Subjective Expectations and Overreaction in the Mutual Fund Industry

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Abstract

Focusing on forecast revisions, we study professional analysts' forecasts of mutual fund performance. Consistent with the notion that professional forecasters overreact to processes that show little persistence, overreact for long forecast horizons, and overreact to the most recent observation, we find that mutual fund analysts' long-term forecasts overreact to recent past fund returns: future fund returns are *lower* than past fund returns when analysts revise their forecasts *upward*. Moreover, the probability of a downgrade increases after an upgrade, indicating that analysts correct their initial overreactions. Overall, our results align with the conventional wisdom that both investors and analysts in the mutual fund industry naïvely chase past returns.

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1 Introduction

A growing literature on subjective expectations in economics and finance documents systematic biases. An unsettling fact is that these biases tend to vary depending on the setting, contributing to the notion that such biases are chance results (see, e.g., Fama, 1998). For instance, some studies document overreaction to news, whereas others document that subjective expectations underreact.[1] To reconcile these findings, recent work shows that overreaction is stronger for less persistent processes, for longer forecast horizons, and that forecasts display significant overreaction to the most recent observation (see, e.g., Bordalo, Gennaioli, Ma, and Shleifer, 2020; Afrouzi, Kwon, Landier, Ma, and Thesmar, 2023).

We contribute to this debate with evidence from the mutual fund industry. Returns of actively managed mutual funds famously show little persistence (see, e.g., Carhart, 1997), yet money flows into funds that have performed well in the past (see, e.g., Sirri and Tufano, 1998). The conventional interpretation of these empirical facts is that mutual fund investors naïvely chase and overreact to past performance (see, e.g., Ben-David, Li, Rossi, and Song, 2022). However, the facts are also commonly interpreted as rational learning in equilibrium (see, e.g., Berk and Green, 2004; Berk and van Binsbergen, 2015). These two opposing conclusions are not necessary surprising as behavioral and rational interpretations often are observationally equivalent using prices and quantities alone (see, e.g., Cochrane, 2017). One way to discipline either interpretation is through the use of subjective expectations.

Focusing on forecast revisions (see, e.g., Coibion and Gorodnichenko, 2015), we study the long-term expectations of professional analysts who forecast mutual fund returns. We find evidence consistent with overreaction. Figure 1 motivates our main analysis and highlights our results. Panel (a) shows net-of-fee abnormal fund returns before and after analysts revise their forecast of future fund returns *upward*. If accurate, such upward revisions should predict

[1] For overreaction in expectations, see, e.g., DeBondt and Thaler (1990), Amromin and Sharpe (2014), Greenwood and Shleifer (2014); for underreaction, see, e.g., Bouchaud, Krüger, Landier, and Thesmar (2019).

higher returns going forward. However, the figure shows that fund returns tend to be *lower* after an upward revision. Vice versa, Panel (b) shows that fund returns tend to be higher after a downward revision. Moreover, consistent with overreaction to recent news, fund returns four quarters before an upward revision are high, whereas fund returns preceding a downward revision are low. Relatedly, we find that the probability of a downgrade (upgrade) increases after an upgrade (downgrade), indicating that analysts themselves realize that they have overreacted. Finally, we show that investors follow analysts' recommendations.

Data on subjective expectations

We obtain subjective expectations of fund returns from analyst ratings provided by Morningstar, a leading financial services firm in the mutual fund industry. Morningstar has provided analyst ratings for a large number of funds since 2011. Analysts assign the ratings according to a five-tier scale with three recommended ratings of Gold, Silver, and Bronze, as well as a Neutral and a Negative rating. The Morningstar Analyst Rating reflects analysts' predictions of future fund returns on a risk-adjusted basis over the long term, meaning a period of at least five years. In contrast to some of the literature, we do not study consensus forecasts as we do not observe multiple forecasts for a given fund. The data contain exactly one analyst forecast for a given fund, but there are many funds.

Time-series versus cross-sectional identification

Central to our paper is the distinction between time-series and cross-sectional identification. A large literature shows that fund returns are predictable in the cross-section of funds (for an overview, see Jones and Mo, 2021). Notably, Carhart (1997) shows that, for the worst performing funds, performance persists. Hence, it would be surprising if professional analysts were not able to differentiate between good- and bad-performing funds. Consistent with this view and with earlier research on Morningstar's Analyst Ratings (see Armstrong, Genc, and Verbeek, 2019), we find that a better Analyst Rating predicts larger abnormal returns in the cross-section of funds.

As in Coibion and Gorodnichenko (2015) and Bordalo et al. (2020), the innovation of our paper is to focus on forecast revisions. We estimate regressions of future monthly abnormal fund returns on rating dummy variables and fund fixed effects. The inclusion of fund fixed effects implies that the coefficients in these regressions are identified using time-series variation. That is, the coefficients are identified using changes in abnormal returns in response to changes in the Analyst Ratings (i.e., forecast revisions). Strikingly, the predictive ability of the Analyst Ratings reverses. A better rating predicts *lower* future returns in the time series for a given fund, consistent with Figure 1. In our simplest specification with just one dummy variable for whether a fund is recommended or not, an *upward* revision predicts a statistically significant 1.94-percentage-point *lower* annual abnormal return.

Explaining overreactions

What do analysts overreact to? Guided by theory (see, e.g., Berk and Green, 2004), we correlate decisions to up- or downgrade a particular fund with variables related to fund performance, including past abnormal returns, changes in fund size, and changes in fund fees. As hinted by Figure 1, larger past abnormal returns predict rating upgrades, whereas lower past abnormal returns predict rating downgrades, indicating that analysts overreact to past performance. Consistent with the notion that participants in the mutual fund industry misunderstand returns to scale in active management (see Choi and Robertson, 2020; Dahlquist, Ibert, and Wilke, 2024), rating upgrades (downgrades) are preceded by increases (decreases) in fund size. If there are decreasing returns to scale in actual fund returns (see, e.g., Chen, Hong, Huang, and Kubik, 2004; Pástor, Stambaugh, and Taylor, 2015; Zhu, 2018), such increases (decreases) in size should lead to *lower* expectations of future returns, holding everything else constant. Lastly, there is little evidence that changes in fees precede rating changes, perhaps because fees in the mutual fund industry are rather persistent (see, e.g., Cooper, Halling, and Yang, 2020).

We emphasize again that mutual fund analysts are able to discern good funds from bad funds. Nonetheless, we provide evidence that analysts tend to overreact to recent returns. An analogy using earnings forecasts is perhaps useful. We expect a professional analyst to be able to predict whether Microsoft or Apple has higher earnings per share in a given quarter. Nonetheless, systematic biases can exist when forecasting Microsoft's earnings in a quarter relative to Microsoft's earnings in the previous quarter.

Predictive power of past rating changes for future rating changes

Contrasting consecutive analyst decisions provides further evidence supporting analyst overreaction. If a rating upgrade is swiftly followed by a downgrade, it aligns with the notion of an analyst overreacting and subsequently rectifying that decision. By correlating decisions to up- or downgrade a specific fund with past ratings decisions, while controlling for variables associated with fund performance, we find that the probability of a rating downgrade increases by up to 68% following a rating upgrade. Although the evidence for the relationship between downgrades and future upgrades is weaker, there is still predictive power. Overall, the evidence is consistent with analysts overreacting, in particular when upgrading funds.

Analysts and investors

As is common in the literature on subjective expectations, which often uses forecasts from the Survey of Professional Forecasters, the Blue Chip surveys, or the Institutional Brokers' Estimate System, our paper employs forecasts of professional analysts. Professional analysts' expectations need not resemble investors' expectations, albeit this assumption is commonly invoked.

One advantage of working with mutual fund data is that we can test whether investors actually follow analysts' recommendations. They do, both in the time series and in the cross section. Specifically, monthly fund flows increase by 0.46 percentage points on average when a given fund switches from not being recommended by analysts to being recommended by analysts. This result is robust to controlling for the popular Morningstar Star Rating and similar in magnitude to the effect of the Star Rating on flows.

Forecast errors and forecast revisions

Speaking more directly to the literature on forecast revisions, we turn to Coibion and Gorodnichenko (2015) (CG) regressions. These regressions correlate forecast errors with forecast revisions. Since 2019, Morningstar analysts have provided detailed forecasts about a fund's future alpha, which allows us to run CG regressions since then. The coefficient estimates in these regressions are around -0.6. Consistently, Afrouzi et al. (2023) find CG regression coefficients of around -0.6 for processes with zero autocorrelation, both based on their data of professional forecasters as well as their experimental data.

Related literature

Our paper relates to several strands of literature. First, a large literature examines over- and underreaction using equity return forecasts (see, e.g., Amromin and Sharpe, 2014; Greenwood and Shleifer, 2014; Dahlquist and Ibert, 2024), earnings forecasts (see, e.g., DeBondt and Thaler, 1990; Weber, 2018; Bordalo, Gennaioli, La Porta, and Shleifer, 2019; Bouchaud et al., 2019), interest rate forecasts (see, e.g., d'Arienzo, 2020; Wang, 2021), and various macroeconomic variables (see, e.g., Coibion and Gorodnichenko, 2012, 2015; Bordalo et al., 2020; Kohlhas and Walther, 2021; Bianchi, Ma, and Ludvigson, 2022). We contribute to this literature with evidence from the mutual fund industry. Our results support the emerging consensus that overreaction is more pronounced for less persistent processes, for long forecast horizons, and that forecasters overreact to the most recent observation (see, e.g., Afrouzi et al., 2023).

Second, the literature on mutual funds has reached two opposing conclusions regarding the rationality and sophistication of participants in this industry. On one hand, some researchers interpret a positive flow-performance relationship as naive return chasing (see, e.g., Ben-David et al., 2022). On the other hand, other researchers interpret a positive flow-performance relationship as rational learning (see, e.g., Berk and Green, 2004; Berk and van Binsbergen, 2015; van Binsbergen, Kim, and Kim, 2021; Barras, Gagliardini, and Scaillet, 2022). Subjective expectations may help distinguish between rational and behavioral interpretations, but few researchers have employed data on subjective expectations in this literature (for exceptions, see Choi and Robertson, 2020; Bender, Choi, Dyson, and Robertson, 2022, who survey retail investors).

Finally, Dahlquist et al. (2024) contrast analyst alphas to alphas implied by a rational expectations learning model and find that analysts' expectations are difficult to reconcile with the model-implied expectations. While we share similar conclusions, our approach is different from theirs. First, we study a panel of analyst forecasts from 2011 to 2021 as opposed to their cross-sectional focus. Second, our results do not rest on any particular model-implied benchmark.

2 Data

We obtain mutual fund data, including returns, AUM, ratings, and fees for active open-end equity mutual funds from Morningstar Direct. The data contain both U.S.-domiciled and non-U.S.-domiciled funds. We convert all returns and assets to USD. As is common in the literature, we aggregate share-class-level variables (e.g., fees, ratings and returns) to the fund level by taking an AUM-weighted average.

To estimate abnormal fund returns, we use the full time series available in Morningstar. First, we estimate fund benchmark exposures in expanding-window regressions:

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

where $R_{i,t}$ represents the gross (i.e., before-fee) return of fund i in month t, $R_{f,t}$ is a risk-free rate proxy, and $R_{b,i,t}$ is a fund-specific benchmark return, the fund's Morningstar Category Index. This is the same benchmark that analysts use when forecasting abnormal fund performance. We then compute abnormal fund returns in month t as

$$AR_{i,t} = R_{i,t} - R_{f,t} - \hat{\beta}_{i,t-1}(R_{b,i,t} - R_{f,t}), \tag{2}$$

where the $t-1$ subscript in $\hat{\beta}_{i,t-1}$ indicates that the estimation of a fund's benchmark exposure incorporates information up to month $t-1$. The monthly sample for the estimation starts in January 1979, the first month for which Morningstar provides benchmark returns, and ends in December 2021.

The steps to construct our active equity mutual fund data up to this point, as outlined above, correspond to the procedure as described in Wilke (2023). Then, we drop funds that are not analyst-rated and we exclude platform funds.[2] Finally, we drop fund-months in which the analyst rating is Under Review. This rating designation indicates that the review of a fund is ongoing. If the rating is under review for a maximum of three months, we record possible rating changes by comparing ratings before and after the review period. Otherwise, if the review period extends beyond three months, we treat the fund as if coverage newly started and do not record rating changes. Our final panel data set comprises 173,068 fund-month observations for 3,049 unique funds, spanning September 2011 to December 2021.

Table 1 presents summary statistics. The average mutual fund has USD 4,123 million in AUM, charges annual fees of 1.2%, and is 20 years old. Fund flows are negative on average, reflecting net outflows from actively managed funds in the last decade. Analysts assign higher Analyst Ratings to larger funds, suggesting that they expect the largest funds to

[2]These are Australian and New Zealand funds that are also offered as platform versions, which can have negotiable fees and for which reliable expense ratio data can be hard to come by according to Morningstar. The analyst rating is issued for the flagship fund, and ratings are linked to all related platform versions (up to 2019) and are therefore duplicates. We only keep the flagship fund.

outperform. Moreover, analyst-rated funds have performed well in the past. The median Star Rating is four stars, indicating that a fund's past performance ranks in the top third within its peer group. The majority of funds (68%) are recommended by analysts (i.e., rated Bronze, Silver, or Gold), indicating that fund selection is skewed towards funds that analysts believe to outperform.

Table 2 shows a transition matrix for analyst ratings. In the monthly panel data, ratings are very persistent. We record 2,061 analyst rating changes, thereof 838 upgrades and 1,223 downgrades. If ratings change, they predominantly change by one notch. Note that the high persistence of ratings in the monthly data stems partly from analysts regularly reviewing and updating ratings following an annual schedule. Considering only the 11,699 fund-months in which analysts publish updated ratings, analysts revise 18% of all ratings up- or downward.[3]

3 Main empirical results

3.1 Overreaction to past performance

Figure 1 illustrates our main result. The figure shows net-of-fee abnormal fund returns leading up to and following rating changes. Panel (a) shows that average returns decrease after a rating upgrade compared to the period preceding the revision. Conversely, Panel (b) displays an opposite trend for downward rating revisions. These findings suggest that analysts tend to overreact to past performance when revising ratings. Figures 2 and 3 confirm that the identified patterns are visible within every rating category.

Next, we present regression evidence that a better rating predicts lower future returns in the time series of a given fund. Table 3 shows regressions of monthly net-of-fee abnormal fund returns on analyst rating dummy variables. First, we include fund fixed effects and

[3]Only the latest analyst rating publication date is stored as a variable in Morningstar Direct and not the entire time series. However, we obtain historical publication dates of analyst ratings from analyst reports, which accompany every rating, collected by Wilke (2023).

use time-series variation to identify the effect of analyst ratings on future fund performance. This is conceptually similar to the comparison of average returns prior to and after rating revisions in Figure 1. Specification (1) employs a simple dummy variable that is equal to one if a fund is recommended by Morningstar analysts (Gold-, Silver-, or Bronze-rated), and zero otherwise. An upward rating revision from not recommended to recommended predicts a 1.94-percentage-point (12×-0.162pp) decrease in annual abnormal return.

Specification (2) delves into the different rating categories individually, revealing a clear pattern. The coefficient estimates decrease as the rating category improves. For instance, an upward rating revision from Neutral to Bronze predicts a 1.61-percentage-point (12×-0.134pp) decline in annual abnormal return, and a rating increase from Neutral to Gold predicts a 2.99-percentage-point (12×-0.249pp) lower annual return.

Finally, we also identify the coefficients using cross-sectional variation by including year-month fixed effects. Specification (3) again focuses on the simple dummy variable for recommended funds. Strikingly, in contrast to the fund fixed effects specification, the estimated coefficient is positive and statistically significant. An upward rating revision now predicts a 0.37-percentage-point (12×0.031pp) increase in annual abnormal return, consistent with earlier evidence on the predictive ability of analyst ratings in the cross-section of funds (Armstrong et al., 2019).

Specification (4) examines the individual rating categories. Gold-rated funds outperform Neutral-rated funds by 0.86 percentage points per year (12×0.072pp), whereas Bronze-rated funds do not significantly outperform Neutral-rated funds in a statistical sense. This result shows that analysts possess the ability to identify outperforming funds within the cross-section of funds.

3.2 Flows

The mutual fund setting offers an advantage over other settings employing professional forecasts because it allows us to examine whether analysts' recommendations are important to investors. We investigate the relationship between analyst ratings and investor fund flows, which we compute as

$$\text{Flow}_{i,t} = \frac{\text{AUM}_{i,t} - \text{AUM}_{i,t-1}(1 + R^{net}_{i,t})}{\text{AUM}_{i,t-1}(1 + R^{net}_{i,t})}, \tag{3}$$

where $R^{net}_{i,t}$ is the net-of-fee return, and $\text{AUM}_{i,t}$ are a fund's assets under management. Table 4 presents the regression results. Our findings indicate that fund flows follow ratings, suggesting that analysts' recommendations matter to some investors.

Similar to the regressions of performance on ratings, we first use time-series variation and then cross-sectional variation to identify the effect of analyst ratings on fund flows. Specifications (1) and (2) incorporate fund fixed effects and demonstrate a positive relationship between upward rating revisions and fund flows. Following a rating increase, investors allocate more money to the respective fund compared to the preceding period when the rating was lower. For instance, a rating revision from Neutral to Bronze increases annualized flows by 5.04 percentage points (12×0.420pp).

Next, we include year-month fixed effects in specifications (3) and (4). In the cross-section of funds, better-rated funds attract larger flows. For example, flows going into Gold-rated funds exceed flows going into Neutral-rated funds by 9.65 percentage points (12×0.804pp) per year.

We want to assure that the positive relationship between ratings and flows is not the result of an omitted variable bias. Therefore, we add various lagged variables that are potentially correlated with both contemporaneous analyst ratings and future investor fund flows. In addition to year-month and fund fixed effects, we incorporate both Morningstar

Category and Star Rating fixed effects. Moreover, we include a battery of control variables, including the logarithm of AUM, the logarithm of fund family AUM, fund age (logarithm of number of months since fund inception), fees, 12-month fund returns, 12-month volatility of fund returns, 12-month average fund family returns, 12-month average fund flows, 12-month average fund family flows, maximum manager tenure, a dummy for a team-managed fund, and managerial multitasking (average number of additional funds that managers of a fund manage). These variables help to explain fund flows, resulting in an increased R^2 of 19%. Importantly, even after accounting for these factors, the positive relationship between analyst ratings and flows remains strong.

Through the lens of equilibrium models such as that of Berk and Green (2004), our results may seem consistent with the idea that mutual fund analysts do not take into account that investors follow their recommendations, thereby changing the fund's size. Due to decreasing returns to scale, this should feed back into the original forecast. For instance, suppose an analyst issues an upward revision, perhaps because the analyst has identified a fund that runs far below its optimal capacity. Investors follow the positive recommendation and money flows into the fund. This increases the fund's size and deteriorates the fund's ability to generate abnormal returns, invalidating the initial analyst prediction that the fund is going to generate higher abnormal returns than before. Had investors not followed the analyst's recommendation, perhaps the initial analyst forecast would have been correct.

However, for similar increases in flows as the ones in Table 4, Reuter and Zitzewitz (2021) find little evidence of decreasing returns to scale using a regression discontinuity design involving Morningstar Star Ratings. Thus, an increase in fund size as a result of an upgrade in an analyst's recommendation is unlikely to drive the decrease in returns that we observe.

In summary, our findings highlight that analyst ratings are important to some investors. They allocate more money to better-rated funds within the cross-section of funds, and they increase flows into a given fund after an upward rating revision.

3.3 Why do analysts upgrade or downgrade?

Standard models suggest past abnormal returns, changes in fund size, and changes in fund fees as determinants of fund performance (see, e.g., Berk and Green, 2004). These variables serve as candidates that analysts might (over)react to when predicting future fund performance. To examine the relationship, we estimate a linear probability model of rating changes and present the results in Table 5.

First, we estimate the model in the full sample. In the monthly panel data, the mean probability of an upward rating revision is 0.49%. We find that upward revisions are positively associated with abnormal returns over the past three years. Specifically, a one-standard-deviation increase in the latest annual return leads to a 37% increase in the probability of an upgrade (from 0.49pp to 0.67pp). In specification (3), one-standard-deviation increases in two- and three-year lagged annual performance result in a 7% and 17% higher probability of an upgrade, respectively. Additionally, increases in fund size over the past year show a positive relationship with upward rating revisions.

Downward rating revisions exhibit a negative correlation with abnormal returns over the past three years. One-standard-deviation decreases in the three lagged annual returns increase the mean probability of a downgrade (0.72%) by 13–24% in specification (6). Moreover, a decline in fund size over the past two years is associated with a higher probability of a rating downgrade.

Next, we restrict the sample to fund-months in which updated analyst ratings are published and re-estimate the linear probability model. The coefficient estimates in specifications (7) to (12) reflect probabilities of rating changes conditional upon analysts revising ratings. The mean probabilities to upgrade and downgrade are naturally larger compared to the estimates from the full sample model and amount to 7.2% and 10.5%, respectively. The interpretation of the coefficient estimates remains qualitatively similar to the full sample model.

Finally, we want to make sure that the results do not depend on our particular model choice. Therefore, we additionally investigate the relationship between determinants of fund performance and rating changes using a logistic regression model. Table 6 presents estimated average marginal effects. The results are similar to the results of the linear probability model.

3.4 Do rating changes predict opposite future changes?

An attempt to correct a ratings decision through a subsequent opposite rating change constitutes a salient sign of an analyst overreaction. If a rating upgrade predicts future rating downgrades, this indicates that an analyst overreacted when upgrading and wants to correct for it by downgrading again. To investigate this hypothesis, we re-estimate the linear probability model of rating changes (see Table 5) and include dummy variables for past upgrades and downgrades. Table 7 presents the results.

In the monthly panel data, an upgrade within the past year corresponds to a 59% increase (from 0.71pp to 1.13pp) in the probability of a downgrade in specification (2). Conversely, past downgrades do not significantly predict upgrades in specification (1). The results are qualitatively similar when using a three-year window to construct the dummy variables for past upgrades and downgrades in Panel B.

Next, we again restrict the sample to fund-months in which updated analyst ratings are published. The advantage of this version is that the coefficients are easier to interpret. The upgrade probability of 7% increases by 23% following a downgrade in the past year and by 34% following a downgrade in the past three years (specification 3), with only the latter being statistically significant. The downgrade probability of 10% rises by 68% (49%) after an upgrade within the past year (past three years).

In essence, our findings indicate a significant association between prior rating upgrades and subsequent downgrades, suggesting analysts may seek to rectify initial overreactions by revising their assessments downward.

3.5 Forecast errors and forecast revisions

In this section, we adopt the framework of Coibion and Gorodnichenko (2015) to examine the predictability of forecast errors from analysts' forecast revisions. This approach establishes a connection between a forecast revision and a forecaster's information set, while being agnostic about the exact nature of the new information prompting the revision.

So far, we use analyst forecasts on an ordinal scale (i.e., the five-tier analyst rating) which is a challenge when aiming to compute forecast errors. However, in October 2019, Morningstar implemented a revised methodology for their Analyst Rating, which now involves constructing a distribution of forward-looking net-of-fee abnormal returns (alphas) and subsequently grouping alphas to arrive at the final Analyst Ratings. Dahlquist et al. (2024) replicate Morningstar's new methodology and recover analyst alphas. We follow their procedure and compute analyst alphas for funds rated under Morningstar's updated methodology from October 2019 to December 2021. These alphas serve as forecasts of net-of-fee abnormal mutual fund performance, and we calculate forecast errors over a 12-month horizon. Then, we run panel regressions of fund-level future forecast errors on analysts' forecast revisions (we omit fund and analyst subscripts for simplicity):

$$FE_{t,t+12} = a + bFR_{t-1,t} + \epsilon_{t,t+12}, \tag{4}$$

where we define forecast errors as realizations of net-of-fee abnormal return minus forecasts thereof:

$$FE_{t,t+12} = \alpha_{t,t+12} - E_t[\alpha_{t,t+12}], \tag{5}$$

and forecast revisions as differences between current forecasts and the previous period's expectations of fund returns:

$$FR_{t-1,t} = E_t[\alpha_{t,t+12}] - E_{t-1}[\alpha_{t,t+12}]. \tag{6}$$

Under the assumption of rational expectations, the correlation between individual-level forecast errors and forecast revisions, denoted by the b coefficient, is zero (see, e.g., Bordalo et al., 2020). When this correlation is positive, upward revisions predict higher realizations relative to the forecasts, meaning that the forecasts underreact relative to rational expectations. Conversely, when this correlation is negative, upward revisions predict lower realizations relative to the forecasts, meaning that the forecasts overreact relative to rational expectations.

Panle A of Table 8 presents the regression results. Specifications (1) and (2) use the full sample, while specifications (3) and (4) restrict the sample to fund-months where analysts publish updated ratings. Specifications (2) and (4) add forecaster fixed effects and thus control for analyst characteristics that are fixed over the sample period. In all specifications, forecast revisions negatively predict forecast errors. The estimated coefficients on forecast revisions are around –0.6 and are statistically significant at the 10% level. This finding indicates that analysts overreact to past performance when revising analyst ratings. Moreover, the magnitude of the CG regression coefficients aligns with the results reported by Afrouzi et al. (2023) for processes with zero autocorrelation.

In Panel B, we apply the updated Morningstar Analyst Rating methodology back in time and predict analyst alphas for ratings constructed under the old methodology. Even though Morningstar did not use alphas to construct its analyst ratings up to 2019 as far as we know, it is still straightforward to apply the new methodology and obtain analyst alphas for the remaining sample under mild assumptions.[4] While the coefficients are somewhat larger and

[4] This prediction exercise involves transforming fund-level pillar scores, which are inputs to the final analyst ratings, on a three-tier scale under the old methodology to a five-tier scoring scale using a regression

between –0.3 and –0.5, the interpretation of the results remains qualitatively similar.

There are several caveats to this analysis. First, the time-series of analyst alphas is relatively short because Morningstar only adopted its new analyst rating methodology in 2019 and gradually updated funds over the following year. Second, Morningstar indicates that analyst alphas capture expected outperformance over a full business cycle or at least five years. Given the shorter time-series in our study, we assume that the unobserved one-year forecast is equal to the average annual performance expected over the extended period. Third, Kučinskas and Peters (2022) identify problems in applying Coibion and Gorodnichenko (2015) regressions to individual-level data, as in Bordalo et al. (2020). Since the forecast simultaneously enters both sides of Equation (4), albeit with different signs, measurement error simultaneously enters both sides of the equation if individual forecasts are measured with error. This non-standard measurement problem arising from the interaction between the measurement errors on both sides of the regression equation leads to a biased estimate of b and can misleadingly suggest overreaction even when expectations exhibit no overreaction.

Overall, we consider our CG regressions as supporting evidence that complement the analyses presented in the preceding sections. Using CG regressions allows us to compare the results to existing literature and, interestingly, the magnitude of the coefficients is similar to the findings of other studies for nonpersistent processes.

4 Conclusion

In this paper, we contribute to the debate on subjective expectations by examining the mutual fund industry and the expectations of professional analysts who forecast mutual fund returns. Our analysis provides evidence consistent with overreaction by analysts. We find

approach. See section E.2 in the internet appendix of Dahlquist et al. (2024) for a detailed discussion.

that when analysts revise their forecast of future fund returns upward, the subsequent fund returns tend to be lower, and vice versa for downward revisions. These findings suggest that analysts tend to overreact to recent news and past performance when revising their ratings.

The conventional interpretation of mutual fund investor behavior suggests that investors naively chase and overreact to past performance. We provide evidence that professional analysts themselves exhibit overreaction tendencies. Moreover, we also shed light on the interaction between analysts and investors in the mutual fund industry. Our analysis shows that investors follow analysts' recommendations, as evidenced by the increase in fund flows when a fund receives a positive recommendation from analysts. This suggests that analysts' forecasts have a significant impact on investor decision-making and fund flows. Furthermore, this finding emphasizes the importance of subjective expectations in understanding market dynamics and highlights the role of analysts' forecasts in shaping investor behavior.

In conclusion, our study provides empirical evidence of overreaction in the mutual fund industry, as observed through the forecast revisions of professional analysts. By highlighting the role of subjective expectations and the interaction between analysts and investors, our research contributes to a better understanding of mutual fund market dynamics.

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Table 1: Summary statistics

	N	Mean (V.W.)	Mean (E.W.)	S.D.	10%	25%	50%	75%	90%
AUM	173068		4123	11728	126	375	1138	3427	8848
Fund age	173068	355	236	151	81	135	211	300	397
Fund flow (%)	173049	–0.35	–0.30	4.50	–3.22	–1.49	–0.48	0.65	2.61
Fees (%)	173068	0.86	1.20	0.53	0.67	0.90	1.11	1.44	1.86
12m return (%)	172353	14.97	12.12	18.07	–8.48	–0.17	10.81	22.04	33.66
12m return vol. (%)	172353	4.14	4.55	2.02	2.49	3.14	4.16	5.47	7.16
12m family return (%)	173028	13.20	11.53	14.91	–5.96	0.67	10.82	19.68	28.65
12m avg. flow (%)	171838	–0.20	–0.25	2.54	–2.60	–1.42	–0.53	0.61	2.33
12m avg. family flow (%)	172914	0.48	0.26	1.29	–0.92	–0.37	0.13	0.73	1.53
12m abn. return (%)	170329	1.63	1.50	6.40	–5.27	–1.94	1.18	4.55	8.52
Log fund family AUM	173068	12.44	10.74	2.18	7.81	9.39	10.80	12.47	13.26
Managerial multitasking	168087	6.33	4.85	7.67	0.50	1.50	3.00	5.86	9.00
Manager tenure	168123	178	124	80	31	65	113	169	229
Management team	168123	0.72	0.65	0.48	0	0	1	1	1
Analyst Rating	173068	3.70	3.09	0.98	2	2	3	4	4
Star Rating	168656	3.74	3.52	1.01	2	3	4	4	5

The table shows value-weighted (by assets under management, AUM) and equal-weighted means, standard deviations, and various percentiles for global active equity mutual funds. The sample spans September 2011 to December 2021. The statistics include AUM (fund sizes in millions of USD), fund age (number of months since fund inception), fund flows, fees, 12-month fund returns, 12-month volatility of fund returns, 12-month average fund family returns, 12-month average fund flows, 12-month average fund family flows, 12-month abnormal fund returns (relative to the Morningstar Category Index), the logarithm of fund family AUM, managerial multitasking (average number of additional funds that managers of a fund manage), maximum manager tenure (in months), a dummy for a team-managed fund, Analyst Rating, and Star Rating. Analyst Ratings are translated into a numerical form (Gold=5, Silver=4, Bronze=3, Neutral=2, and Negative=1).

Table 2: Transition matrix

Panel A: Fund-months

	Gold	Silver	Bronze	Neutral	Negative
N	15563	41871	60554	52533	2547

Panel B: Transition matrix

	Lagged rating				
Rating	Gold	Silver	Bronze	Neutral	Negative
Gold	15152	157	10	0	0
Silver	147	40636	361	14	0
Bronze	25	381	58621	277	0
Neutral	16	83	522	50589	19
Negative	0	0	4	45	2390

Panel C: Transition matrix (in %)

	Lagged rating				
Rating	Gold	Silver	Bronze	Neutral	Negative
Gold	98.77	0.38	0.02	0.00	0.00
Silver	0.96	98.49	0.61	0.03	0.00
Bronze	0.16	0.92	98.49	0.54	0.00
Neutral	0.10	0.20	0.88	99.34	0.79
Negative	0.00	0.00	0.01	0.09	99.21

The table shows monthly summary statistics for Morningstar Analyst Ratings. Panel A reports the number of fund-months in the sample per rating category. Panel B shows a transition matrix, in which ratings are tabulated in rows and lagged ratings in columns (e.g., row=Bronze and column=Neutral indicates a rating change from Neutral to Bronze). Panel C presents the transition matrix in percentage terms.

Table 3: Fund performance on Analyst Ratings

	(1)	(2)	(3)	(4)
Recommended	-0.162^{***}		0.031^{**}	
	(0.032)		(0.014)	
Gold		-0.249^{***}		0.072^{***}
		(0.075)		(0.023)
Silver		-0.224^{***}		0.030
		(0.043)		(0.018)
Bronze		-0.134^{***}		0.016
		(0.029)		(0.014)
Neutral				
Negative		0.186^{***}		-0.062
		(0.068)		(0.041)
N	170790	170790	170796	170796
Adj. R^2	0.01	0.01	0.04	0.04
Time FE	No	No	Yes	Yes
Fund FE	Yes	Yes	No	No

The table shows coefficient estimates obtained from OLS regressions using a panel of monthly active equity fund data that spans 2011–2021. The dependent variable is net-of-fee abnormal fund returns. The independent variables of interest are, in (1) and (3), a recommended rating indicator variable that is equal to one if the fund is recommended by Morningstar analysts (Gold-, Silver-, or Bronze-rated; not recommended, i.e. Neutral- or Negative-rated, is the omitted category) that month, and zero otherwise, and in (2) and (4), Morningstar Analyst Rating indicator variables (Gold, Silver, Bronze, and Negative; Neutral is the omitted category) that are equal to one if the fund is rated in the indicated category that month, and zero otherwise. Abnormal returns are relative to each fund's Morningstar Category benchmark. Standard errors are presented in parentheses and double clustered by fund and year-month. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively, for the null hypothesis of a zero coefficient.

Table 4: Fund flows on Analyst Ratings

	(1)	(2)	(3)	(4)	(5)	(6)
Recommended	0.458***		0.660***		0.365***	
	(0.084)		(0.058)		(0.066)	
Gold		0.527***		0.804***		0.686***
		(0.177)		(0.096)		(0.130)
Silver		0.536***		0.673***		0.519***
		(0.112)		(0.070)		(0.084)
Bronze		0.420***		0.570***		0.326***
		(0.085)		(0.064)		(0.067)
Neutral						
Negative		−0.498**		−0.492***		−0.347*
		(0.230)		(0.184)		(0.205)
Five-star					1.381***	1.371***
					(0.063)	(0.062)
Four-star					0.646***	0.639***
					(0.039)	(0.039)
Three-star						
Two-star					−0.560***	−0.554***
					(0.055)	(0.055)
One-star					−0.986***	−0.966***
					(0.121)	(0.121)
No-star					0.618**	0.611**
					(0.246)	(0.245)
N	171535	171535	171538	171538	165627	165627
Adj. R^2	0.11	0.11	0.01	0.01	0.19	0.19
Controls	No	No	No	No	Yes	Yes
Morningstar Category FE	No	No	No	No	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	No	No	Yes	Yes

The table shows coefficient estimates obtained from OLS regressions using a panel of monthly active equity fund data that spans 2011–2021. The dependent variable is monthly realized fund flows. The independent variables of interest are, in (1), (3) and (5), a recommended rating indicator variable that is equal to one if the fund is recommended by Morningstar analysts (Gold-, Silver-, or Bronze-rated; not recommended, i.e. Neutral- or Negative-rated, is the omitted category) that month, and zero otherwise, and in (2), (4) and (6), Morningstar Analyst Rating indicator variables (Gold, Silver, Bronze, and Negative; Neutral is the omitted category) that are equal to one if the fund is rated in the indicated category that month, and zero otherwise. Lagged fund characteristics are included as control variables in specifications (5) and (6) and include the logarithm of assets under management (AUM, in millions of USD), the logarithm of fund family AUM, fund age (logarithm of the number of months since fund inception), fees, past-12-month fund returns, 12-month volatility of fund returns, 12-month average fund family returns, 12-month average fund flows, 12-month average fund family flows, maximum manager tenure, a dummy for a team-managed fund, and the average number of additional funds that the managers of a fund manage. Standard errors are presented in parentheses and double clustered by fund and year-month. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively, for the null hypothesis of a zero coefficient.

Table 5: Determinants of rating changes: linear probability model

	Full sample						Publication months					
	Upgrades			Downgrades			Upgrades			Downgrades		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Net abn. return (y-1)	0.185***	0.180***	0.177***	−0.185***	−0.180***	−0.173***	2.566***	2.448***	2.418***	−2.908***	−2.910***	−2.828***
	(0.023)	(0.023)	(0.024)	(0.029)	(0.029)	(0.029)	(0.337)	(0.343)	(0.349)	(0.465)	(0.464)	(0.465)
Δ AUM% (y-1)	0.059**	0.071**	0.079**	−0.120***	−0.081**	−0.087**	1.308**	1.564**	1.677***	−2.041***	−1.300**	−1.393*
	(0.029)	(0.033)	(0.033)	(0.031)	(0.035)	(0.040)	(0.548)	(0.619)	(0.604)	(0.585)	(0.637)	(0.743)
Δ Fees (y-1)	−0.020	−0.007	−0.008	0.014	0.012	0.009	−0.434	−0.081	−0.035	0.225	0.232	0.065
	(0.018)	(0.015)	(0.016)	(0.017)	(0.021)	(0.022)	(0.363)	(0.330)	(0.345)	(0.344)	(0.435)	(0.460)
Net abn. return (y-2)		0.040**	0.036*		−0.154***	−0.148***		0.712**	0.623**		−2.604***	−2.487***
		(0.018)	(0.018)		(0.028)	(0.028)		(0.282)	(0.292)		(0.420)	(0.407)
Δ AUM% (y-2)		0.029	−0.008		−0.088***	−0.084**		0.276	−0.252		−1.286***	−1.144**
		(0.029)	(0.028)		(0.028)	(0.033)		(0.412)	(0.403)		(0.391)	(0.467)
Δ Fees (y-2)		0.010	0.009		0.012	0.003		0.317	0.305		0.365	0.182
		(0.016)	(0.020)		(0.018)	(0.018)		(0.327)	(0.369)		(0.356)	(0.368)
Net abn. return (y-3)			0.084***			−0.090***			1.427***			−1.680***
			(0.023)			(0.026)			(0.322)			(0.402)
Δ AUM% (y-3)			−0.029			−0.007			−0.510*			−0.115
			(0.020)			(0.026)			(0.302)			(0.402)
Δ Fees (y-3)			−0.001			−0.002			0.167			−0.025
			(0.018)			(0.023)			(0.309)			(0.355)
Constant	0.489***	0.495***	0.493***	0.712***	0.714***	0.716***	7.159***	7.194***	7.111***	10.476***	10.451***	10.422***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.036)	(0.036)	(0.462)	(0.471)	(0.463)	(0.465)	(0.444)	(0.443)
N	170046	166533	162331	170046	166533	162331	11580	11420	11213	11580	11420	11213
Adj. R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.014	0.015	0.017	0.014	0.023	0.025

The table shows estimated coefficients of a linear probability model of rating changes. In specifications (1)–(3) and (7)–(9), the dependent variable is a dummy that is equal to one if the analyst rating increases, and zero otherwise. In specifications (4)–(6) and (10)–(12), the dependent variable is a dummy that is equal to one if the analyst rating decreases, and zero otherwise. Specifications (1)–(6) use the full sample of analyst-rated funds. The sample is restricted to fund-months, in which a new analyst rating is published in specifications (7)–(12). All independent variables are standardized to have a mean of zero and a standard deviation of one to ease interpretation. The coefficient estimates are multiplied by 100. Standard errors are presented in parentheses and clustered by fund and year-month. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively, for the null hypothesis of a zero coefficient.

Table 6: Determinants of rating changes: logistic regression model

	Full sample						Publication months					
	Upgrades			Downgrades			Upgrades			Downgrades		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Net abn. return (y-1)	0.140***	0.136***	0.133***	−0.165***	−0.166***	−0.161***	2.208***	2.102***	2.047***	−2.707***	−2.895***	−2.863***
	(0.015)	(0.015)	(0.016)	(0.031)	(0.031)	(0.032)	(0.323)	(0.324)	(0.323)	(0.488)	(0.489)	(0.497)
Δ AUM% (y-1)	0.036**	0.039***	0.043***	−0.302**	−0.194*	−0.197	0.796***	0.910***	1.024***	−4.706***	−2.839*	−2.884*
	(0.014)	(0.015)	(0.014)	(0.120)	(0.116)	(0.120)	(0.274)	(0.306)	(0.320)	(1.792)	(1.680)	(1.699)
Δ Fees (y-1)	−0.017	−0.005	−0.006	0.011	0.008	0.005	−0.371	−0.033	0.030	0.213	0.208	0.088
	(0.015)	(0.014)	(0.015)	(0.016)	(0.020)	(0.021)	(0.303)	(0.294)	(0.310)	(0.398)	(0.493)	(0.519)
Net abn. return (y-2)		0.038**	0.033**		−0.132***	−0.129***		0.703***	0.602**		−2.280***	−2.257***
		(0.015)	(0.016)		(0.027)	(0.027)		(0.266)	(0.271)		(0.416)	(0.406)
Δ AUM% (y-2)		0.023	−0.002		−0.208*	−0.194*		0.254	−0.163		−3.134*	−2.685*
		(0.018)	(0.024)		(0.114)	(0.117)		(0.277)	(0.376)		(1.630)	(1.631)
Δ Fees (y-2)		0.007	0.006		0.006	−0.003		0.251	0.248		0.305	0.151
		(0.014)	(0.017)		(0.018)	(0.020)		(0.268)	(0.309)		(0.396)	(0.420)
Net abn. return (y-3)			0.073***			−0.084***			1.305***			−1.687***
			(0.019)			(0.027)			(0.276)			(0.420)
Δ AUM% (y-3)			−0.029			−0.003			−0.528			−0.019
			(0.024)			(0.038)			(0.362)			(0.571)
Δ Fees (y-3)			−0.001			−0.006			0.189			−0.031
			(0.014)			(0.026)			(0.287)			(0.402)
Constant	0.463***	0.465***	0.458***	0.655***	0.632***	0.629***	7.232***	7.206***	7.006***	10.557***	10.054***	9.896***
	(0.037)	(0.037)	(0.037)	(0.043)	(0.039)	(0.039)	(0.541)	(0.553)	(0.537)	(0.700)	(0.628)	(0.630)
N	170046	166533	162331	170046	166533	162331	11580	11420	11213	11580	11420	11213
Pseudo R^2	0.012	0.013	0.015	0.012	0.017	0.018	0.023	0.026	0.030	0.027	0.040	0.044

The table shows the results of estimating a logistic regression model of rating changes. We report average marginal effects for all independent variables, odds ratios for the constant, and the pseudo R^2 of the logit regressions. In specifications (1)–(3) and (7)–(9), the dependent variable is a dummy that is equal to one if the analyst rating increases, and zero otherwise. In specifications (4)–(6) and (10)–(12), the dependent variable is a dummy that is equal to one if the analyst rating decreases, and zero otherwise. Specifications (1)–(6) use the full sample of analyst-rated funds. The sample is restricted to fund-months, in which a new analyst rating is published in specifications (7)–(12). All independent variables are standardized to have a mean of zero and a standard deviation of one to ease interpretation. The coefficient estimates are multiplied by 100. Standard errors are presented in parentheses and clustered by year-month. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively, for the null hypothesis of a zero coefficient.

Table 7: Past and future rating changes

	Full sample		Publication months	
	Upgrades	Downgrades	Upgrades	Downgrades
	(1)	(2)	(3)	(4)
Panel A: Rating changes within last year				
Upgrade	-0.368^{***}	0.419^{**}	-5.108^{***}	6.847^{***}
	(0.056)	(0.164)	(0.847)	(2.124)
Downgrade	0.015	-0.262^{***}	1.694	-0.965
	(0.091)	(0.080)	(1.587)	(1.311)
Constant	0.513^{***}	0.713^{***}	7.293^{***}	10.092^{***}
	(0.040)	(0.037)	(0.481)	(0.421)
N	162331	162331	11213	11213
Adj. R^2	0.001	0.002	0.019	0.028
Controls	Yes	Yes	Yes	Yes
Panel B: Rating changes within last three years				
Upgrade	-0.137^{***}	0.348^{***}	-1.887^{***}	4.854^{***}
	(0.051)	(0.109)	(0.689)	(1.485)
Downgrade	0.094	-0.150^{**}	2.407^{**}	-0.397
	(0.066)	(0.061)	(1.066)	(0.926)
Constant	0.495^{***}	0.698^{***}	7.030^{***}	9.920^{***}
	(0.040)	(0.036)	(0.484)	(0.420)
N	162331	162331	11213	11213
Adj. R^2	0.001	0.002	0.019	0.028
Controls	Yes	Yes	Yes	Yes

The table shows estimated coefficients of a linear probability model of rating changes. The independent variables of interest are dummy variables that are equal to one if a fund's rating was upgraded or downgraded within the past year (Panel A) or the past three years (Panel B), and zero otherwise. In specifications (1) and (3), the dependent variable is a dummy that is equal to one if the analyst rating increases, and zero otherwise. In specifications (2) and (4), the dependent variable is a dummy that is equal to one if the analyst rating decreases, and zero otherwise. Specifications (1) and (2) use the full sample of analyst-rated funds. The sample is restricted to fund-months, in which a new analyst rating is published in specifications (3) and (4). The set of independent variables employed in Table 5 are included as control variables but the estimated coefficients are omitted to save space. The coefficient estimates are multiplied by 100. Standard errors are presented in parentheses and clustered by fund and year-month. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively, for the null hypothesis of a zero coefficient.

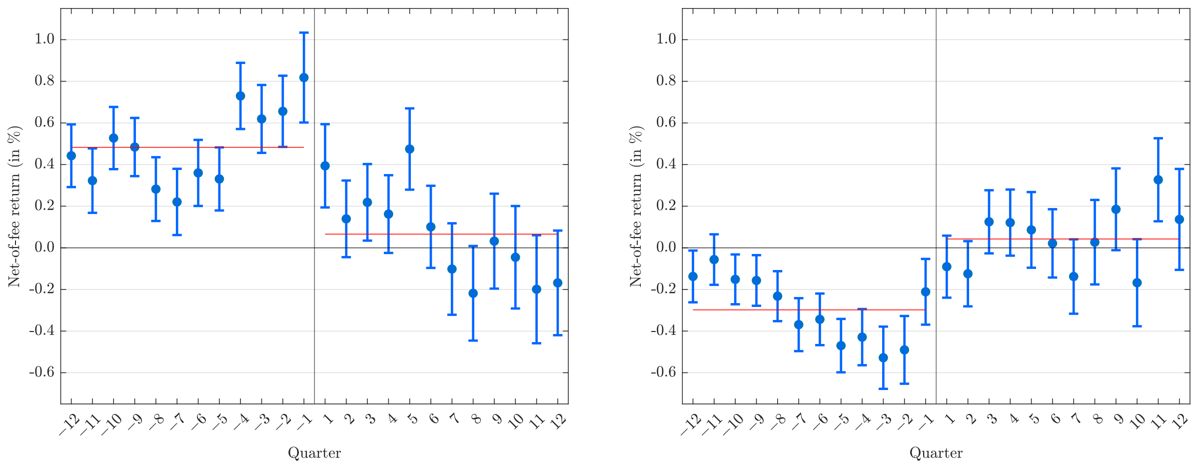
Table 8: Forecast errors on forecast revisions

	Full sample		Publication months	
	(1)	(2)	(3)	(4)
Panel A: Alphas from new analyst ratings				
Forecast revision	-0.609^{*}	-0.622^{*}	-0.582^{*}	-0.735^{**}
	(0.319)	(0.337)	(0.286)	(0.259)
Constant	0.012^{***}		0.013^{***}	
	(0.003)		(0.003)	
N	12776	12771	1690	1683
Adj. R^2	0.001	0.076	0.003	0.037
Forecaster FE	No	Yes	No	Yes
Panel B: Alphas predicted from old analyst ratings				
Forecast revision	-0.417^{**}	-0.492^{***}	-0.340^{*}	-0.422^{**}
	(0.187)	(0.186)	(0.181)	(0.180)
Constant	-0.002		-0.003^{*}	
	(0.001)		(0.002)	
N	134317	124926	9146	9065
Adj. R^2	0.000	0.042	0.001	0.029
Forecaster FE	No	Yes	No	Yes

The table shows regressions of forecast errors on forecast revisions in the style of Coibion and Gorodnichenko (2015). Forecast errors are the difference between 1-year-ahead per annum realized abnormal returns, $\alpha_{t,t+12}$, and current expectations of per annum abnormal returns, $E_t[\alpha_{t,t+12}]$. Forecast revisions are differences between current forecasts and the previous period's expectations of per annum abnormal returns, $E_t[\alpha_{t,t+12}] - E_{t-1}[\alpha_{t,t+12}]$. Panel A restricts the sample to funds rated under Morningstar's updated Analyst Rating methodology from October 2019 to December 2021. Panel B applies the new methodology back in time and predicts alphas for analyst ratings under the old methodology since 2011. Expectations of future outperformance are from Morningstar analysts. Realized abnormal returns are relative to each fund's Morningstar Category benchmark. Standard errors are presented in parentheses and double clustered by fund and year-month. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively, for the null hypothesis of a zero coefficient.

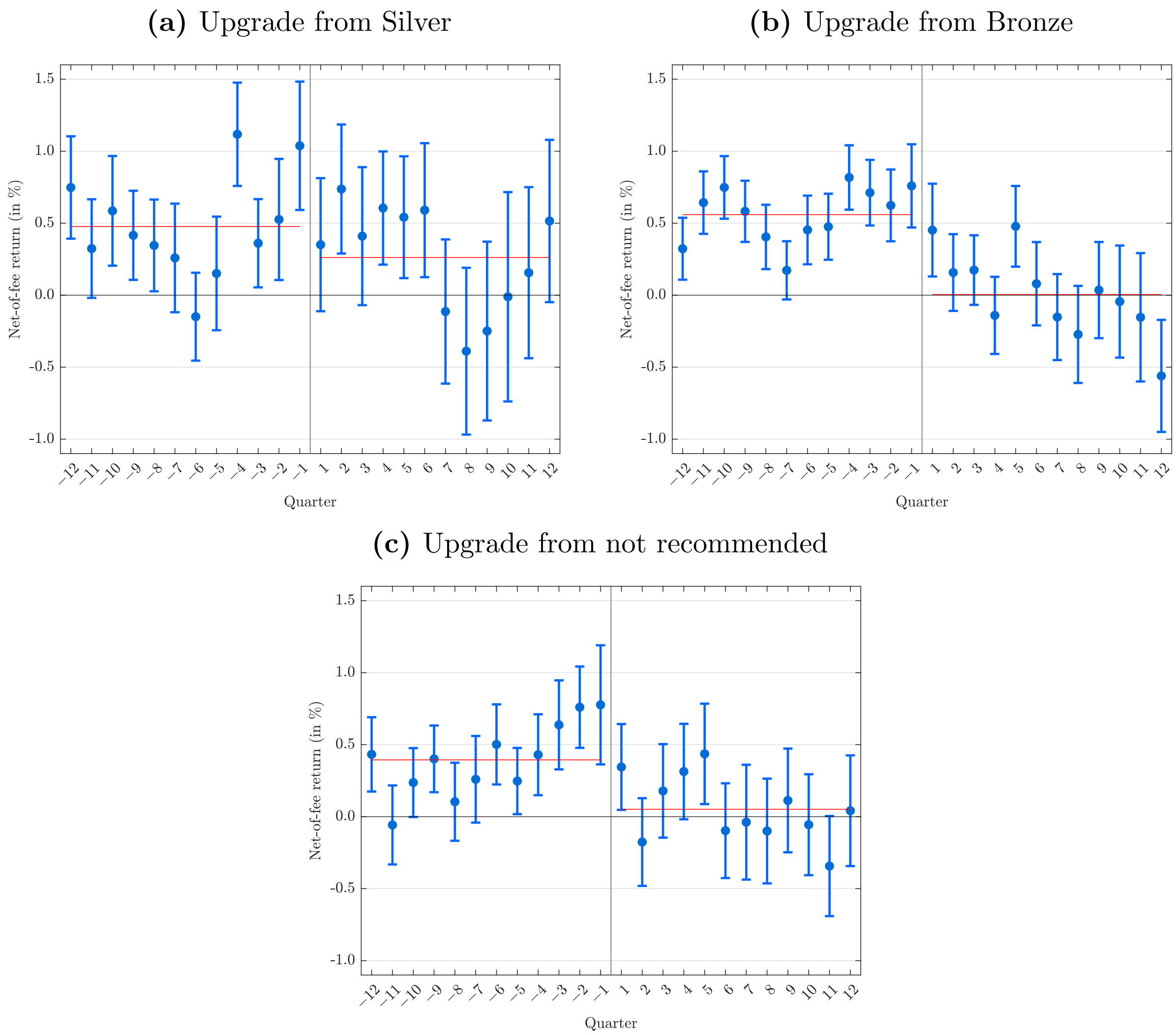
Figure 1: Returns around analyst rating changes

(a) Upgrades **(b)** Downgrades



This figure plots quarterly net-of-fee abnormal returns of global active equity mutual funds for the 12 quarters leading up to an analyst rating change and the following 12 quarters after a rating change. Panel (a) restricts the sample to rating upgrades and Panel (b) to rating downgrades. The two red horizontal lines reflect average quarterly returns before and after rating revisions, respectively. Abnormal returns are relative to each fund's Morningstar Category benchmark. The error bars are 90% confidence bands.

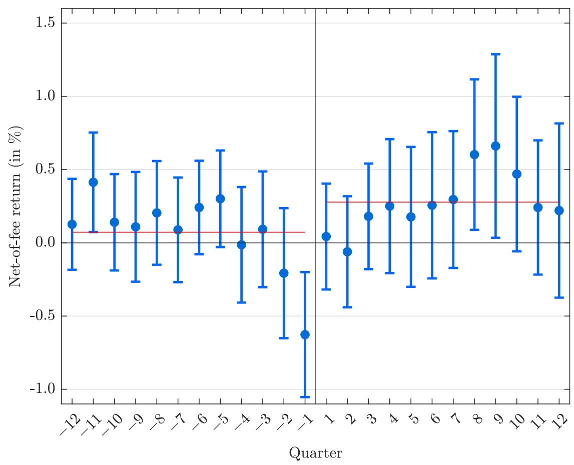
Figure 2: Returns around analyst rating upgrades within rating groups



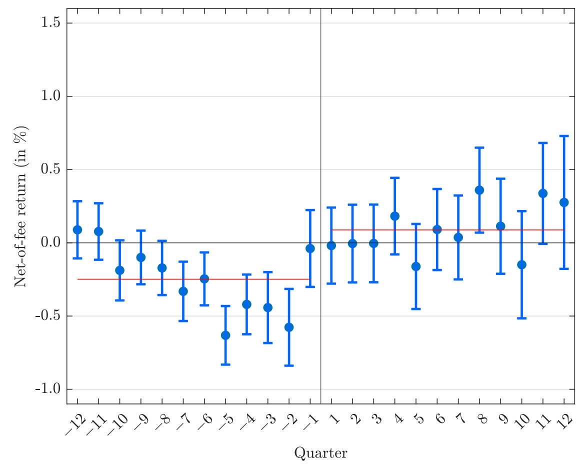
This figure plots quarterly net-of-fee abnormal returns of global active equity mutual funds for the 12 quarters leading up to an analyst rating upgrade and the following 12 quarters after a rating upgrade. The three panels condition on the rating prior to the upgrade. Neutral and Negative ratings are grouped to form the not recommended category. The two red horizontal lines reflect average quarterly returns before and after rating revisions, respectively. Abnormal returns are relative to each fund's Morningstar Category benchmark. The error bars are 90% confidence bands.

Figure 3: Returns around analyst rating downgrades within rating groups

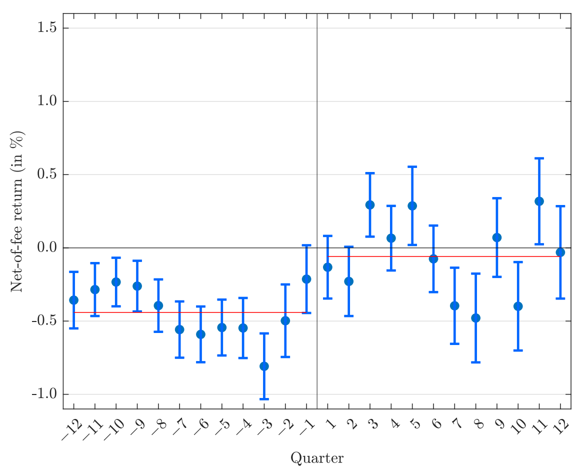
(a) Downgrade from Gold



(b) Downgrade from Silver



(c) Downgrade from Bronze



This figure plots quarterly net-of-fee abnormal returns of global active equity mutual funds for the 12 quarters leading up to an analyst rating downgrade and the following 12 quarters after a rating downgrade. The three panels condition on the rating prior to the downgrade. Neutral and Negative ratings are grouped to form the not recommended category. The two red horizontal lines reflect average quarterly returns before and after rating revisions, respectively. Abnormal returns are relative to each fund's Morningstar Category benchmark. The error bars are 90% confidence bands.