Are Subjective Expectations Formed as in Rational Expectations Models of Active Management?

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Abstract

We recover forward-looking expected net-of-fee abnormal returns (alphas) for active equity mutual funds from analyst ratings. In contrast to the typical equilibrium implication of zero alphas, analyst alphas are negative for most funds, but positive for the largest funds. We compare analysts' subjective expectations with expectations from a rational expectations learning model. The model's rational learner believes that an increase in fund size leads to a decrease in returns, but we find no evidence that analysts believe so. Overall, analysts' expectations and the capital that follows analysts' recommendations are difficult to reconcile with existing rational expectations models of active management.

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1 Introduction

Rational expectations models of active management make precise predictions about how return expectations are formed (see, e.g., Berk and Green, 2004), yet data on subjective expectations have largely been missing from the debate surrounding these models. Using investors' fund flows and realized returns to examine the predictions of these models, existing research has reached mixed conclusions.[1] This paper recovers forward-looking expected net-of-fee abnormal returns (henceforth, "alphas") as perceived by analysts for virtually all active equity mutual funds worldwide from analyst ratings provided by Morningstar.

Are analysts' subjective expectations formed as in rational expectations models of active management? Hardly so. First, in contrast to the typical equilibrium implication of zero alphas, not all analyst alphas are zero. Second, we do not find any evidence that analysts' expectations decrease as a fund's size increases. If anything, analysts' expectations *increase* as a fund's size increases. In contrast and consistent with a large literature on decreasing returns to scale, we do find that *realized* fund returns decrease as a fund's size increases (see, e.g., Chen, Hong, Huang, and Kubik, 2004; Pástor, Stambaugh, and Taylor, 2015; Zhu, 2018; Roussanov, Ruan, and Wei, 2021).

We find an economically and statistically significant effect of analysts' ratings on fund flows, indicating that some investors follow analysts' recommendations. The effect of analysts' ratings on flows is up to 82% of the effect of the popular Star Ratings. Ultimately, misunderstandings of returns to scale in active management could help explain why many funds grow too large and underperform.

[1] Consistent with the rational expectations paradigm, some researchers interpret a positive flow–performance relationship as evidence of sophisticated learning (see, e.g., Franzoni and Schmalz, 2017; van Binsbergen, Kim, and Kim, 2021; Barras, Gagliardini, and Scaillet, 2022) and realized alphas close to zero as the result of the competitive supply of capital (see, e.g., Berk and van Binsbergen, 2015). In contrast, other researchers interpret similar evidence as unsophisticated return chasing (see, e.g., Ben-David, Li, Rossi, and Song, 2022) and lack of managerial skill (see, e.g., Fama and French, 2010).

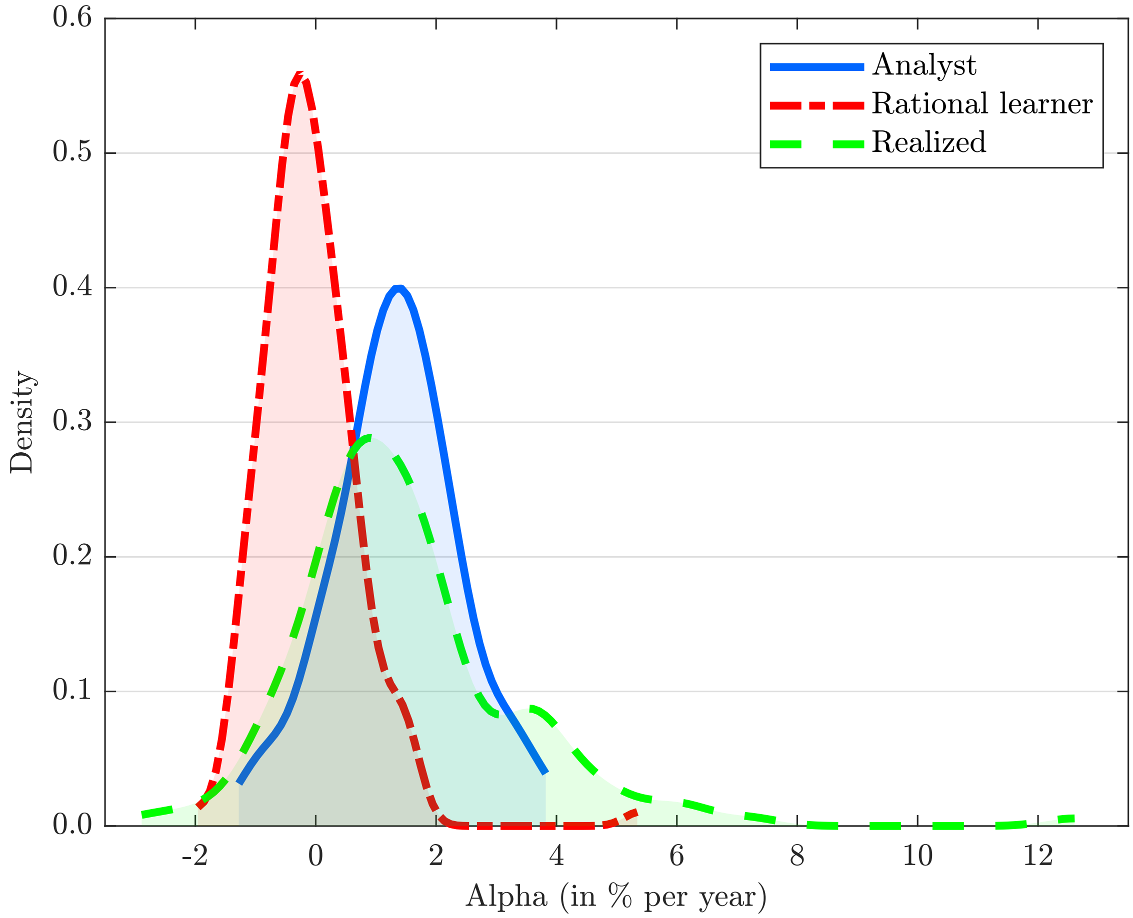
Predictions of rational expectations models

In the typical rational expectations model of active management, investors are uncertain about some parameters of the economy (e.g., managerial skill) and update their expectations from observed fund returns, which decrease as a fund's size increases. This latter concept of decreasing returns to scale is central to understanding the typical model. The decreasing returns to scale in realized returns that we and the literature document do not necessarily imply that a large fund will likely perform worse than a smaller fund. Decreasing returns to scale imply that—all else being equal—an increase in size leads to a decrease in returns relative to the passive benchmark, summarizing the notion that good investment ideas are not arbitrarily scalable. Finally, in equilibrium investors allocate capital to funds competitively such that alphas are zero (see, e.g., Berk and Green, 2004) or close to zero (see, e.g., Pástor and Stambaugh, 2012).

Data on subjective expectations

We recover expectations from analyst ratings provided by Morningstar, a leading financial services firm in the USD 13 trillion active equity mutual fund industry. As Morningstar overhauled the methodology for its forward-looking ratings in October 2019 and then provided a detailed description of how the overhauled ratings are constructed, we can recover detailed measures of expectations since then. Analysts assign the ratings according to a five-tier scale with three positive ratings of Gold, Silver, and Bronze, as well as a Neutral rating and a Negative rating. Under the new methodology, Morningstar constructs a distribution of alphas and then groups the alphas (which are not reported in the database) to arrive at the final Morningstar Analyst Ratings (which are reported in the database). We replicate Morningstar's methodology to recover the alphas that the analysts use. When we translate our alphas into ratings, we can replicate 93% of the ratings.

Figure 1: Alphas of the ten percent largest analyst-rated funds



The figure shows the cross-sectional distributions of analyst alphas (in blue) and alphas as implied by a rational expectations learning model (in red), as well as backward-looking historically realized alphas (in green), all as of December 2020. Realized alphas are computed over the lifetime of a fund. The sample is restricted to the ten percent largest funds with an Analyst Rating as of December 2020. On average, these 145 funds have existed for 30 years and grown their assets under management (AUM) from USD 1 billion to USD 30 billion, managing about 30% of worldwide AUM in the active equity mutual fund industry as of December 2020. Alphas are relative to each fund's Morningstar Category benchmark.

Analysts' expectations versus model-implied expectations

Figure 1 illustrates our main results. The figure shows analyst alphas (in blue), alphas implied by a rational expectations learning model that we estimate and introduce below (in red), and backward-looking historically realized alphas (in green), all for the cross-section of the largest ten percent of analyst-rated funds in December 2020.

First, the Berk and Green (2004) equilibrium implication of a zero alpha for each and every fund is trivially counterfactual when compared with analyst alphas: not all analyst alphas are zero. In fact, analyst alphas are only positive for the largest funds (shown in Figure 1), but negative for most other funds (not shown in Figure 1). That said, it is well known that not all realized alphas are zero (see, e.g., Kosowski, Timmermann, Wermers, and White, 2006; Fama and French, 2010; Harvey and Liu, 2021) and previous research indeed interprets rational expectations models of active management in an approximate sense (see, e.g., Berk and Tonks, 2007). Thus, in what follows we relax the equilibrium implication of zero alphas.

Second, once the zero-alpha equilibrium implication is relaxed, the key prediction of rational expectations models of active management concerns decreasing returns to scale.[2] Consider now the distributions of analyst alphas and historically realized alphas. Figure 1 restricts the sample to the largest funds as of December 2020 because, if anywhere, the effect of decreasing returns to scale should be visible for these funds. On average, they have grown their assets under management (AUM) from USD 1 billion to USD 30 billion over the last 30 years. These increases in AUM are among the greatest in both absolute and relative terms. However, despite the growth in AUM, the figure shows that analysts extrapolate from past returns: they expect these funds to at least sustain the returns that they have earned in the past (in blue and green).[3] Such extrapolation for the funds that have seen the greatest

[2] Fama and French (2010) write: "For many readers, the important insight of Berk and Green (2004) is their assumption that there are diseconomies of scale in active management, not their detailed predictions about net fund returns (which are rejected in our tests)."

[3] In fact, for around 50% of the funds in Figure 1, analysts predict *larger* alphas going forward than these funds' historically realized alphas, despite that these funds operate at record-high sizes. Similar to Linnainmaa (2013), in a simple learning model you would expect a fund's alpha going forward to be bounded by a reasonable prior, say zero, and the historically realized alpha—unless you believe increases in size actually increase future returns.

increases in size is inherently difficult to reconcile with a belief in decreasing returns to scale.

Third, what do typical rational expectations models imply about expected returns going forward for the funds that have grown to be the largest? The distribution shown in red in Figure 1 is implied by a Berk and Green (2004)-type model once the equilibrium implication of zero alphas is relaxed. Without the equilibrium implication, their model is a filtering problem: a rational learner who is uncertain about managerial skill updates beliefs from past fund returns to form expectations of future returns. Any such Bayesian learning model can in principle "rationalize" analysts' expectations by imposing arbitrary priors (e.g., a prior belief in no decreasing returns to scale together with a high certainty around that prior). An important point of our paper is to take Bayesian models to the data rigorously and so we estimate the Berk and Green (2004) model using an empirical Bayes method as in Roussanov et al. (2021).[4] As in Roussanov et al. (2021), the estimation uncovers decreasing returns to scale in realized fund returns and so the distribution of alphas perceived by the rational learner shown in Figure 1 is notably shifted to the left for the funds that have grown to be the largest.

By imposing structure via the rational expectations learning model, we can also extend the results in Figure 1 to all funds (not just the largest ones). One advantage of the estimated rational expectations learning model is that its predictions can be tested using a simple cross-sectional regression of analyst alphas on the fund characteristics in the model: perceived managerial skill, size, and fees. Consistent with the rational expectations learning model, analyst alphas decrease with fees and increase with perceived skill. Inconsistent with the model, a 100% increase in AUM *increases* analysts' expectations by 9 basis points. Mirroring the results in the literature on decreasing returns to scale, the rational learner instead believes

[4] In fact, estimating the model corresponds to the definition of "rational expectations" in this literature (see, e.g., p. 1274 in Berk and Green, 2004). The rational expectations paradigm has strict implications for the distribution of priors and other parameters in a Bayesian model: they cannot be arbitrary, but need to conform with the distribution of true parameters, which for any given model can be estimated from the data.

that a doubling of AUM leads to a 17-basis-points-decrease in alpha.

Potential concerns

You may be concerned that our results rest on the particular rational expectations learning model that we benchmark analyst alphas against, but they hardly do. The distributions of analyst alphas and historically realized alphas shown in Figure 1 do not rely on any particular rational expectations model. As long as there are decreasing returns to scale in realized fund returns, one would expect a forecast incorporating decreasing returns to scale to be shifted to the left for this set of funds. This is in particular so given 30 years of potential learning to resolve any parameter uncertainties.

Apart from that, our results are robust to various extensions of the rational expectations learning model (including features from, among others, Pástor and Stambaugh, 2012; Pástor et al., 2015; Berk and van Binsbergen, 2015; Barras et al., 2022), they are robust when we control for additional manager and fund characteristics in reduced form, they are not confined to a particular cross-section of funds, and we also find decreasing returns to scale in realized fund returns using the estimator in Zhu (2018). Among the additional characteristics that matter for analysts' expectations are manager ownership (Khorana, Servaes, and Wedge, 2007; Evans, 2008; Ibert, 2019), manager tenure (Greenwood and Nagel, 2009), and fund family fixed effects.

Ultimately, attempts to reconcile analysts' expectations with rational expectations models of active management would need to generate measures of perceived managerial skill that, once controlled for, could flip the estimates on size from positive to negative in our regressions. With R^2 values above 60%, our specifications that control for additional manager and fund characteristics in reduced form leave little room for that. If such measures existed, they would be crucial for future model development and in turn highlight the importance of our key contribution: contrasting the rational expectations paradigm for mutual funds with subjective expectations.

Another potential concern is that analysts' forecasts may not represent their best attempts. Instead, their forecasts could also reflect incentive structures or career concerns. Morningstar is an independent research firm, has a substantial business reputation at stake, and previous research has used the Morningstar Analyst Rating as a *benchmark* of independent analysis (see, e.g, Cookson, Jenkinson, Jones, and Martinez, 2021). Moreover, our textual analysis of more than 20,000 reports and notes that accompany the Morningstar Analyst Ratings suggests that analysts do discuss fund size, and even more so in the case of larger funds. We conclude that analysts' forecasts are their best attempts to forecast future returns, but that analysts seem to misjudge returns to scale in active management.

Related literature

Our paper relates to several strands of literature. First, a large literature examines the predictions of the Berk and Green (2004) model, including the key prediction whether an increase in size leads to a decrease in realized fund returns.[5] Contrasting the rational expectations paradigm for mutual funds with analysts' subjective expectations is novel. In their study of how leading financial theories describe individual investor behavior, Choi and Robertson (2020) also include a statement about decreasing returns to scale and report that only 18% of respondents believe in decreasing returns to scale (see also Bender, Choi, Dyson, and Robertson, 2022). Apart from their different focus, the usual caveats regarding survey data apply. It is unclear whether the surveyed investors are representative and whether they act on their expectations. Framing also matters: their statement does not allow for expectations to increase with size—something our results suggest. Overall, we view analysts'

[5]See Berk and van Binsbergen (2017) for a review of this literature. For recent studies that examine decreasing returns to scale in realized returns, in addition to the papers already cited, see, e.g., McLemore (2019), Pástor, Stambaugh, and Taylor (2020), Roussanov, Ruan, and Wei (2020), Dyakov, Jiang, and Verbeek (2020), Busse, Chordia, Jiang, and Tang (2021), Reuter and Zitzewitz (2021), Harvey, Liu, Tan, and Zhu (2021), and Pástor, Stambaugh, Taylor, and Zhu (2022).

expectations as an important addition to survey-based expectations.

Second, our paper relates to a literature that examines expectations regarding fund performance (see, e.g., Jenkinson, Jones, and Martinez, 2016; Jones and Martinez, 2017; Armstrong, Genc, and Verbeek, 2019; Cookson et al., 2021). The analyst alphas we recover are an important improvement over previous work, as they can be confronted with model-implied alphas and, ultimately, can be used to compute forecast errors for virtually every fund in the universe of active equity mutual funds.[6]

Third, our paper relates to a literature on models of active management. The rational expectations model and its perturbations, as presented here, are most closely related to the model of Berk and Green (2004). Compared to their model, the models of Dangl, Wu, and Zechner (2008), Glode and Green (2011), and Pástor and Stambaugh (2012) share similar features, that is, learning about some parameters, returns that decrease with size, and the competitive provision of capital. For a different modeling approach see, e.g., Gârleanu and Pedersen (2018). The models of Gennaioli, Shleifer, and Vishny (2015) and Spiegler (2020) allow for deviations from rational expectations.

Fourth, our paper relates to broader recent efforts in economics and finance to study subjective expectations (see, e.g., Coibion and Gorodnichenko, 2012, 2015; Bordalo, Gennaioli, La Porta, and Shleifer, 2019; Bordalo, Gennaioli, Ma, and Shleifer, 2020). As analysts' expectations are diametrically opposed to the rational expectations model, our results are conceptually similar to those of Greenwood and Shleifer (2014), who show that subjective stock market return expectations are diametrically opposed to expectations implied by rational expectations asset pricing models. Similar to their survey evidence, mutual fund analysts' expectations are hard to reconcile with an equilibrium in which analysts' expectations are

[6] Armstrong et al. (2019) examine the ability of Analyst Ratings to predict fund performance from 2011 to 2015 and find some evidence for it. It is impossible to recover analyst alphas before October 2019. That professional analysts' recommendations have some predictive power is not inconsistent with our results, but expected: Carhart (1997) shows that even a simple measure such as past returns has some predictive power for future returns, at least for the worst-performing funds.

the expectations of a representative agent. This is because expectations that increase with size imply that unlimited amounts of capital should flow into all funds.

2 Forward-looking Morningstar Ratings

2.1 Old and new ratings

Morningstar has provided Analyst Ratings for a selected number of funds since 2011. Unlike the backward-looking Morningstar Rating (often referred to as the "Star Rating"), the Analyst Rating is the summary expression of Morningstar's forward-looking long-term analysis of a fund. Morningstar analysts assign the Analyst Ratings on a five-tier scale with three positive ratings of Gold, Silver, and Bronze, as well as a Neutral rating and a Negative rating. The Internet Appendix presents an example of how the Analyst Rating is displayed on Morningstar's website.

Up to October 2019, an Analyst Rating was based on an analyst's conviction of a fund's ability to outperform its peer group *and/or* relevant benchmark on a risk-adjusted basis over the long term. In October 2019, Morningstar overhauled its Analyst Rating system. The most important changes were a greater emphasis on fees and a share-class-specific rating in contrast to a fund-level rating. Different share classes of the same fund generally earn the same return before fees, but fees differ across share classes. Under the new rating system, a fund is expected to beat both its peer group *and* a relevant benchmark on a risk-adjusted basis to earn a medalist rating (i.e., a Bronze, Silver, or Gold rating). The new rating system is therefore informative about alpha, as alpha measures the performance relative to a passive benchmark. In contrast, the old rating system is not necessarily informative about alpha, as a fund may have received a medalist rating if it was expected to outperform its peers, but not a passive benchmark.

In addition, in an effort to increase transparency, Morningstar for the first time also published a document detailing how the Analyst Ratings are constructed under the new methodology. Under the new methodology, Morningstar constructs alphas by combining a strategy's overall potential with pillar ratings for a fund's "Parent," "People," and "Process." Morningstar then groups the resulting alphas (which are not published in their database) into the aforementioned ratings (which are published in their database).

The number of funds that receive an Analyst Rating is limited by the size of the Morningstar analyst team. There are currently 72 unique analysts. To expand the number of funds covered, since 2017 Morningstar has also provided forward-looking Quantitative Ratings. These are similar to Analyst Ratings, but are based on a machine-learning algorithm that attempts to mimic a human analyst's decision-making process. Morningstar assigns Quantitative Ratings to funds not covered by human analysts. Each fund can receive either an Analyst Rating or a Quantitative Rating, but in general not both. We also include funds with a Quantitative Rating in most of our analyses. Table 1 provides a summary of the different Morningstar ratings.

2.2 Analyst and Quantitative Ratings methodology

This section details how Morningstar constructs its ratings and how we recover analyst alphas. The Internet Appendix contains additional details about our replication and the data.

Morningstar's exact methodology for constructing the ratings follows a three-step process. First, for each fund, Morningstar estimates performance-evaluation regressions on a rolling window starting in January 2000:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{b,i,t} - R_{f,t}) + \zeta_{i,t}, \tag{1}$$

where t runs over a rolling 36-month window, $R_{i,t}$ is the gross (i.e., before-fee) return of fund i, $R_{f,t}$ is a risk-free rate proxy, and $R_{b,i,t}$ is a fund-specific benchmark return. The performance-evaluation regressions are estimated on the fund level, not the share-class level. The estimated intercepts are grouped by fund strategy (e.g., U.S. equity large-cap blend) to form a distribution of realized alphas. Morningstar then calculates the semi-interquartile range (SIQR) of the distribution (i.e., the 75th percentile minus the 25th percentile divided by 2). The SIQR measures the historically realized alpha dispersion and summarizes Morningstar's assessment of the potential of a given strategy.

Second, Morningstar analysts score a fund based on the three individual pillars "People," "Parent," and "Process." Under the new methodology, the scores range from –2 to +2. The labels of the scores –2, –1, 0, +1, and +2 are "Low," "Below Average," "Average," "Above Average," and "High," respectively, and written as such in Morningstar products. The Analyst Rating pillar scores are assigned based on an in-depth analysis, must be approved by a ratings committee, and are explained in detail in a written report for each rated fund. The Internet Appendix includes an anonymized example of such a report. The Quantitative Rating pillar scores are assigned using the aforementioned machine-learning algorithm. The SIQR and the pillar scores are then combined to give an estimate of the expected gross abnormal return of a fund:

$$\mathrm{E}_t^s[r_{i,t+1} + f_{i,t+1}] = \mathrm{SIQR}_{k,t} \times \left(0.10 \times \mathrm{Parent}_{i,t} + 0.45 \times \mathrm{People}_{i,t} + 0.45 \times \mathrm{Process}_{i,t}\right), \quad (2)$$

where E_t^s is the analyst's subjective expectation and $r_{i,t+1} + f_{i,t+1}$ is the fund's gross-of-fee abnormal return. The SIQR depends on the type of strategy, k, and acts as a scaling factor. The pillar ratings determine whether a fund receives a positive or negative gross analyst alpha.

Third, Morningstar subtracts the share-class-specific fee to arrive at a net-of-fee alpha for each share class, j, of fund i, that is, $\mathrm{E}_t^s[r_{i,j,t+1}]$. Conditional on a positive net alpha within a particular Morningstar Category, the top 15% of share classes receive a Gold rating, the next 35% receive a Silver rating, and the bottom 50% receive a Bronze rating. Conditional on a negative or zero net alpha within a particular category, the top 70% of share classes receive a Neutral rating and the bottom 30% receive a Negative rating.

The SIQR is not reported in the Morningstar database, so we need to recover Morningstar's SIQR estimate. Morningstar groups funds from around the world in closely related Morningstar Categories to estimate the SIQR, but is not explicit about the grouping. We group funds according to their Global Category (a Morningstar variable that groups closely related Morningstar Categories from different fund domiciles), use a fund's Morningstar Category Index as the benchmark, and use the three-month Treasury bill rate as the risk-free rate. In contrast to the SIQR, the pillar scores and fees are reported in the database, so we have all the inputs needed in order to recover the alphas before they are binned into the final ratings.

2.3 Replication

The predictions of the rational expectations model introduced below can be tested using a simple cross-sectional regression. We can recover analyst alphas since October 2019, but use the cross-section of analyst alphas in December 2020 for our main analysis. Funds with an Analyst Rating have been gradually updated since October 2019 using the new methodology, and this process was completed by December 2020. All funds with a Quantitative Rating are rated under the new methodology as of October 2019. We discuss the use of panel data in the robustness section and the Internet Appendix.

Table 2 shows that we can replicate the vast majority of Morningstar's Analyst and Quantitative Ratings, suggesting that we indeed recovered the alphas that Morningstar uses to construct the ratings. Panel A shows that for the 8697 share classes with an Analyst Rating under the new methodology, Morningstar assigns a Neutral rating to 3218 share classes.

In this case, we assign a Neutral rating in 3035 cases, yielding a replication rate of 94%. Our overall replication rate for the Analyst Ratings is 89%. Panel B shows our replication of the Morningstar Quantitative Ratings. Our overall replication rate for Quantitative Ratings is 93%. In total, we can replicate 92.7% of all ratings (the average of 89% and 93% weighted by the number of share classes that have an Analyst or Quantitative Rating, respectively).

While we believe that we can replicate Morningstar's methodology reasonably well to recover analyst alphas, there is measurement error in the dependent variable. Under standard assumptions, measurement error in the dependent variable does not bias coefficient estimates, but inflates standard errors. This works against finding significant results, as our standard errors are larger than they would be without measurement error.

3 Data

We obtain gross returns, AUM, ratings, and fees for active open-end equity mutual funds from Morningstar Direct. We include all funds in the database to correctly replicate Morningstar's methodology. The sample contains both U.S.-domiciled and non-U.S.-domiciled funds. Morningstar only uses data as of January 2000 to construct the Analyst Ratings, so we use the same data in our replication of the ratings. In addition, we use the full time series available in Morningstar to estimate the rational expectations model of fund performance. The monthly sample for the estimation starts in January 1979, the first month for which Morningstar provides benchmark returns, and ends in December 2020. We convert all returns and assets to USD. As is common in the literature, we aggregate share-class-level variables (e.g., fees, returns, and analyst alphas) to the fund level by taking an AUM-weighted average.

Figure 2 plots the AUM of funds with an Analyst Rating, a Quantitative Rating, or no rating over time. As is evident from the figure, Morningstar assigns ratings to the vast majority of funds in the 13 USD trillion active equity fund industry. Table 3 presents summary statistics for the cross-section of funds in December 2020. The number of funds with a Quantitative Rating is large but the assets of these funds are much smaller on average. Moreover, the table shows that funds with Analyst Ratings have much larger analyst alphas and larger perceived skill (a measure of past performance adjusted for decreasing returns to scale, which is introduced below). Put differently, Morningstar assigns Analyst Ratings as opposed to Quantitative Ratings to funds that are larger and have performed better in the past, and to funds that Morningstar expects to perform well in the future.

We report our main results for both the sample of "all funds" (i.e., the sample of funds with an Analyst Rating or a Quantitative Rating) and the sample of funds with only an Analyst Rating. In the former case, the sample contains virtually all global equity mutual funds. Concerns about sample selection and the representativeness of funds in our sample should therefore be small. In the latter case, a narrower interpretation of our results is that they "only" apply to the USD 7 trillion managed by the funds with an Analyst Rating.

4 Baseline rational expectations model

In this section, we outline the baseline rational expectations model with which to compare analyst alphas. Similar to Berk and Green (2004), we model the abnormal return of fund i in year $t+1$ as

$$r_{i,t+1} + f_{i,t+1} = a_{i,t} - c(\mathrm{AUM}_{i,t}) + \epsilon_{i,t+1}, \tag{3}$$

where $\epsilon_{i,t+1} \sim N(0, \sigma_\epsilon^2)$, $r_{i,t+1}$ is the fund's net abnormal return, $f_{i,t+1}$ is fees, $a_{i,t}$ is unobservable managerial skill, and the function $c(\mathrm{AUM}_{i,t})$ captures decreasing returns to scale. We refer to $\mathrm{E}_t[r_{i,t+1}]$ as the alpha implied by the rational expectations model.

Following Roussanov et al. (2021), we generalize Berk and Green (2004) to allow for time-varying skill:

$$a_{i,t+1} = (1-\rho)a_0 + \rho a_{i,t} + \sqrt{1-\rho^2} \cdot \nu_{i,t+1}, \tag{4}$$

where $\rho \in [0,1]$, the shock is distributed as $v_{i,t+1} \sim N(0, \sigma^2_{a,0})$, and skill when a fund is born is distributed as $N(a_0, \sigma^2_{a,0})$. A rational learner updates her beliefs about managerial skill, i.e., $a_{i,t+1}$ (the only parameter she is uncertain about), from past returns. Allowing for time-varying skill allows the learner to rationally place a greater weight on more recent past performance. A Kalman filter argument implies that beliefs at each point in time are given by:

$$\widehat{a}_{i,t+1} = \rho \left(\widehat{a}_{i,t} + \frac{\widehat{\sigma}^2_{a,t}}{\widehat{\sigma}^2_{a,t} + \sigma^2_\epsilon} (r_{i,t+1} - \widehat{a}_{i,t} + c(\mathrm{AUM}_{i,t}) + f_{i,t+1}) \right) + (1-\rho)a_0, \tag{5}$$

$$\widehat{\sigma}^2_{a,t+1} = \rho^2 \widehat{\sigma}^2_{a,t} \left(1 - \frac{\widehat{\sigma}^2_{a,t}}{\widehat{\sigma}^2_{a,t} + \sigma^2_\epsilon} \right) + (1-\rho^2)\sigma^2_{a,0}, \tag{6}$$

where $\widehat{\sigma}^2_{a,t+1}$ describes the uncertainty concerning the perceived skill, $\widehat{a}_{i,t+1}$, given initial conditions a_0 and $\sigma^2_{a,0}$. We assume a logarithmic specification for the decreasing returns to scale; that is, $c(\mathrm{AUM}) = \eta \log(\mathrm{AUM})$, where η is a parameter capturing the sensitivity of fund returns to an increase in AUM. We examine a more flexible functional form in Section 7.1 and in the Internet Appendix. The results in the Internet Appendix suggest that the logarithmic specification fits the data well.[7]

We use maximum likelihood to estimate the model on the fund level (using gross fund returns and fund size).[8] We run a performance-evaluation regression as in Equation (1), but

[7]In the most general version of our model with indexing in Section C.2 of the Internet Appendix, if $\gamma = 1$ (the parameter controlling the shape of decreasing returns to scale) and $\rho = 1$ (constant managerial skill), our model collapses to the model and parameterization in Berk and Green (2004) (see their Equation [11] and their parameterization in their Section IV).

[8]The model assumes that the residuals are uncorrelated across observations. This assumption is more likely to hold for fund returns than share class returns, as the share class returns of a given fund are highly correlated.

over the entire life of a fund using the same benchmark that analysts use, and then form $r_{i,t+1} + f_{i,t+1} = \widehat{\alpha}_i + \zeta_{i,t+1}$, where $\widehat{\alpha}_i$ is the sample average of realized gross abnormal returns.[9] We then annualize the monthly abnormal returns to form the annual abnormal returns. The AUM is measured at the end of the previous year in millions of 2020 USD. Together with the log specification for the decreasing returns to scale, this implies that $a_{i,t}$ is the return on the first USD 1 million invested in the fund.

Table 4 presents the parameter estimates and their standard errors. Our parameter estimates are similar to those of Roussanov et al. (2021). Note that their sample differs from ours, as they focus on U.S.-domiciled funds, whereas we also include funds from other domiciles to be consistent with Morningstar's methodology. The estimated prior mean of managerial skill is 2.30% per year, the prior standard deviation is 2.09%, the residual volatility is 8.11%, and the persistence parameter is 0.95. With a standard deviation of log(AUM) of 1.90, the decreasing returns to scale parameter estimate of 0.25% implies that a one-standard-deviation increase in log(AUM) leads to a 0.48-percentage-point decrease in returns. Alternatively, a doubling of AUM, corresponding to a log increase of 0.69, leads to a 0.17-percentage-point decrease in returns.

The model laid out so far is a filtering problem, independent of the equilibrium argument of Berk and Green (2004). Their equilibrium implication is that alphas are zero at any point in time. Otherwise, the money of risk-neutral investors would flow into and out of funds, affecting alphas through decreasing returns to scale and ultimately competing away any alphas. In contrast, a rational learner who is agnostic to the equilibrium concept expects

[9] One concern is that this procedure could create a bias towards finding decreasing returns to scale similar to the bias that troubles finite-sample fixed effects regressions (see, e.g., Pástor et al., 2015, and note that $\widehat{\alpha}_i$ is a fund fixed effect that is computed using information over the entire life of a fund). In the Internet Appendix, we alternatively estimate $\widehat{\alpha}_i$ using three-year rolling window averages, which eliminates this potential bias. The results are similar.

the abnormal return net of fees to be

$$\mathrm{E}_t[r_{i,t+1}] = \widehat{a}_{i,t} - \eta \log(\mathrm{AUM}_{i,t}) - f_{i,t+1}, \tag{7}$$

which may or may not equal zero. If the rational learner also has rational expectations, she uses the true parameter values of a_0, $\sigma_{a,0}$, η, σ_ϵ, and ρ, which are approximated by our estimates, to form her expectations. We assume rational expectations to form the alphas in December 2020, for every fund according to Equation (7).

5 Main empirical results

5.1 Descriptive statistics

Table 3 shows that analyst alphas are dispersed and obviously inconsistent with the equilibrium implication of a zero alpha for every fund. In fact, analysts actually expect most funds to underperform their benchmarks. The median analyst alpha for the sample of funds with an Analyst or a Quantitative Rating is −124 basis points per year.

Initial evidence that analysts' expectations are tilted towards larger funds comes from the equal- and value-weighted means in Table 3. For the sample of funds with an Analyst or a Quantitative Rating, the equal-weighted mean of analyst alphas is −139 basis points, whereas the value-weighted mean is 51 basis points. This implies that analysts expect the largest funds to outperform significantly.

5.2 Analyst alphas and perceived skill, size, and fees

According to the rational expectations model, three variables determine alphas: perceived skill, fund size, and fees. We start by investigating the univariate relationship between alphas and size. We sort funds into deciles according to their size in December 2020 and then compute average alphas across deciles for both analysts and the rational learner.

Panel (a) of Figure 3 shows the results for the sample of funds with an Analyst Rating and Panel (b) shows the results for the sample of funds with an Analyst or a Quantitative Rating. Analysts' expectations increase with size, whereas the rational learner's expectations are unrelated to size. In general, analysts are more optimistic about funds with an Analyst Rating than about funds with a Quantitative Rating. Since funds with a Quantitative Rating constitute most of the sample in Panel (b), the average analyst alphas are significantly lower in Panel (b) than in Panel (a). The figure also shows that, while analysts are optimistic about the largest funds, they are excessively pessimistic about the smallest funds. This again foreshadows our main conclusion that analysts' expectations are difficult to square with a belief in decreasing returns to scale. However, a belief that larger funds perform better does not necessarily imply a belief in increasing returns to scale: analysts may simply expect larger funds to be able to hire better managers and so perceived managerial skill is an omitted variable. In a similar vein, larger funds may simply charge lower fees.

Therefore, we formally evaluate the rational expectations model in multivariate regressions. One advantage of the model's predictions is that they can be tested using a simple cross-sectional regression. Equation (7), together with the assumption of rational expectations, makes clear predictions for a regression of analyst alphas on size (measured as the logarithm of AUM), perceived skill, and fees: the coefficient estimates should be $-\eta$, 1, and –1, respectively.[10] Table 5 presents two cross-sectional regressions: specification (1) uses the sample of funds with an Analyst Rating; specification (2) uses the sample of funds with an Analyst or a Quantitative Rating. In brackets, we report p-values for the null hypothesis that the coefficients equal the values predicted by the rational expectations model.

[10]Moreover, in theory the constant should be zero and the R^2 should be 100%; similarly, in theory the error terms are homoscedastic. In our empirical analysis, we allow for more conservative standard errors clustered by fund family. For our main results, we also focus on net-of-fee alphas; the main result is similar when we take fees out of the equation and impose the restriction that the coefficient on fees is equal to -1.

Fund size. The estimate on size is statistically positive in both columns and has the opposite sign to that of the model's prediction, which leads us to reject the rational expectations model. For instance, in specification (2) the coefficient estimate on size is 0.13% as opposed to -0.25%.

Perceived skill. As the rational expectations model predicts, greater perceived skill is associated with a larger analyst alpha. However, the coefficient estimate on perceived skill is smaller than and statistically different from one in both specifications.

Fees. As the rational expectations model predicts, an increase in fees is associated with a decrease in analyst alpha. The coefficient estimate on fees is not statistically different from minus one in specification (1), but is statistically different from minus one in specification (2).

You may be concerned that our regressions omit other variables, correlated with both analysts' unobserved perceptions of managerial skill and size, that bias the coefficient estimate on size. This is a valid concern—exogenous variation in size is difficult to obtain.

However, Figure 1 shows that we do not even need to identify the effect of size on analysts' expectations to argue that analysts' expectations are tilted too much towards larger funds. That said, the figure is consistent with two interpretations. Under a first interpretation, analyst alphas for the funds that have grown to be the largest are too large because analysts perceive these funds to be me much more skilled than they actually are (a too large $\widehat{a}_{i,t}$)—while still believing that an increase in size deteriorates future returns. Under a second interpretation, analyst alphas for the largest funds are too large because analysts do not believe that an increase in size actually deteriorates future returns (a wrong η). By imposing structure and modeling alphas as a linear function of perceived managerial skill and size, the results of this subsection support the latter interpretation.

Finally, we add additional variables to our empirical specifications in the next subsection and extend the model in various ways in the robustness section, but the estimates on size remain positive.

5.3 Additional determinants of expectations

Morningstar's methodology suggests that the rational expectations model omits variables relevant to analysts' expectation formation. We are guided by Morningstar's methodology and previous research in choosing additional variables to explain analysts' expectations. We group variables corresponding to the three pillars "People," "Process," and "Parent." Most of our variables can be obtained directly from Morningstar Direct, which ensures that they are available to analysts. We then simply include these variables in reduced form in our cross-sectional regressions.[11]

For "People," we include manager tenure (the longest tenure, in months, of the managers of a fund), manager ownership (the average dollar amount managers of a fund personally invest in the fund), managerial multitasking (the average number of additional funds that the managers of a fund manage), and a dummy for whether a fund is team managed. Manager ownership has been shown to predict fund performance in the U.S. and Sweden (see, e.g., Khorana et al., 2007; Ibert, 2019). However, since ownership information is only publicly available for U.S.-domiciled funds, our sample is restricted.[12]

For "Process," we include a fund's top 10 assets (the percentage of AUM in the ten largest positions), a fund's tracking error (the standard deviation of returns in excess of the benchmark over the life of the fund), fund turnover (as reported to the SEC), a dummy

[11] An alternative approach would be to include additional variables in our structural estimation via the measurement equation, Equation (3). One caveat to this approach is that, for many of our additional variables, time series are not readily available from Morningstar Direct.

[12] As of 2005, the SEC requires that mutual fund managers publicly report personal investments in their own funds. Managers must report whether their dollar ownership in their funds falls into one of the following ranges: USD 0, USD 1–10,000, USD 10,001–50,000, USD 50,001–100,000, USD 100,001–500,000, USD 500,001–1,000,000, or above USD 1,000,000. As done by Khorana et al. (2007), we use midpoints of the disclosed ownership ranges to calculate manager ownership, except for the maximum range, "USD 1,000,001 and above," for which we use the bottom of the range.

for whether a fund is primarily held by retail investors, and a dummy for whether a fund is primarily sold through a broker.[13] Top 10 assets and tracking error serve as measures of diversification and activeness, respectively. There is evidence that more active funds outperform (see, e.g., Cremers and Petajisto, 2009). In contrast, broker-sold funds and funds held primarily by retail investors have underperformed on average (Bergstresser, Chalmers, and Tufano, 2009; Del Guercio and Reuter, 2014).

For "Parent," we include fund family fixed effects. The literature on the role of the fund family has highlighted the fund family's impact on individual fund performance (see, e.g., Massa, 2003; Gaspar, Massa, and Matos, 2006; Ferreira, Matos, and Pires, 2018).

Since our measure summarizing past fund performance—perceived skill—requires a belief in decreasing returns to scale to compute it, we also control for alternative measures of past performance that analysts may consider. Morningstar Star Ratings are a prominent alternative measure of past performance, so we include Morningstar Star Rating fixed effects. We also include Morningstar Category and Sustainability Rating fixed effects. Overall, our set of controls is extensive. The effect of size on analyst alphas is identified from variation across funds within the same fund family, within the same category, with the same Star and Sustainability ratings, and with the same levels of the various observables we consider.

Table 6 shows four specifications. The first two are for the sample of U.S.-domiciled funds with an Analyst Rating and the last two are for the sample of all rated U.S.-domiciled funds. Specifications (1) and (3) replicate the specifications in Table 5 for the restricted sample of U.S.-domiciled funds and show similar results. Specifications (2) and (4) include "People" and "Process" variables as well as various fixed effects. We standardize "People" and "Process" variables to mean zero and unit standard deviation, but leave perceived skill,

[13] We winsorize fund turnover at the 1st and 99th percentiles as done by Pástor, Stambaugh, and Taylor (2017) and do the same with the top 10 assets. The retail dummy takes the value of one if more than 2/3 of a fund's assets come from share classes open to retail investors. The broker-sold dummy takes the value of one if more than 2/3 of a fund's assets come from share classes that charge front-end or back-end loads or a 12b-1 fee of more than 0.25%.

size, and fees unstandardized for comparison to previous tables.

As expected, other characteristics besides perceived skill, size, and fees are important to analysts' expectation formation. In both specifications (2) and (4), manager tenure, manager ownership, and managerial multitasking are positively related to analysts' expectations. In specification (4), one-standard-deviation increases in tenure and ownership increase analyst alphas by 0.25- and 0.19-percentage-points, respectively. In contrast, funds predominantly held by retail investors are expected to perform worse, consistent with earlier evidence on the realized performance of such funds.

The point estimates on fund size become smaller both economically and statistically, suggesting that some of the additional characteristics are correlated with both size and expected returns. Nonetheless, the point estimates on size remain positive in all columns. Most importantly, the point estimates are still far from the -0.25 point estimate implied by the rational expectations model. The p-value for the null hypothesis that the coefficient equals -0.25 is 0.00.

Another piece of evidence comes from the coefficient estimates on fees. The impact of fund size on fund returns is perhaps hard to grasp given the sophistication required to detect decreasing returns to scale in realized fund returns and some mixed empirical evidence in previous studies. However, common sense suggests that, all else being equal, a one-percentage-point increase in fees should decrease expected returns by one percentage point. The estimates on fees in (2) and (4) are close to minus one and not statistically different from minus one, suggesting that these specifications satisfy this basic principle of common sense. These specifications give us confidence that we have not overlooked other important characteristics that could, once included, lead to a negative coefficient estimate on size.

In fact, R^2 values of above 60% suggest that specifications (2) and (4) capture analyst alphas reasonably well. The increases in R^2 values are driven by the inclusion of fund family fixed effects. We hypothesize that governance and incentives could play a large role. For instance, fund manager compensation practices are likely important and have been shown to differ systematically across fund families (Ibert, Kaniel, Van Nieuwerburgh, and Vestman, 2018; Ma, Tang, and Gómez, 2019).

6 Analysts' expectations and investors' expectations

We study *analysts'* subjective expectations. Analysts could be akin to sophisticated investors, but in general our paper says little about *investors'* subjective expectations. A valid approach for learning about investors' subjective expectations is to directly survey investors. However, surveys entail well-known drawbacks, as is explained in detail in Choi and Robertson (2020). For instance, it is unclear whether survey respondents act on their expectations and, thus, whether their expectations are reflected in their capital allocations.

While we do not observe investors' subjective expectations, one advantage of working with mutual fund data is that we can test whether better ratings lead to larger investor fund flows. The Internet Appendix shows that they do, using the ordinal ratings that are available for a longer time series. That flows follow ratings shows that analysts' expectations matter to some investors, regardless of whether these investors have the same expectations of future performance, have different expectations, or have even formed their expectations.

Figure 4 summarizes the results regarding flows shown in the Internet Appendix. The figure shows coefficient estimates on Star Rating dummies, Analyst Rating dummies, and Quantitative Rating dummies in a regression of monthly fund flows on the dummies, a battery of control variables, and fund, year–month, as well as category fixed effects (see also Armstrong et al., 2019). The effect of the Analyst Rating on flows can be close to the effect of the popular Star Rating. For instance, when a fund with no Star Rating is assigned a five-star rating, monthly flows increase by 1.39 percentage points (i.e., $= 1.56 - 0.17$).

Similarly, when a fund with no Analyst Rating is assigned a Gold Analyst Rating, monthly flows increase by 1.14 percentage points. In contrast, while statistically significant, the effect of Quantitative Ratings on flows is considerably smaller.

7 Additional issues

7.1 Robustness

This section summarizes some robustness tests. The Internet Appendix discusses these and other robustness tests in more detail.

The results are robust to controlling for value added, a generic measure of skill that does not rely on any model's particular assumptions to derive perceived managerial skill (Berk and van Binsbergen, 2015). For our main results, we have assumed a logarithmic functional form for the decreasing returns to scale technology. We re-estimate the baseline model using a more flexible functional form (see also Roussanov et al., 2020). The results suggest that the logarithmic assumption fits the data well. We also consider specifications that allow the impact of size on returns to vary across funds based on common characteristics. Consistent with Pástor et al. (2015), we do find that funds with higher turnover, funds that invest in small-cap stocks, and funds that are more active face steeper decreasing returns to scale in realized fund returns. However, none of these patterns are mirrored in analysts' expectations. We also extend the baseline model to account for uncertainty in the decreasing returns to scale parameter and industry size (Pástor and Stambaugh, 2012). In the former case, the effect of size on returns varies fund-by-fund (as in Barras et al., 2022), just like managerial skill. While we cannot estimate cross-sectional regressions in this case, our conclusion is robust: as in our main analysis, analysts' expectations are too large for the largest funds and too small for the vast majority of other funds. To allow for a structural break in the relationship between returns, skill, size, and fees in our model, we also estimate the baseline model using only funds incepted since 2000, which is the first year of data that enters Morningstar's methodology through the SIQR computation. Again, the results are robust.

Our regressions of expectations on fund characteristics identify the coefficient estimate on size using cross-sectional variation. The Internet Appendix shows that our results are robust to estimating an ordered logit model with fund fixed effects using the ordinal ratings that are available since 2011. These regressions are analogous to the regressions that researchers have estimated using realized before-fee fund returns and identify the coefficient estimate using time-series variation (see, e.g., Pástor et al., 2015). However, fund fixed effects are less powerful in our context. Intuitively, fund fixed effects control for analysts' perceptions of skill that remain constant over time, but such perceptions most likely vary over time as analysts update their beliefs about true skill.[14] We also document robust evidence of decreasing returns to scale in realized returns using the fund fixed effects recursive demeaning estimator of Zhu (2018). After the initial writing of this paper, we have also updated the data up to December 2021 and conducted an out-of-sample test of our main results. Again, the Internet Appendix shows that the results are robust.

7.2 Conflicts of interest

A general concern when studying analysts' expectations is that biases in expectations may not necessarily reflect cognitive misunderstandings. For instance, if Morningstar or its analysts had misguided incentives to assign better ratings to larger funds, analysts' expectations would not necessarily reflect a genuine cognitive misunderstanding of returns to

[14]For a similar reason, the predictability of forecast errors would not be powerful evidence against rational expectations models of active management. Too see this, consider the investors in Pástor and Stambaugh (2012). Investors in their model continue to expect positive returns from active management even though active management repeatedly underperforms. Thus, forecast errors are predictable, even though the investors in Pástor and Stambaugh (2012) clearly have rational expectations. Similarly, forecast errors in Berk and Green (2004) and in the models of our paper are predictable. The reason for the predictability of forecast errors in all these cases is the wedge between true skill and perceived skill that is induced by parameter uncertainty and learning.

scale.

We believe that such conflicts of interest are limited. Morningstar claims that its research activities are independent of its commercial activities. Moreover, as a leading financial services firm in the mutual fund industry, Morningstar has a substantial business reputation at stake. In contrast to credit-rating issuers, Morningstar does not receive a fee from fund issuers for its fund analysis. Finally, Morningstar's primary business model does not entail acting as a seller of mutual funds, so it is likely not subject to the conflicts of interest that have been shown to affect broker-sold funds (see, e.g., Bergstresser et al., 2009). In line with these arguments, Cookson et al. (2021) use the Morningstar Analyst Rating as a benchmark of independent analysis when studying investment platforms' mutual fund recommendations.

7.3 Textual analysis of written reports

In a similar vein, one may wonder whether the Analyst Ratings do not account for the effect of fund size on return expectations by design. There is no pillar rating for the effect of fund size on fund returns, so it is not immediately clear at which point in Morningstar's methodology such an effect should enter. On one hand, if true, such a design flaw would of course trivially support our conclusion: realized returns decrease with size, but expected returns do not (by design). On the other hand, this conclusion would perhaps be less interesting, as expectations would not truly reflect a cognitive misunderstanding of returns to scale in active management by analysts, but rather a design flaw on Morningstar's part.

To provide evidence that analysts account for fund size in forming their expectations, even though size is not explicitly considered in the pillar ratings, we perform a textual analysis of more than 20,000 reports and notes that analysts wrote to accompany the ratings. The textual analysis follows the methodology outlined by Wilke (2022), who collects an exhaustive list of size-related words in the spirit of a negative word list and other sentiment dictionaries (see, e.g., Loughran and McDonald, 2011). Candidate words are used in the context of discussing a fund's AUM. Importantly, these words are specific to this topic and rarely used otherwise, to avoid contextual misclassifications. Panel (a) of Figure 5 shows that analysts use words related to fund size in the "Process" and "Parent" pillars. Thus, even though there is no explicit pillar rating for fund size, analysts seem concerned with fund size. Panel (b) shows that analysts focus on fund size even more in the case of larger funds, corroborating the evidence of Panel (a).

Overall, while it is not possible to look inside analysts' minds, the textual analysis suggests that Morningstar's methodology does not restrict analysts from incorporating fund size into their assessments. In the context of Figure 1, analysts' extrapolation of past returns also does not happen mechanically: nothing restricts analysts from assigning lower pillar scores to the funds that have grown to be the largest to bring down expectations of future returns.

8 Conclusion

Recent years have seen a surge of research that uses data on subjective expectations to discipline rational expectations models in all areas of finance and economics. In this paper, we introduce data on subjective expectations to the mutual fund literature. We find that there is little evidence that analysts form their expectations as in a workhorse model and so a discussion seems warranted about whether we—researchers in this area—can build more realistic models of active management.

Given no evidence of decreasing returns to scale in analysts' expectations even after decades of potential learning, building rational expectations models to match analysts' expectations might be challenging. Future research could also depart from the rational expectations assumption in developing models to match analysts' expectations. Such development would be similar to the development of asset pricing models to match extrapolative subjective stock market return expectations (see, e.g., Barberis, Greenwood, Jin, and Shleifer, 2015; Adam, Marcet, and Beutel, 2017; Nagel and Xu, 2022). The models of active management of Gennaioli et al. (2015) and Spiegler (2020) allow for deviations from rational expectations and therefore could constitute starting points.

As mentioned in the introduction, such models could hardly be representative agent models: expectations that increase with size imply that all funds should receive unlimited amounts of capital. Expectations that merely do not decrease with size—as opposed to increase with size—imply that all funds with a negative alpha should manage no capital and all funds with a positive alpha should manage unlimited amounts of capital. It follows that misunderstandings of returns to scale in active management could help explain the enormous size and poor performance of the active fund industry. An investor who believes that returns increase with size allocates more and more capital to funds in the hope that the additional capital aids funds to earn better future returns. However, this additional capital actually deteriorates future returns due to decreasing returns to scale in realized returns.

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Table 1: **Overview of Morningstar's fund ratings**

	Star Rating	Analyst Rating	Quantitative Rating	Sustainability Rating
Introduction	1985	2011	2017	2016
Key inputs	Historical fund returns	*New*: Three-pillar ratings (People, Process, and Parent), SIQR (dispersion of CAPM alphas of fund strategy), and share-class fees *Old*: Five-pillar ratings (People, Process, Parent, Performance, and Price)	*New*: Three-pillar ratings (People, Process, and Parent) estimated using a machine-learning algorithm, SIQR (dispersion of CAPM alphas of fund strategy), and share-class fees *Old*: Five-pillar ratings (People, Process, Parent, Performance, and Price) estimated using a machine-learning algorithm	Sustainalytics' company-level ESG Risk Rating
Backward- or forward-looking	Backward-looking	Forward-looking	Forward-looking	Forward-looking
Rating scale	***** **** *** ** *	Gold Silver Bronze Neutral Negative	Gold Silver Bronze Neutral Negative	5 globes 4 globes 3 globes 2 globes 1 globe
Rating level	Share class	*New*: Share class *Old*: Fund	Share class	Fund
Ranking metric to award ratings	Morningstar Risk-Adjusted Return	Share-class alphas from Analyst and Quantitative Rating methodology	Share-class alphas from Analyst and Quantitative Rating methodology	Morningstar Historical Portfolio Sustainability Score

Continued on next page

Table 1 continued from previous page

	Star Rating	Analyst Rating	Quantitative Rating	Sustainability Rating
Rating peer group	Morningstar Category	Morningstar Category	Morningstar Category	Morningstar Global Category
Medalist ranking (Gold, Silver, and Bronze) requirement		*New*: Beat benchmark index *and* peer group average *Old*: Beat benchmark index *and/or* peer group average	*New*: Beat benchmark index *and* peer group average *Old*: Beat benchmark index *and/or* peer group average	
Major updates	06/2002: Ratings assigned within Morningstar Categories (before broad asset classes, e.g., equity)	10/2019: Ratings assigned at share-class level based on expected net-of-fee alphas, reduction to three pillars, and higher bar for medalist ranking	10/2019: Ratings assigned at share-class level based on expected net-of-fee alphas, reduction to three pillars, and higher bar for medalist ranking	10/2019: Replacement of Sustainalytics' company ESG Rating with its ESG Risk Rating
Selected academic sources and sample periods for the analysis	Ben-David et al. (2022), 1991–2011; Blake and Morey (2000), 1992–1997; Del Guercio and Tkac (2008), 1996–1999; Evans and Sun (2021), 1999–2005; Khorana and Nelling (1998), 1992–1995; Sharpe (1998)	Armstrong et al. (2019), 2011–2015		Hartzmark and Sussman (2019), 2016–2017

The table compares key features of Morningstar fund ratings. The Morningstar Rating (commonly referred to as the Star Rating) is a purely quantitative, backward-looking measure of a fund's past performance. The Morningstar Analyst Rating is forward looking and conveys an analyst's conviction of a fund's investment merits. The Morningstar Quantitative Rating is derived from a machine-learning model and attempts to replicate the Analyst Rating a human Morningstar analyst might assign to a fund. The Morningstar Sustainability Rating assesses the risk exposure of an investment portfolio to environmental, social, and governance (ESG) factors.

Table 2: Replication of Morningstar Analyst and Quantitative Ratings

Panel A: Morningstar Analyst Ratings

	Replicated rating						
Actual rating	Negative	Neutral	Bronze	Silver	Gold	Total	Rate
Negative	80	15	0	0	0	95	84%
Neutral	60	3035	121	2	0	3218	94%
Bronze	2	167	2293	201	10	2673	86%
Silver	0	1	213	1731	107	2052	84%
Gold	0	0	0	88	571	659	87%
Total	142	3218	2627	2022	688	8697	89%

Panel B: Morningstar Quantitative Ratings

	Replicated rating						
Actual rating	Negative	Neutral	Bronze	Silver	Gold	Total	Rate
Negative	12557	503	0	0	0	13060	96%
Neutral	416	26150	396	1	0	26963	97%
Bronze	2	906	6378	376	12	7674	83%
Silver	0	12	559	4252	179	5002	85%
Gold	0	3	1	312	2328	2644	88%
Total	12975	27574	7334	4941	2519	55343	93%

The table shows how well Morningstar Analyst and Quantitative Ratings on the share class level under the new ratings methodology are replicated for the cross-section of funds in December 2020. The actual Morningstar Analyst Ratings are tabulated in rows, whereas the replicated ratings are tabulated in columns. The column *Rate* indicates the percentage of ratings that we can replicate (e.g., we assign a Neutral rating to 3035 out of 3218 analyst-rated share classes receiving a Morningstar Analyst Rating of Neutral, yielding a replication rate of 94%).

Table 3: Summary statistics

	N	Mean (V.W.)	Mean (E.W.)	S.D.	10%	25%	50%	75%	90%
Panel A: Assets under management									
Analyst Rating	1454		4760	14036	154	406	1248	3882	10098
Quantitative Rating	12480		409	1257	10	30	100	336	931
All ratings	13934		863	4871	12	34	126	464	1477
No rating	4512		155	1251	6	13	37	112	291
All	18446		690	4290	9	25	89	341	1144
Panel B: Fees									
Analyst Rating	1454	0.79	1.06	0.39	0.64	0.84	1.00	1.24	1.59
Quantitative Rating	12480	1.11	1.44	0.72	0.65	0.96	1.36	1.82	2.27
All ratings	13934	0.92	1.40	0.70	0.64	0.94	1.29	1.77	2.23
No rating	4512	1.28	1.65	0.93	0.78	1.06	1.63	1.97	2.44
All	18446	0.94	1.46	0.77	0.67	0.95	1.37	1.84	2.27
Panel C: Perceived skill									
Analyst Rating	1454	3.21	2.90	0.92	1.84	2.28	2.78	3.39	4.10
Quantitative Rating	12480	2.69	2.29	0.94	1.27	1.75	2.26	2.74	3.39
All ratings	13934	2.99	2.36	0.95	1.32	1.79	2.30	2.83	3.50
No rating	4512	2.96	2.41	1.10	1.38	1.96	2.30	2.63	3.58
All	18446	2.99	2.37	0.99	1.34	1.83	2.30	2.78	3.51
Panel D: Analyst alphas									
Analyst Rating	1454	1.29	0.60	1.35	–1.09	–0.25	0.69	1.42	2.24
Quantitative Rating	12480	–0.55	–1.62	2.48	–4.82	–3.21	–1.57	0.04	1.50
All ratings	13934	0.51	–1.39	2.49	–4.67	–2.99	–1.24	0.34	1.66

The table shows value-weighted (V.W., by assets under management, AUM) and equal-weighted (E.W.) means, standard deviations, and various percentiles of AUM, fees, skill, and analyst alphas for global active equity mutual funds in December 2020. AUM is the fund size in millions of USD. Perceived skill is managerial skill estimated from a rational model of fund performance. Alphas are relative to each fund's Morningstar Category benchmark. Fees, perceived skill, and analyst alphas are expressed in % per year.

Table 4: Parameter estimates of the rational fund performance model

Parameter	Description	Estimate
η	Decreasing returns to scale (%)	0.251***
		(0.013)
a_0	Prior mean (%)	2.296***
		(0.063)
$\sigma_{a,0}$	Prior standard deviation (%)	2.095***
		(0.042)
σ_ϵ	Residual standard deviation (%)	8.111***
		(0.015)
ρ	Skill persistence	0.948***
		(0.006)

The table shows the parameter estimates of the rational fund performance model in % per year. Standard errors are shown in parentheses. The model is estimated using fund-year observations from 1979 to 2020. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively, for the null hypothesis of a zero coefficient.

Table 5: Cross-sectional regressions of alphas on fund characteristics

	Analyst Ratings	Analyst and Quantitative Ratings
	(1)	(2)
Perceived skill	0.382***	0.706***
	(0.066)	(0.041)
	[0.000]	[0.000]
Size (× 100)	0.066**	0.133***
	(0.032)	(0.025)
	[0.000]	[0.000]
Fees	−0.959***	−1.536***
	(0.150)	(0.060)
	[0.787]	[0.000]
Constant (× 100)	0.042	−1.553***
	(0.276)	(0.174)
	[0.878]	[0.000]
N	1454	13934
Adj. R^2	0.15	0.32

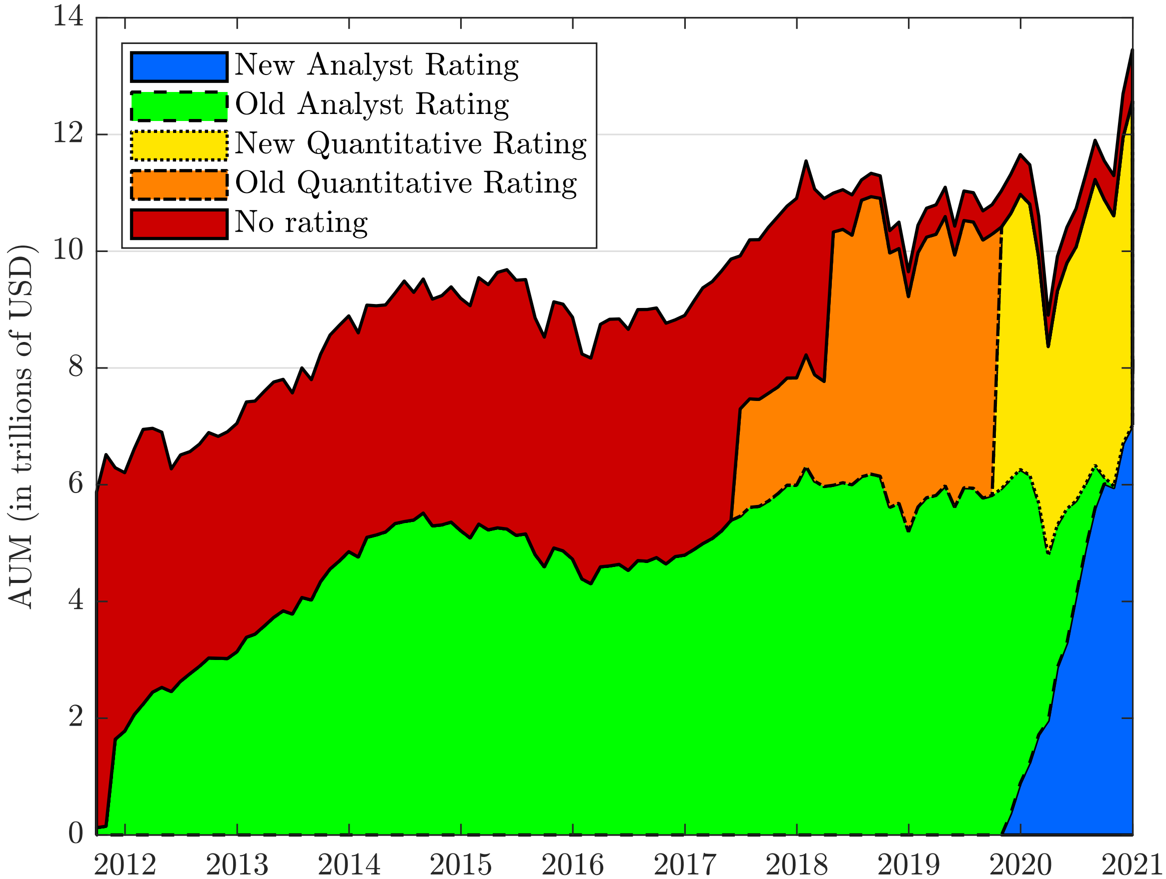
The table shows regressions of Morningstar analyst alphas on skill as perceived by a rational learner, fund size (logarithm of assets under management in millions of USD), and fees for cross-sections of funds in December 2020. Specification (1) uses funds with an Analyst Rating. Specification (2) uses funds with an Analyst Rating or a Quantitative Rating. Alphas are relative to each fund's Morningstar Category benchmark. Standard errors are clustered by fund family and shown in parentheses. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively, for the null hypothesis of a zero coefficient. In brackets are p-values for the null hypothesis that the coefficients of skill, size, fees, and the constant equal the model-predicted parameters of +1, −0.251 (the estimate of η in Table 4), −1, and 0, respectively.

Table 6: Cross-sectional regressions of alphas on additional fund characteristics

	Analyst Ratings		Analyst and Quantitative Ratings	
	(1)	(2)	(3)	(4)
Rational learner				
Perceived skill	0.268***	0.106	0.860***	0.342***
	(0.066)	(0.071)	(0.080)	(0.058)
Size (× 100)	0.164***	0.078**	0.111***	0.052*
	(0.045)	(0.038)	(0.028)	(0.029)
Fees	−1.350***	−0.947***	−1.768***	−0.960***
	(0.146)	(0.115)	(0.195)	(0.211)
People				
Manager tenure		0.111***		0.247***
		(0.040)		(0.033)
Manager ownership		0.115**		0.192***
		(0.054)		(0.041)
Managerial multitasking		0.645***		0.576***
		(0.205)		(0.193)
Management team		0.094		0.496***
		(0.109)		(0.114)
Process				
Top 10 assets (%)		0.128		−0.028
		(0.131)		(0.091)
Tracking error		−0.010		−0.154*
		(0.064)		(0.093)
Turnover ratio		−0.486***		−0.108
		(0.156)		(0.081)
Retail		−0.290***		−0.157*
		(0.092)		(0.088)
Broker-sold		−0.267**		−0.068
		(0.116)		(0.105)
N	698	650	2830	2626
Adj. R^2	0.26	0.62	0.29	0.64
Sustainability FE	No	Yes	No	Yes
Star FE	No	Yes	No	Yes
Morningstar Category FE	No	Yes	No	Yes
Fund Family FE	No	Yes	No	Yes

The table shows regressions of Morningstar analyst alphas on fund and manager characteristics for cross-sections of funds in December 2020. Specifications (1) and (2) use U.S.-domiciled funds with an Analyst Rating. Specifications (3) and (4) use U.S.-domiciled funds with an Analyst Rating or a Quantitative Rating. Alphas are relative to each fund's Morningstar Category benchmark. Manager tenure is the maximum tenure (in months) taken over all managers, manager ownership is the average amount managers of a fund personally invest in the fund, managerial multitasking is the average number of additional funds that managers of a particular fund manage, and management team is a dummy for team-managed funds. Top 10 assets is the percentage of AUM in the ten largest positions, tracking error is the standard deviation of returns in excess of the benchmark over the life of the fund, turnover is a fund's trading activity as reported to the SEC, retail is a dummy for whether a fund is primarily held by retail investors, and broker-sold is a dummy for whether a fund is primarily sold through brokers. "People" and "Process" variables are standardized to zero mean and unit standard deviation (except for the dummy variables), and the coefficient estimates are multiplied by 100. Standard errors are clustered by fund family and shown in parentheses. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively, for the null hypothesis of a zero coefficient.

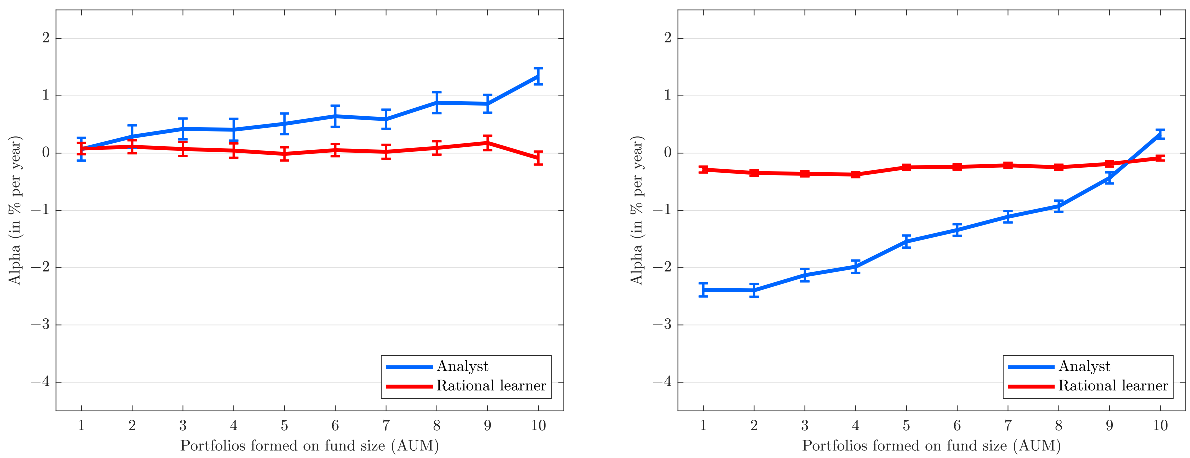
Figure 2: Size of active equity mutual fund industry



The figure shows the assets under management (AUM) of actively managed equity mutual funds up to December 2020. New Analyst Rating indicates funds with a Morningstar Analyst Rating according to the new methodology. Old Analyst Rating indicates funds with a Morningstar Analyst Rating under the old methodology. Similarly, Old Quantitative Rating and New Quantitative Rating indicate funds with a Morningstar Quantitative Rating under the old and new methodologies, respectively.

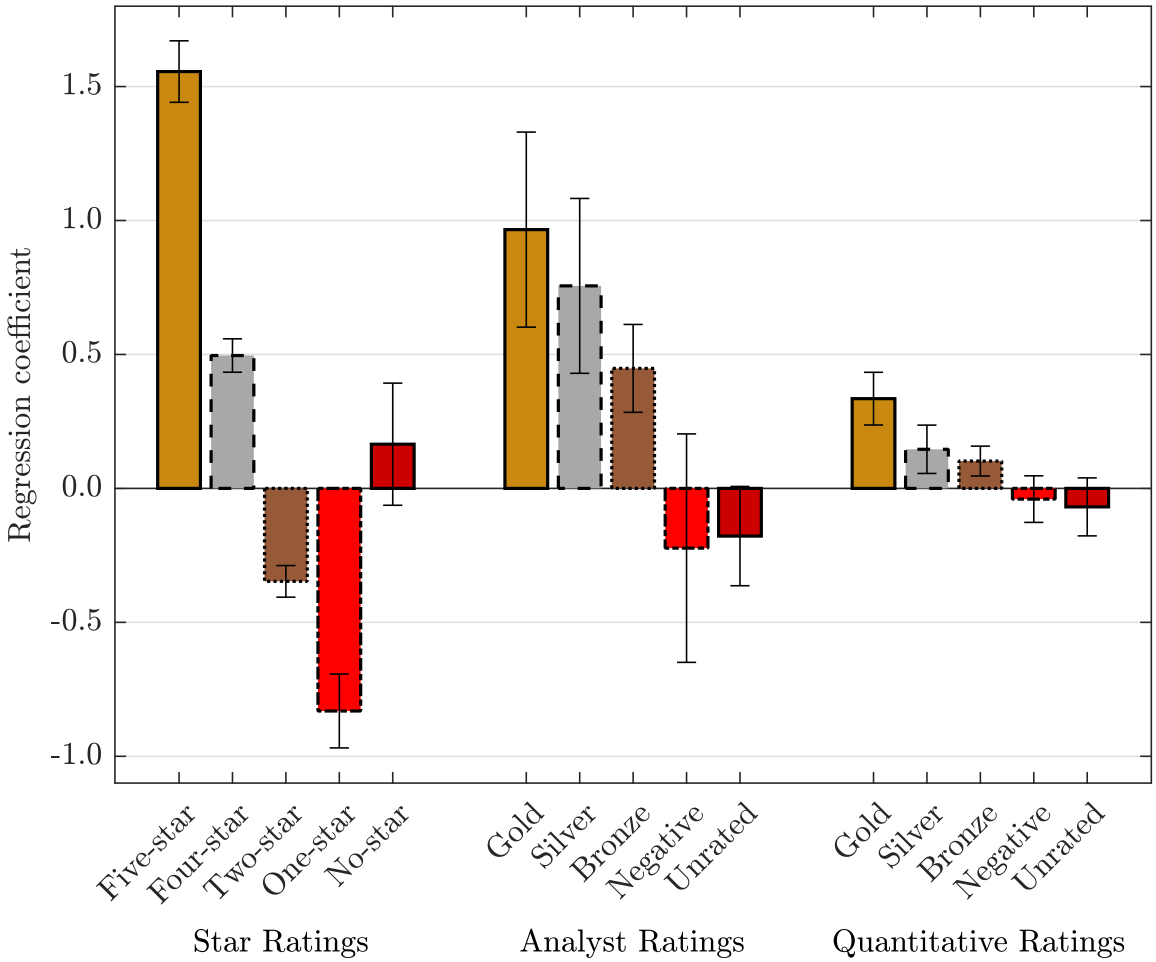
Figure 3: Alphas against fund size

(a) Analyst Ratings **(b)** Analyst and Quantitative Ratings



The figure shows alphas against fund size (AUM) as of December 2020 for analysts (in blue) and for a rational learner (in red). Panel (a) includes funds with an Analyst Rating. Panel (b) includes funds with an Analyst Rating or a Quantitative Rating. Alphas are relative to each fund's Morningstar Category benchmark. The bars indicate 90% confidence bands.

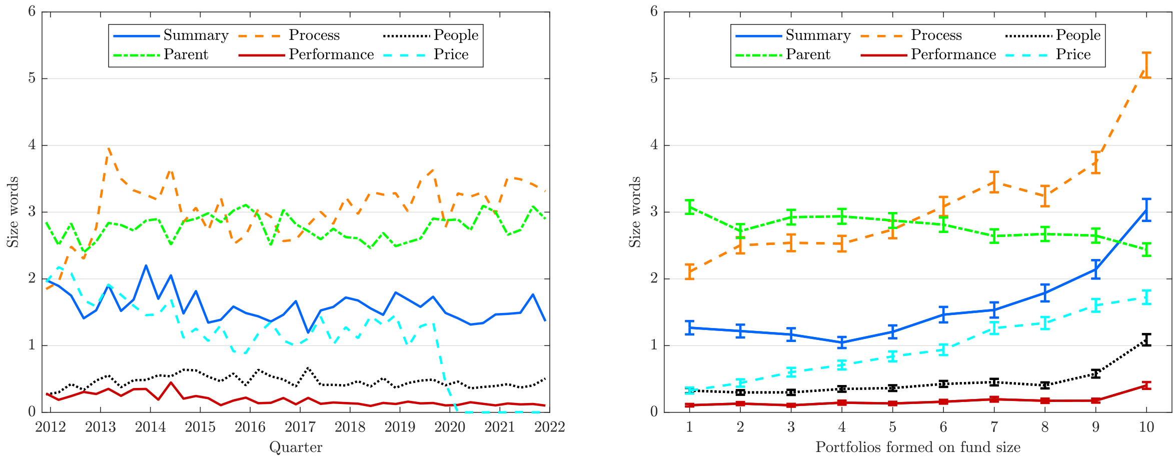
Figure 4: Fund flows and ratings



The figure shows coefficient estimates on Morningstar Star Rating, Analyst Rating, and Quantitative Rating dummy variables in a regression of monthly percentage equity mutual fund flows on the dummy variables, various observables, and fund, year–month, as well as category fixed effects. The coefficient estimates are from specification (4) of Table F1 in the Internet Appendix. The regression omits the three-star, the neutral-analyst, and the neutral Quantitative Rating dummy variables. The bars indicate 90% confidence bands.

Figure 5: Size-related words in analyst reports

(a) Size-related word count **(b)** Size-related words against fund size



Panel (a) shows the number of size-related words mentioned in each part of the analyst report, averaged over all reports published per quarter from Q4 2011 to Q4 2021. Panel (b) shows the number of size-related words against fund size (AUM). Note that "Performance" and "Price" pillar commentary is still part of written analyst reports, even though "Performance" and "Price" pillar ratings ceased to exist under the new methodology in 2019. Only the remaining three pillar ratings (i.e., "People," "Parent," and "Process") feed into the calculation of the final Analyst Rating. The size-related words are from Wilke (2022) and are ASSET, ASSETS, AUD, AUM, BALLOON, BALLOONED, BALLOONING, BASE, BASES, BILLION, BILLIONS, BLOAT, BLOATED, CAD, CAPACITY, CHF, CLOSED, CLOSES, CLOSING, CLOSURE, CORPUS, EUR, FUM, GBP, GIRTH, INFLOW, INFLOWS, INR, JPY, MILLION, MILLIONS, NIMBLE, NIMBLENESS, NIMBLER, NOK, NZD, OUTFLOW, OUTFLOWS, RECLOSE, RECLOSED, REOPEN, REOPENED, REOPENING, SCALE, SGD, SIZE, SIZES, SURGING, SWELL, SWELLED, SWELLING, TRILLION and USD. The bars indicate 90% confidence bands.