Analyst	Experienced Analyst	Junior Analyst
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	MS_Overall	MS_Overall	MS_People	MS_People	$FRET_{3Y}$	$FRET_{3Y}$
CONNECTED ×POST	-0.164	-0.229*	-0.233**	-0.008		
	(-0.98)	(-1.84)	(-2.11)	(-0.25)		
CONNECTED	0.104	0.170**	0.172**	-0.012		
	(0.95)	(2.02)	(2.16)	(-0.57)		
POST	0.014	-0.021*	0.012	0.029***		
	(0.91)	(-1.73)	(0.86)	(2.72)		
MS_Overall ×CoverageIncrease					0.014***	-0.006
					(4.61)	(-0.44)
MS_Overall					0.000	0.034
					(0.02)	(1.36)
CoverageIncrease					-0.002	0.004
					(-0.24)	(0.93)
LagRet	0.107	-0.226	0.106**	0.005	-0.002	0.017
	(1.53)	(-1.40)	(2.25)	(0.05)	(-0.05)	(0.31)
FundSize	0.028	0.006	0.006	0.005	-0.015**	-0.031***
	(1.47)	(0.50)	(0.80)	(0.91)	(-2.91)	(-3.79)
Exp_ratio	0.120	0.771***	-0.078	0.157	-0.251**	-0.443**
	(0.48)	(4.47)	(-0.52)	(1.37)	(-2.58)	(-2.31)
LagFundFlow	0.013	0.003	0.004	0.007	0.003	0.016
	(1.28)	(0.20)	(0.76)	(0.90)	(1.49)	(1.52)
PercentageMale	-1.664	-0.360	-0.961	-0.849	-0.000	-0.004
	(-1.57)	(-0.59)	(-1.58)	(-1.67)	(-0.36)	(-0.74)
AvgManagerTenure	0.014	0.053***	0.015*	0.028*	-0.002	0.004
	(0.59)	(2.73)	(1.94)	(1.71)	(-0.24)	(0.93)
AvgManagerAge	0.000	0.001	-0.001	0.003	-0.002	0.017
	(0.04)	(0.09)	(-0.18)	(0.36)	(-0.05)	(0.31)
AnalystTenure	-0.006	-0.054	-0.004	-0.004	-0.015**	-0.031***
	(-0.85)	(-1.49)	(-1.66)	(-0.49)	-0.002	0.004
Analystgender	-0.012	-0.366*	0.001	-0.066	(-0.24)	(0.93)
	(-0.62)	(-1.70)	(0.06)	(-0.55)	-0.002	0.017
Diff Experienced-Junior		0.065*		-0.225**		0.020*
Constants	Y	Y	Y	Y	Y	Y
Fund-ShareClass FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	84,897	102,182	84,897	102,182	84,897	102,182
R-squared	0.896	0.892	0.818	0.829	0.373	0.412
Adj. R-squared	0.892	0.888	0.811	0.822	0.350	0.390

Table 9. Analyst Performance and the Effects of AI Adoption

This table presents the tests of the effects of AI adoption on the levels and the quality of the Morningstar overall rating and people pillar rating for the subsample of analysts with high and low past performance. $CONNECTED$ is the number of managers that are alumni of the same institution as the analyst. $MS\_Overall$ is the overall Morningstar rating for the fund, MS_People, MS_Parent, MS_Price, $MS\_Process$, and $MS\_Performance$ are the people, parent, price, process, and performance pillar ratings, respectively. $POST$ is an indicator variable that equals to 1 for the period after June 2017, 0 otherwise. $CoverageIncrease$ is the percentage of benchmark funds with Morningstar ratings in the same Morningstar category with the focal fund. $LagRet$ is last month's fund return. $FundSize$ is the natural log of last month's fund net asset value. Exp_ratio is the fund's expense ratio. $LagFundFlow$ is the changes in fund net asset values from the past month. $AvgManagerTenure$ is the mean years of experience of all the fund managers in the management team for a given fund. $PercentageMale$ is the percentage of male managers in the management team for a given fund. $AnalystTenure$ is the number of years the fund analyst has worked at Morningstar. $AnalystGender$ is an indicator variable that equals 1 if the analyst is a male, 0 if the analyst is a female. T-statistics are presented in parentheses. The differences between the interaction terms between high and low performers are presented with the significance levels of the chi-squared tests denoted in stars. *** indicates that the estimated coefficient is significantly different from zero at the 1% level, ** at the 5% level, and * at the 10% level. The standard errors are clustered at the Morningstar category level.

	High Performer	Low Performer	High Performer	Low Performer	High Performer	Low Performer
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	MS_Overall	MS_Overall	MS_People	MS_People	$FRET_{3Y}$	$FRET_{3Y}$
CONNECTED×POST	-0.306*	0.028	-0.402**	-0.079		
	(-1.77)	(0.36)	(-2.29)	(-1.01)		
CONNECTED	0.040	-0.033	0.090	0.149**		
	(0.46)	(-0.26)	(1.50)	(2.72)		
POST	-0.001	-0.050*	-0.010	0.003		
	(-0.02)	(-1.88)	(-0.39)	(0.26)		
MS_Overall ×CoverageIncrease					0.026***	0.020***
					(5.19)	(6.42)
MS_Overall					(7.69)	(2.15)
					0.026***	0.020***
CoverageIncrease					-0.184***	-0.038
					(-3.49)	(-1.71)
LagRet	-0.272	0.059	-0.105	-0.056	-0.420***	-0.494***
	(-1.07)	-0.7	(-1.14)	(-0.61)	(-11.75)	(-16.74)
FundAge	-0.131	-0.136*	0.029	0.034	0.014	-0.001
	(-1.55)	(-2.10)	(0.56)	(1.40)	(0.41)	(-0.06)
FundSize	0.029	0.039*	0.016**	0.010	-0.011	-0.004
	(1.24)	(1.92)	(2.35)	(1.06)	(-1.58)	(-1.11)
Exp_ratio	0.375*	0.312*	-0.079	0.057	0.004	0.039
	(2.07)	(1.94)	(-0.56)	(0.79)	(0.21)	(1.41)
LagFundFlow	0.011	-0.005	0.009	0.008	-0.023**	-0.023***
	(0.67)	(-0.39)	(0.96)	(1.36)	(-2.81)	(-3.44)
PercentageMale	0.024	0.211	0.193	0.397	-0.157	-0.125***
	(0.07)	(0.41)	(0.83)	(1.30)	(-1.68)	(-6.46)
AvgManagerTenure	0.014	0.023	0.029**	0.019	0.001	0.002
	(0.93)	(1.59)	(2.44)	(1.71)	(0.48)	(0.45)
AvgManagerAge	0.004	0.010**	0.001	0.005	-0.000	-0.001
	(1.18)	(2.16)	(0.38)	(1.74)	(-0.14)	(-0.61)
AnalystTenure	0.003	0.001	0.001*	-0.001	0.000	0.000
	(1.42)	(0.28)	(1.77)	(-0.52)	(0.39)	(0.43)
Analystgender	0.065*	0.002	0.008	-0.019	-0.000	-0.008
	(2.02)	(0.11)	(0.80)	(-1.22)	(-0.02)	(-0.95)
Diff High-Low		0.334***		-0.032**		0.006*
Constants	Y	Y	Y	Y	Y	Y
Fund-ShareClass FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	91,133	95,946	91,133	95,946	91,133	95,946
R-squared	0.919	0.918	0.839	0.845	0.488	0.491
Adj. R-squared	0.904	0.903	0.807	0.817	0.387	0.399

Table 10. Analyst Report Characteristics and AI Adoption

This table presents the tests of the effects of AI adoption on the characteristics of analyst reports for the subsample of analysts with high and low past performance. $Polarity$ is the difference between positive and negative word counts as a percentage of total word counts of the analyst reports. $Subjectivity$ is the subjectivity score of the analyst reports. $CONNECTED$ is the number of managers that are alumni of the same institution as the analyst. $CoverageIncrease$ is the percentage of benchmark funds with Morningstar ratings in the same Morningstar category with the focal fund. $MS\_Overall$ is the overall Morningstar rating for the fund, MS_People, MS_Parent, MS_Price, $MS\_Process$, and $MS\_Performance$ are the people, parent, price, process, and performance pillar ratings, respectively. $POST$ is an indicator variable that equals to 1 for the period after June 2017, 0 otherwise. $LagRet$ is last month's fund return. $FundSize$ is the natural log of last month's fund net asset value. Exp_ratio is the fund's expense ratio. $LagFundFlow$ is the changes in fund net asset values from the past month. $AvgManagerTenure$ is the mean years of experience of all the fund managers in the management team for a given fund. $PercentageMale$ is the percentage of male managers in the management team for a given fund. $AnalystTenure$ is the number of years the fund analyst has worked at Morningstar. $AnalystGender$ is an indicator variable that equals 1 if the analyst is a male, 0 if the analyst is a female. T-statistics are presented in parentheses. *** indicates that the estimated coefficient is significantly different from zero at the 1% level, ** at the 5% level, and * at the 10% level. The standard errors are clustered at the Morningstar category level.

	Full Sample	Full Sample	Long Tenure	Long Tenure	Short Tenure	Short Tenure
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Polarity	Subjectivity	Polarity	Subjectivity	Polarity	Subjectivity
CONNECTED ×POST	-0.016*	-0.013*	-0.028***	-0.023**	0.000	-0.005
	(-1.69)	(-1.77)	(-3.14)	(-2.49)	(0.04)	(-0.47)
CONNECTED	0.007	0.013*	0.016***	0.025***	0.003	0.011
	(0.95)	(1.90)	(2.78)	(2.67)	(0.61)	(1.27)
POST	-0.003	0.001	-0.001	-0.002	0.004	0.006
	(-1.34)	(0.24)	(-0.14)	(-0.36)	(0.77)	(1.33)
LagRet	-0.005	-0.029**	0.047	0.034	-0.033	0.009
	(-0.47)	(-2.08)	(1.57)	(0.97)	(-1.08)	(0.28)
FundAge	-0.001	-0.005***	-0.003	-0.007	0.002	0.002
	(-0.36)	(-2.91)	(-0.60)	(-1.44)	(0.43)	(0.52)
FundSize	0.001	0.001*	-0.002	-0.001	-0.002	0.001
	(1.24)	(1.75)	(-1.10)	(-0.59)	(-0.95)	(0.82)
Exp_ratio	-0.011***	0.005	0.001	-0.002	-0.013**	0.001
	(-3.16)	(1.11)	(0.07)	(-0.09)	(-2.18)	(0.16)
LagFundFlow	0.005*	-0.006*	0.006	0.003	-0.005	0.002
	(1.96)	(-1.94)	(1.12)	(0.64)	(-0.93)	(0.36)
PercentageMale	-0.033**	-0.024*	-0.079*	-0.086***	-0.020	-0.043
	(-2.12)	(-1.75)	(-1.80)	(-4.11)	(-0.96)	(-1.08)
AvgManagerTenure	0.001	-0.000	0.000	0.002	0.001	-0.000
	(1.01)	(-0.08)	(0.24)	(0.86)	(1.07)	(-0.15)
AvgManagerAge	0.000	-0.000	-0.000	-0.001**	-0.000	0.001***
	(0.13)	(-0.97)	(-0.09)	(-2.18)	(-0.07)	(2.77)
AnalystTenure	0.000	-0.000	0.001	-0.001	-0.002	0.001
	(0.02)	(-0.27)	(0.38)	(-0.37)	(-0.61)	(0.37)
AnalystGender	0.001	0.002	-0.001	0.015*	0.005	0.002
	(0.52)	(1.41)	(-0.17)	(1.95)	(1.02)	(0.18)
Constant	0.098***	0.447***	0.136	0.524***	0.091**	0.402***
	(4.61)	(18.32)	(1.57)	(7.06)	(2.37)	(8.81)
Fund-ShareClass FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	10,237	10,237	3,699	3,699	6,538	6,538
R-squared	0.725	0.723	0.717	0.724	0.709	0.766
Adj.R-squared	0.632	0.630	0.611	0.621	0.559	0.646