Do Mutual Funds Manipulate Star Ratings? Evidence from Portfolio Pumping

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Abstract

This paper reveals that mutual fund managers manipulate Morningstar ratings by inflating their month-end portfolio values when they are likely to finish the month near rating cutoffs. This star rating manipulation is more pronounced among funds with greater incentives and abilities to pump their portfolios and manipulate star ratings. Following heightened regulatory scrutiny, portfolio pumping to manipulate star ratings has largely migrated from quarter/year-ends to less prominent month-ends. Improving star ratings, portfolio pumping increases fund flows, especially in the month of a rating upgrade. Placebo tests exploiting the June 2002 change in Morningstar's rating methodology yield expected null effects.

JEL classification: G23, G24, G28, K22

Keywords: Morningstar ratings, managerial incentives, mutual funds, portfolio pumping, performance manipulation

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"We are all in the gutter, but some of us are looking at the stars."

– Oscar Wilde

1 Introduction

Since its introduction in 1985, Morningstar's five-star rating system has become widely accepted in the mutual fund industry (Del Guercio and Tkac (2008)).[1] Unlike performance measures commonly used in academia (e.g., Jensen (1969), Carhart (1997), Daniel et al. (1997)), Morningstar star ratings offer less sophisticated investors a simple and intuitive tool to use to allocate their capital across mutual funds. Prior studies find that discrete star ratings have a powerful influence on fund flows, independent of the underlying continuous performance metric used to rank funds (Del Guercio and Tkac (2008), Reuter and Zitzewitz (2015)). Evans and Sun (Forthcoming) show that mutual fund investors use simple heuristics such as star ratings, rather than asset-pricing models, for risk adjustment. Ben-David et al. (2019) further argue that star ratings explain mutual fund investors' behavior better than asset pricing models, concluding that star ratings are the main determinant of capital allocation across mutual funds.

Whereas how star ratings influence the behavior of mutual fund *investors* is well-documented, little is known about how star ratings distort the incentives of mutual fund *managers*. In this paper, I argue that the closer fund rankings are to rating cutoffs, the greater the incentive to inflate the underlying performance metric that Morningstar uses to determine star ratings. The incentive to manipulate star ratings arises because even a small increase in fund rankings (such as going from 89^{th} percentile to 90^{th} percentile) can induce discrete changes in star ratings (such as going from four stars to five stars), which in turn leads to a large jump in fund flows (Reuter and Zitzewitz (2015)). Consistent with my prediction, I find strong evidence that U.S. equity mutual

[1] Mutual fund share classes are rated at the end of each month on a scale of one star (lowest) to five stars (highest) on the basis of Morningstar Risk-Adjusted Returns (MRAR). The top 10% of funds receive five stars, the next 22.5% four stars, the middle 35% three stars, the next 22.5% two stars, and the bottom 10% one star, approximately following a normal distribution.

fund managers manipulate star ratings by inflating their month-end portfolio values when they are likely to finish the month in the vicinity of rating thresholds.

At the end of every month, mutual fund share classes are rated by Morningstar on the basis of Morningstar Risk-Adjusted Returns (MRAR) over the prior three, five, and ten years, depending on data availability. "Overall" star ratings are then determined by taking weighted-averages of three, five, and ten-year star ratings, rounded to the nearest integer value.[2] Following the literature, my paper focuses on overall star ratings, which are most prominently featured by Morningstar as well as mutual fund companies.

On June 30, 2002, Morningstar implemented a major change to its star rating methodology. In addition to changing the risk adjustment process, Morningstar refined its peer groups used to rank mutual funds.[3] Incorporating the June 2002 change, I rank mutual fund share classes each month on the basis of MRAR computed following Blume (1998) until May 2002 and Morningstar (2016) starting in June 2002, relative to the peer groups Mornigstar used before and after the change, respectively. To estimate rankings *prior to* monthly rating updates, I use trailing returns over the prior 36, 60, and 120 months, depending on data availability, that are cumulative only up to the *second-to-last* trading day of the month in the computation of MRAR. Then, I compute "overall" percentile rankings by taking weighted-averages of three, five, and ten-year percentile rankings. Last, I compute the distance to a rating threshold as the distance between overall percentile rankings and the nearest rating threshold.

[2]Mutual fund share classes less than three years old are not rated. Share classes at least three years old but less than five years old are rated based only on three-year star ratings. Share classes at least five years old but less than ten years old are rated based on three-year star ratings (40 percent weight) and five-year star ratings (60 percent weight). Share classes at least ten years old are rated based on three-year star ratings (20 percent weight), five-year star ratings (30 percent weight), and ten-year star ratings (50 percent weight).

[3]Morningstar started raking U.S. equity mutual funds within nine (three-by-three) investment style categories (market-cap interacted with value/growth), whereas all U.S. equity mutual funds were ranked within a single category prior to the change. The revised formula of the MRAR measures the annualized estimate of the certainty equivalent geometric excess return for an investor with CRRA utility (Morningstar (2016)), whereas the older version of the MRAR adjusts for the downside risk (See Blume (1998) for a detailed explanation of the algorithm used to calculate the MRAR).

I begin my empirical analysis by confirming and extending prior results that mutual fund managers tend to inflate their portfolio values at the end of the month (e.g., Carhart et al. (2002), Patel and Sarkissian (Forthcoming)). Whereas prior studies focus on quarter-ends (especially year-ends), my paper focuses on all month-ends. In my sample, mutual funds on average earn 7 basis point excess returns over the S&P 500 index on the last trading day of the month, while earning negative 3 basis point excess returns on the first trading day of the subsequent month. This turn-of-the-month return reversal has been largely presented as evidence of an illegal trading practice known as "portfolio pumping" (Zweig (1997), Carhart et al. (2002)). Since open-end mutual funds calculate their portfolio values from the closing prices of their holdings, fund managers can artificially inflate the closing prices of their holdings by aggressively purchasing stocks they already own.[4]

Connecting portfolio pumping to Morningstar star ratings, I examine the cross-sectional difference in the extent to which fund managers engage in portfolio pumping. Specifically, I find that compared to their distant peers, funds near rating thresholds earn significantly higher returns on the last trading day of the month. In addition, this negative relation partially reverses on the first trading day of the subsequent month. The economic magnitude of month-end performance inflation is also meaningful given that returns are accumulated over just one day. The baseline results suggest that compared to funds farther away (11.25^{th} to 17.5^{th} percentile), funds near rating thresholds on average earn 0.56 to 1.35 basis point higher returns on the last trading day of the month.

Although my results are consistent with mutual fund managers pumping their portfolios to inflate star ratings, some may concern that the higher returns on the last trading day of the month earned by funds near rating thresholds could be driven by other factors that are also correlated with the distance to a rating threshold prior to monthly rating updates. To address potential

[4] Bhattacharyya and Nanda (2013) present an equilibrium model where a fund manager rewarded on short-term performance will engage in portfolio pumping to bolster the short-run measured value of her fund even when it adversely impacts her fund's long-term performance. In their model, pumping lowers long-term performance due to trades undertaken at distorted prices and the manager optimally trades off short-term benefits of pumping with diminished long-term performance.

endogeneity concerns and establish causality, I exploit the June 2002 change in Morningstar star rating methodology. Specifically, I conduct placebo tests by reversing the June 2002 change in the MRAR ranking procedure: I compute *placebo* percentile rankings using the new rating methodology until May 2002 and the old one starting in June 2002. In placebo tests based on percentile rankings that do *not* follow the exact Morningstar rating methodology, I find that the relation between the distance to a rating threshold and month-end performance inflation disappears.[5] The null results in placebo tests corroborate that the month-end performance inflation that I document is indeed specifically designed to inflate star ratings. Furthermore, the null effects from a slight distortion of MRAR rankings also support the key identifying assumption that fund managers have at least rough estimates of their rankings prior to monthly rating updates.

To further support that the negative relation between the distance to a rating threshold and month-end performance inflation is indeed driven by fund managers pumping their portfolios to inflate star ratings, I investigate whether this relation is more pronounced among funds with greater incentives and abilities to pump their portfolios and manipulate star ratings.

The first set of cross-sectional tests build on the observation that not all star ratings are created equal: three-year star ratings are the easiest to manipulate and the five-star status has the greatest impact on fund flows. First, because the assignment of star ratings is subject to data availability, it becomes much more difficult for funds to manipulate star ratings as their return history extends further.[6] While completely determining overall star ratings for funds with return

[5]Specifically, I measure *placebo* within-category percentile rankings by reversing the June 2002 change in peer groups. That is, I rank U.S. equity mutual funds within Morningstar categories until May 2002, while ranking all U.S. equity mutual funds against each other as a single category group starting in June 2002. Then, I compute the *placebo* distance to a rating threshold as the distance between *placebo* within-category percentile rankings and the nearest rating threshold. Not surprisingly, *placebo* within-category percentile rankings are highly correlated with actual ones (correlation coefficient above 0.8). Nevertheless, reversing peer groups in the ranking procedure makes a big difference when percentile rankings are measured relative to rating thresholds: the correlation between *placebo* distances to rating thresholds and actual ones is less than 0.1.

[6]Furthermore, young mutual funds have greater incentives to inflate their performance figures because the flow-performance relation is more convex among young mutual funds (Chevalier and Ellison (1997)). In a study of monthly return distribution of hedge funds, Bollen and Pool (2009) find that young hedge funds have a greater sensitivity of fund flows to reported losses and are more likely to distort monthly returns to

history of less than five years, three-year star ratings account for only a small faction (20 to 40 percent) of overall star ratings for funds with return history of at least five years. Second, Reuter and Zitzewitz (2015) find that discontinuities in the flow-performance relation are greater at higher rating cutoffs and greatest at the four/five-star cutoff.[7] Thus, funds around the four/five-star rating cutoff should have the strongest incentive to inflate star ratings. Consistent with my cross-sectional predictions, I find that star rating manipulation through portfolio pumping is more pronounced among younger funds with return history of less than five years and funds around the four/five-star rating cutoff.

The next set of cross-sectional tests build on the prior literature on portfolio pumping. First, Carhart et al. (2002) argue that if fund managers are indeed "marking up" their funds' portfolio values, portfolio pumping should be more pronounced among small-cap funds because the closing prices of less liquid stocks would presumably be easier to influence. Second, Patel and Sarkissian (Forthcoming) argue that peer effects among teams such as the presence of peer monitoring and joint monetary incentives are effective in deterring fund managers from engaging in illegal trading activities such as portfolio pumping. Consistent with these prior studies, I find that the negative relation between the distance to a rating threshold and month-end performance inflation is more pronounced among small-cap funds and single-managed funds, weakening as the size of management team increases.

After the initial results of Carhart et al. (2002) drew a great deal of attention from regulators, academics, and practitioners, the U.S. Securities and Exchange Commission (SEC) began to investigate suspicious trading activities (Duong and Meschke (2020)). Recent studies note that following heightened regulatory attention, portfolio pumping has become more evasive (e.g., Hu et al. (2014), Wang (2019)). To examine whether star rating manipulation through portfolio pumping has become more evasive, I conduct sub-period tests by splitting my sample around the June 2002 change

temporarily avoid reporting losses.

[7] Similarly, Del Guercio and Tkac (2008) find that among all rating changes, upgrades from four to five stars have the greatest impact on fund flows.

in Morningstar rating methodology, which approximately coincides with the publication of Carhart et al. (2002). My sub-period tests reveal that portfolio pumping to manipulate star ratings has largely migrated from quarter/year-ends to less prominent month-ends, presumably to evade regulatory attention. In the early period, star rating manipulation through portfolio pumping was more pronounced at quarter/year-ends, consistent with the prior literature's focus on portfolio pumping at quarter-ends (especially year-ends) (e.g., Carhart et al. (2002), Hu et al. (2014)). In the recent period, however, the negative relation between the distance to a rating threshold and month-end performance inflation is more pronounced at month-ends that are not quarter/year-ends, whereas it has become insignificant at quarter/year-ends.

My results thus far suggest that fund managers manipulate star ratings by inflating month-end portfolio values, especially when their funds are likely to finish the month near rating cutoffs. Portfolio pumping, however, could lower performance figures for the next month because a large fraction of gains on the last trading day of the month dissipates on the first trading day of the subsequent month. Theoretical studies also suggest that portfolio pumping, while improving a fund's short-term values, may hurt its long-term values (e.g., Bhattacharyya and Nanda (2013)).

To better understand what fund managers gain from engaging in portfolio pumping, I examine the effect of star rating manipulation on fund flows. Doing so, however, poses an empirical challenge because changes in star ratings (especially upgrades) have a large impact on fund flows (Del Guercio and Tkac (2008)) and a rating upgrade is at most only partially due to portfolio pumping. To tease out the effect of a rating upgrade on fund flows that can attributable to portfolio pumping, I exploit a two-stage least squares (2SLS) estimation. In the first stage, I find that month-end performance inflation is associated with a higher probability of a rating upgrade at the end of the month. Rating upgrades driven by portfolio pumping, however, are more likely to be offset by immediate downgrades in the subsequent months due to the return reversal around the turn of the month. Nevertheless, pumping funds can capture additional fund flows in the month of a rating upgrade without any significant punishment in the subsequent months. In the second stage, I find that star rating manipulation driven by month-end performance inflation significantly increases future fund flows, especially in the month of a rating upgrade.

The remainder of my paper is organized as follows. In the next section, I discuss the contribution of my paper in the context of related literature. Section 3 provides institutional details on Morningstar ratings pertaining to my paper. Section 4 introduces my data sets and describes how I construct key variables used in the my analysis. Section 5 presents evidence of star rating manipulation. Section 6 examines the effects of star rating manipulation through portfolio pumping. Section 7 concludes.

2 Related Literature

To the best of my knowledge, my paper is the first to link portfolio pumping to Morningstar star ratings, thereby contributing to several strands of literature.

First, my paper sheds new light on how star ratings can distort managerial incentives of mutual funds. The prior literature often focuses on the convex flow-performance relation (Ippolito (1992), Sirri and Tufano (1998)) to explain mutual funds' behavior in various settings (e.g., Chevalier and Ellison (1997)). Along this line, Carhart et al. (2002) use the convex flow-performance relation, which becomes increasingly steeper toward the top end of the performance spectrum, to propose that the "leaning-for-the-tape" effect is driving portfolio pumping.[8] Prior studies, however, offer little insight on mutual funds' behavior in less steep regions of the flow-performance relation. My paper complements the prior literature on mutual funds' managerial incentives by connecting it to a growing literature on Morningstar ratings. In particular, Reuter and Zitzewitz (2015) show that mutual fund investors' heavy reliance on star ratings creates discontinuities at rating thresholds in the flow-performance relation. My paper shows that such discontinuities in

[8] However, the result of Carhart et al. (2002) that the magnitude of portfolio pumping is more severe among high-performing funds is sample-specific. Patel and Sarkissian (Forthcoming) find that the magnitude of portfolio pumping is more severe among low-performing funds in their full sample from 1992 to 2015 and almost identical for both high-performing and low-performing funds in their reduced sample ending in 2010.

the flow-performance relation can give mutual fund managers powerful incentives to inflate their performance figures when their performance rankings are near rating cutoffs.

Second, my paper contributes to the literature on portfolio pumping. Departing from the prior literature that focuses on an aggregate level of portfolio pumping among equity mutual funds (and hedge funds) (e.g., Carhart et al. (2002), Ben-David et al. (2013), Hu et al. (2014)), my paper focuses on when mutual fund managers pump their portfolios. That is, rather than comparing funds' daily returns around the turn of the calendar year and quarters with daily returns for the rest of the year, I compare daily returns of funds close to rating thresholds with daily returns of funds farther away from rating thresholds around the turn of each calendar month. Funds that are close to (or farther away from) rating cutoffs change frequently because within-category rankings are based on past performance on a rolling basis. In addition, while prior studies tend to focus on portfolio pumping at quarter-ends (especially year-ends), this paper focuses on the tournament among fund managers at a higher frequency, consistent with Del Guercio and Tkac (2008) who find that the flow response to rating changes occurring at year-end is not different from that of other months.

Since portfolio pumping is an illegal trading practice, pumping managers would likely take caution. Indeed, my findings suggest that mutual fund managers engage in portfolio pumping infrequently and irregularly, and only do so when shifting performance from the next month to the current month is likely to result in the largest benefits. After the results of Carhart et al. (2002) were first disseminated in 2000, the SEC began to investigate suspicious trading activities. Duong and Meschke (2020) document a reduced level of portfolio pumping since late 2000 and other recent studies find that portfolio pumping has become more evasive. Hu et al. (2014) find that in their sample of Abel Noser clients from 1999 to 2010, year-end price inflation derives from depressed institutional selling rather than aggressive institutional buying. Wang (2019) shows that non-top-performing funds pump the portfolios held by top-performing funds in their own fund family at quarter-ends, but only after 2002. Consistent with these studies, my paper shows that following heightened regulatory scrutiny prompted by Carhart et al. (2002), portfolio pumping induced by star ratings has largely migrated from quarter/year-ends to less prominent month-ends.

Third, my paper contributes to a growing literature on Morningstar ratings of mutual funds. Del Guercio and Tkac (2008) show that in an event study setting, rating changes have a significant impact on fund flows, independent of the underlying continuous performance measures. Exploiting a regression discontinuity design, Reuter and Zitzewitz (2015) find that a large fraction of the difference in future fund flows received by five- and one-star funds represents a causal effect of the difference in star ratings on fund flows. Evans and Sun (Forthcoming) show that mutual fund investors use simple heuristics such as star ratings, rather than asset-pricing models, for risk adjustment. Ben-David et al. (2019) further argue that star ratings explain mutual fund investors' behavior much better than any asset pricing models. These recent studies cast doubt on the premise that mutual fund investors (most of whom are retail investors) are sophisticated enough to use asset pricing models in their capital allocation across mutual funds, as suggested by Berk and van Binsbergen (2016) and Barber et al. (2016). My paper weighs in on this debate by taking the perspective of mutual fund managers and showing that mutual fund managers themselves also respond strongly to star ratings.

Last, my paper adds to the literature on managerial incentives that exist around various thresholds. Bollen and Pool (2009) uncover a discontinuity in the distribution of hedge fund monthly returns at zero and present evidence that hedge fund managers tend to overstate monthly returns to temporarily avoid reporting losses. Lee et al. (2019) show that mutual fund managers with performance-based contracts and mid-year performance close to their announced benchmarks tend to increase their portfolio risk in the second part of the year. In a corporate setting, Begley (2015) finds that firms close to key Debt/EBITDA thresholds are more likely to reduce R&D and SG&A expenditures, presumably to boost EBITDA and receive higher credit ratings, especially prior to bond issuance.

3 Morningstar Ratings

At the end of each month, mutual fund share classes are rated by Morningstar on an integer scale of one star (the lowest rating) to five stars (the highest rating). Star ratings are determined by within-category rankings of Morningstar Risk-Adjusted Return (MRAR) over the prior three, five, and ten years, depending on data availability. MRAR has gone through several methodological changes over time. In October 2016, Morningstar removed load adjustment from the calculation of star ratings. In June 2002, Morningstar changed the risk-adjustment process in the computation of MRAR, which is currently defined as follows (Morningstar (2016)):

$$MRAR(\gamma) = \left[\frac{1}{T}\sum_{t=1}^{T}(1+ER_t)^{-\gamma}\right]^{-\frac{12}{\gamma}} - 1, \quad \gamma > -1, \gamma \neq 0 \tag{1}$$

where ER_t is the geometric excess return over the risk-free rate in month t, γ is the risk-aversion coefficient, and T is the number of months in the time period. Morningstar sets $\gamma = 2$ in the calculation of star ratings, arguing that doing so results in fund rankings that are consistent with the risk tolerances of typical retail investors.[9] Prior to the June 2002 change, Morningstar used a rather complicated process of adjusting for risk. I refer interested readers to Sharpe (1998) and Blume (1998) for detailed explanations of the risk-adjustment process Morningstar used until May 2002.

In addition to the risk-adjustment process, Morningstar refined its peer groups used to rank mutual funds in June 2002. Specifically, Morningstar started raking U.S. equity mutual funds within its nine (three-by-three style box) categories along the size dimension (small, mid-cap, or large) and value dimension (value, blend, or growth), whereas all U.S. equity mutual funds, as a single category group, were ranked against each other until May 2002. On the basis of within-

[9]Morningstar explains that MRAR is motivated by expected utility theory. To see this, let $ER^{CE}(\gamma)$ denote the certainty equivalent geometric excess return with a risk-aversion coefficient of γ. With a power utility function, $u(1+ER^{CE}(\gamma)) = E[u(1+ER)]$ becomes $(1+ER^{CE})^{-\gamma} = E[(1+ER)^{-\gamma}], \gamma > -1, \gamma \neq 0$. Thus, $MRAR(\gamma)$ is the annualized estimate of the certainty equivalent geometric excess return, $ER^{CE}(\gamma) = E[(1+ER)^{-\gamma}]^{-\frac{1}{\gamma}} - 1$. See Morningstar (2016) for further details.

category rankings of MRAR, the top 10% of mutual fund share classes receive five stars, the next 22.5% four stars, the middle 35% three stars, the next 22.5% two stars, and the bottom 10% receive one star, approximately following a normal distribution.

Overall star ratings are determined by the weighted averages of three, five, and ten-year star ratings, depending data availability, rounded to the nearest integer value. Share classes less than three years old are not rated. Share classes at least three years old but less than five years old are rated based only on three-year star ratings. Share classes at least five years old but less than ten years old are rated based on three-year star ratings (40 percent weight) and five-year star ratings (60 percent weight). Share classes at least ten years old are rated based on three-year star ratings (20 percent weight), five-year star ratings (30 percent weight), and ten-year star ratings (50 percent weight).

Table 1 shows the transition matrix where each element in row i and column j represents the probability of a mutual fund share class receiving rating j at the end of month t conditional on its receiving rating i at the end of month $t-1$. More than 10% of mutual fund share classes experience changes in star ratings each month. Not surprisingly, ten-year star ratings are most persistent, followed by five-year star ratings, and three-year star ratings are least persistent. Being weighted averages, overall star ratings are more persistent than three-year star ratings, but less persistent than five- and ten-year star ratings.

[Insert Table 1]

4 Data and Variable Construction

My primary data come from the survivorship-bias-free Morningstar Direct database, from which I obtain data on returns, total net assets (TNA), Morningstar categories, star ratings, inception dates, expense ratios, turnover ratios, index-fund indicators, and institutional share class indicators for the period from 1990 to 2018. I obtain the risk-free rate from Fama-French Research

Factors.

To obtain within-category percentile rankings that are not contaminated by the outcomes of the last trading session of the month, while replicating the rankings based on Morningstar Risk-Adjusted Returns (MRAR) as closely as possible, I rank mutual fund share classes on the basis of Sharpe ratio calculated using daily returns in excess of the risk-free rate over the prior three, five, and ten-years, but only through the second-to-last trading day of the month. Sharpe (1998) finds that ranking funds based on Sharpe ratio gives results that are very similar to ranking funds based on MRAR in his sample from 1994 to 1996. MRAR, however, has gone through several methodological changes over time. In June 2002, Morningstar changed the risk-adjustment process in the computation of MRAR along with its peer groups used to rank mutual funds. In October 2016, Morningstar removed load adjustment from the calculation of star ratings. Nevertheless, I find that ranking funds based on Sharpe ratio computed using daily returns without load adjustment gives results that are very similar to ranking funds based on MRAR computed using monthly returns and adjusted for sales charges throughout my sample. Specifically, I find that in untabulated results, star ratings replicated based on Sharpe ratio computed using daily returns without load adjustment are highly correlated with star ratings that are actually assigned by Morningstar in my sample from 1990 to 2018 (with a correlation coefficient over 83%). The 83% correlation is only slightly lower than the 90% correlation reported by Evans and Sun (Forthcoming) when the authors replicate star ratings by following the *exact* MRAR as closely as possible over the period from July 1999 to May 2002.

Following the Morningstar rating methodology, I rank all U.S. equity mutual funds against each other as a single category group until May 2002, whereas I rank funds within Morningstar's nine (three-by-three style box) categories along the size dimension (small, mid-cap, or large) and value dimension (value, blend, or growth) starting in June 2002. Index funds are kept in the ranking procedure to be consistent with Morningstar's rating methodology, but excluded from the main analysis because my paper focuses on actively-managed funds. Next, I compute overall within-category percentile rankings by taking weighted-averages of three, five, and ten-year within-category percentile rankings, consistent with how overall star ratings are determined. Share classes less than three years old are excluded from the analysis because they are not rated. For share classes at least three years old but less than five years old, overall rankings equal three-year rankings. For share classes at least five years old but less than ten years old, overall rankings are weighted averages of three-year rankings (40 percent weight) and five-year rankings (60 percent weight). For share classes at least ten years old, overall rankings are weighted averages of three-year rankings (20 percent weight), five-year rankings (30 percent weight), and ten-year rankings (50 percent weight). Finally, I compute the distance to a rating threshold as the distance between overall within-category percentile rankings and the nearest rating threshold at the end of the second-to-last trading day of the month. There are four rating thresholds dividing all mutual funds into five star ratings: 10^{th}, 32.5^{th}, 77.5^{th}, and 90^{th} percentiles. Mutual fund share classes above 95^{th} percentile or below 5^{th} percentile are excluded from the analysis because they are closer to the corners of the performance spectrum where no ratings are separated.

In my later analysis, I conduct placebo tests to corroborate that the negative relation between the distance to a rating threshold and month-end NAV inflation is likely causal. To accomplish this, I calculate *placebo* within-category percentile rankings by reversing the June 2002 change in Morningstar's rating methodology. Specifically, I rank mutual funds within Morningstar categories *prior to* June 2002 while ranking all U.S. equity mutual funds against each other as a single category group staring in June 2002. The *placebo* distance to a rating threshold is then computed based on the *placebo* within-category percentile rankings.

Following the literature, I estimate fund flows for each mutual fund share class i during month t as follows:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}} \tag{2}$$

where $TNA_{i,t}$ is the total net asset at the end of month t and $R_{i,t}$ is the return during month t. Table 2 provides the summary statistics on all variables used in the analysis throughout my paper. All continuous variables are winsorized at 1% and 99%.

[Insert Table 2]

5 Star Rating Manipulation via Portfolio Pumping

I begin this section by presenting evidence that mutual fund managers manipulate star ratings by inflating their month-end portfolio values, especially when their funds are likely to finish the month in the vicinity of a rating threshold. To establish causality, I exploit the June 2002 change in Morningstar's star rating methodology to corroborate that this month-end performance manipulation is indeed designed to influence star ratings. Then, I show that star rating manipulation through portfolio pumping is more pronounced among funds with greater incentives and abilities to pump their portfolios and manipulate star ratings. Last, in sub-period tests, I uncover that portfolio pumping to manipulate star ratings has become more evasive following heightened regulatory scrutiny prompted by Carhart et al. (2002).

5.1 Distance to a Rating Threshold and Performance Inflation

The incentive to inflate month-end performance metrics is greater when funds are near rating cutoffs because even a small increase in performance rankings (such as going from 89^{th} percentile to 90^{th} percentile) can make discrete changes in star ratings (such as going from four stars to five stars), which lead to a large jump in fund flows (Reuter and Zitzewitz (2015)). To test this star rating manipulation hypothesis, I exploit the cross-sectional variation in the distance to a rating threshold prior to rating updates at the end of the month.

As a first path, I visually inspect the relation between the distance to a rating threshold measured at the end of the second-to-last trading day of the month and month-end performance inflation. For each bin with the equal length of one-tenth of a percentile (i.e., 0.001) distance to a rating threshold, I compute average daily returns of mutual fund share classes in excess of S&P 500 returns across each cross-section, weighted by the inverse of the number of share classes belonging to the same fund. Then, I compute the time-series averages of the cross-sectional average excess returns in the spirit of Fama and MacBeth (1973). In addition, I estimate the fitted curve from the regression of the excess return on the squared distance to a rating threshold and report a 95% confidence interval in the shaded area.

Figure 1 reports the results of this exploratory analysis. On the Y-axis are the average excess returns on the last trading day of the month in Panel A and the average excess returns on the first trading day of the next month in Panel B. Mutual funds, all across the board, tend to earn positive excess returns on the last trading day of the month, whereas earning negative excess returns on the next trading day. This turn-of-the-month return reversal, which has been widely presented as a strong evidence of portfolio pumping, is consistent with the prior literature (e.g., Carhart et al. (2002)).

Next, I turn to examining the cross-sectional difference in the extent to which mutual funds engage in portfolio pumping. On the X-axis is the distance to a rating threshold prior to monthly rating updates, measured at the end of the second-to-last trading day of the month. Panel A shows that the distance to a rating threshold prior to monthly rating updates is negatively associated with the excess return on the last trading day of the month. Compared to their distant peers, mutual funds that are close to rating thresholds tend to earn higher returns on the last trading day of the month. In addition, the effect of being closer to a rating threshold appears to be concave, suggesting that the incentive to inflate month-end performance figures diminishes more rapidly as funds are farther away from rating thresholds. Panel B shows that the distance to a rating threshold prior to monthly rating updates is positively associated with the excess return on the first trading day of the subsequent month, reversing the pattern on the previous trading day. This turn-of-the-month return pattern surrounding rating thresholds suggests that the closer fund rankings are to rating thresholds, the more likely mutual fund managers are to engage in portfolio pumping.

[Insert Figure 1]

To formally examine the relation between the distance to a rating threshold and month-end performance inflation, I estimate the variants of the following linear regression model:

$$R_{i,t}^{Last\ day}\ (R_{i,t+1}^{First\ day}) = \beta \times \mathit{Squared\ distance}_{i,t} + \gamma \times \mathit{Covariates}_{i,t-1} + \theta_{i,t} + \varepsilon_{i,t} \tag{3}$$

where i indexes mutual fund share classes and t indexes time in month. The dependent variable is share class i's percentage return in excess of S&P 500 on the last trading day of month t or on the first trading day of month $t+1$. The independent variable of interest, $\mathit{Squared\ distance}_{i,t}$, is the squared distance between share class i's within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. $\mathit{Covariates}_{i,t-1}$ are a vector of share class characteristics that include the logarithmic of total net assets (TNA) (in \$ million), logarithmic of age (in years), turnover ratio, expense ratio (in percent), and an indicator variable for institutional share class at the end of month $t-1$. All regressions include category $\times$ month fixed-effects ($\theta_{i,t}$), consistent with Morningstar's within-category ranking procedure. Standard errors are double-clustered by fund and by month.

Since star ratings are assigned to mutual fund share classes, mutual funds with multiple share classes may have different star ratings. In my sample, about 54% of fund-month observations with multiple share classes have multiple star ratings. Although star ratings are assigned at the share class level, portfolio decisions are made at the fund level. To account for multiplicity of fund-level observations, I estimate share-class-level regressions with the weighted least squares (WLS) estimation in which each share-class-month observation is weighted by the inverse of the number of share classes belonging to the same fund so that each fund-month observation is equally weighted. Alternatively, regressions could be run at the fund level, with share-class-level variables aggregated to the fund-level, as is standard in the mutual fund literature. For robustness checks, I estimate the equivalent regressions at the fund level with the ordinary least squares (OLS) estimation and report the results in the Internet Appendix. All results remain qualitatively and quantitatively similar.

The regression results are presented in Table 3. In the first two columns, the dependent variable is $R_{i,t}^{Last\ day}$. The estimate $\hat{\beta}$ is negative and statistically significant at the 1% level, both with and without controlling for a host of share class characteristics. The results are consistent with the star rating manipulation hypothesis that mutual fund managers are more likely to inflate their month-end performance figures when their rankings are closer to rating thresholds prior to monthly rating updates. The economic magnitude of month-end performance inflation is meaningful given that returns are accumulated over just one day and the average excess return is about 7 basis points on the last trading day of the month. The estimate $\hat{\beta}$ in column (1) suggests that compared to funds that are farther away (11.25^{th} to 17.5^{th} percentile), funds near rating thresholds on average earn 0.56 to 1.35 basis point higher returns on the last trading day of the month.

In the last two columns of Table 3, I replace the dependent variable with $R_{i,t+1}^{First\ day}$. The estimate $\hat{\beta}$ flips in sign and turns positive, and is statistically significant at the 10% level, both with or without controlling for share class characteristics. The comparison of the magnitude of $\hat{\beta}$s across columns suggests that a significant fraction the larger gains on the last trading day of the month earned by funds near rating thresholds dissipate immediately on the first trading day of the subsequent month. This turn-of-the-month return reversal further supports that month-end performance inflation is indeed driven by portfolio pumping (Carhart et al. (2002)). Overall, my results suggest that mutual fund managers manipulate star ratings by shifting a little bit of performance from the next month to the current month, especially when they are likely to finish the month in the vicinity of a rating threshold.

[Insert Table 3]

5.2 Placebo Tests

Some may concern that higher returns on the last trading day of the month earned by funds near rating thresholds could be driven by other factors that are also correlated with the distance to a rating threshold prior to rating updates. To address potential endogeneity concerns, I conduct placebo tests to corroborate that the month-end performance inflation that I document in the previous subsection is indeed specifically designed to inflate star ratings.

5.2.1 Reversing the June 2002 Morningstar's Star Rating Methodology

To establish causality, I exploit the June 2002 change in Morningstar's star rating methodology (e.g., Evans and Sun (Forthcoming)). In addition to changing the risk adjustment process, Morningstar refined its peer groups used to rank mutual funds. In June 2002, Morningstar started raking U.S. equity mutual funds within its nine (three-by-three style box) categories along the size dimension (small, mid-cap, or large) and value dimension (value, blend, or growth), whereas all U.S. equity mutual funds were ranked against each other within a single category group prior to the change.

I measure *placebo* within-category percentile rankings by reversing the June 2002 change in Morningstar's star rating methodology. That is, I rank U.S. equity mutual funds within Morningstar's nine categories on the basis of the new version of MRAR (Morningstar (2016)) until May 2002, while ranking all U.S. equity mutual funds against each other within a single category group on the basis of the old version of MRAR (Blume (1998)) starting in June 2002. Then, I compute the *placebo* distance to a rating threshold as the distance between *placebo* within-category percentile rankings and the nearest rating threshold.

Not surprisingly, *placebo* within-category percentile rankings are highly correlated with the ones that closely follow Morningstar's star rating methodology (correlation coefficient = 0.76), as shown in Panel A of Figure 2. Nevertheless, using a slightly different ranking methodology has a significant impact on within-category percentile rankings when measured relative to rating thresholds. Put differently, a small distortion of within-category percentile rankings results in a large change in distances to rating thresholds. As shown in Panel B of Figure 2, the correlation between *placebo* distances to rating thresholds and the ones that are based on Morningstar's star rating methodology is very low (correlation coefficient = 0.10).

[Insert Figure 2]

Using the *placebo* distance to a rating threshold, I estimate the variants of the following linear regression model:

$$R_{i,t}^{Last\ day}\ (R_{i,t+1}^{First\ day}) = \beta \times Squared\ placebo\ distance_{i,t} + \gamma \times Covariates_{i,t-1} + \theta_{i,t} + \varepsilon_{i,t} \qquad (4)$$

where i indexes mutual fund share classes and t indexes time in month. The dependent variable is share class i's percentage return in excess of S&P 500 on the last trading day of month t or on the first trading day of month $t+1$. $Squared\ placebo\ distance_{i,t}$ is the squared distance between share class i's *placebo* within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. $Covariates_{i,t-1}$ are the same set of share class characteristics as in Equation (3). All regressions include category $\times$ month fixed-effects ($\theta_{i,t}$), consistent with Morningstar's within-category ranking procedure, and are estimated with the weighted least squares (WLS) estimation in which each share-class-month observation is weighted by the inverse of the number of share classes belonging to the same fund. Standard errors are double-clustered by fund and by month.

The regression results are presented in Table 4. In the first two columns, the dependent variable is $R_{i,t}^{Last\ day}$. The estimate $\hat{\beta}$ is close to zero and statistically insignificant, with or without controls for share class characteristics. In addition, the estimate $\hat{\beta}$ is positive, rather than being negative. In the last two columns, I replace the dependent variable with $R_{i,t+1}^{First\ day}$. Again, the estimate $\hat{\beta}$ is close to zero and statistically insignificant. Thus, the *placebo* distance to a rating threshold does not have any discernible impact on month-end performance inflation. The null results in placebo tests corroborate that the month-end performance inflation that I document in Section 5.1 is indeed specifically designed to influence star ratings. Furthermore, the null effects from a slight distortion of within-category percentile rankings from the ones that closely follow Morningstar's star rating methodology also support the implicit identifying assumption that mutual fund managers have fairly precise knowledge about their rankings prior to monthly rating updates.

[Insert Table 4]

5.2.2 Using Index Funds

Unlike actively-managed mutual funds, index mutual funds that are passively tracking benchmark indexes have limited incentives and abilities to pump their portfolios. For this reason, index funds have thus far been excluded from the analysis, although they are kept in the ranking procedure to be consistent with Morningstar's star rating methodology. I conduct additional placebo tests using index mutual funds. Specifically, I re-estimate the linear regression model in Equation (3) using a sample of index funds.

The regression results are presented in Table 5. In the first two columns, the dependent variable is $R_{i,t}^{Last\ day}$. The estimate $\hat{\beta}$ is close to zero and statistically insignificant, with or without controls for share class characteristics. In addition, the estimate $\hat{\beta}$ is positive, rather than being negative. In the last two columns, I replace the dependent variable with $R_{i,t+1}^{First\ day}$. Again, the estimate $\hat{\beta}$ is close to zero and statistically insignificant. Thus, my results suggest that there is no relation between the distance to a rating threshold and month-end performance inflation among index funds. The null results in a sample of index funds further mitigate potential endogeneity concerns that higher returns on the last trading day of the month earned by funds near rating thresholds could be driven by other factors that are also correlated with the distance to a rating threshold prior to rating updates.

[Insert Table 5]

5.3 Are All Star Ratings Created Equal?

Star rating manipulation has unique cross-sectional predictions about the extent to which fund managers manipulate star ratings because not all star ratings are created equal. Building on this observation, I test a set of cross-sectional predictions that star rating manipulation through month-end performance inflation should be more pronounced among mutual funds with greater incentives and abilities to manipulate star ratings.

First, since the assignment of star ratings is subject to data availability, it becomes much more difficult for funds to manipulate star ratings as their return history extends further. While completely determining overall star ratings for mutual fund share classes with a return history of less than five years, three-year star ratings based on the past 36 monthly returns account for only a small faction (20 to 40 percent) of overall star ratings for mutual fund share classes with a longer return history. Second, Reuter and Zitzewitz (2015) find that discontinuities in the flow-performance relation are greater at higher rating cutoffs and strongest at the four/five-star cutoff. Similarly, Del Guercio and Tkac (2008) find that among all rating changes, upgrades from four to five stars have the greatest impact on fund flows. Hence, the negative relation between the distance to a rating threshold and month-end performance inflation should be more pronounced among funds with a return history of less than five years and around the four/five-star cutoff.

To test the above cross-sectional predictions, I add an interaction term in Equation (3) and estimate the variants of the following linear regression model:

$$
\begin{aligned}
R_{i,t}^{Last\ day} = {} & \delta \times Squared\ distance_{i,t} \times Sensitivity_{i,t} \\
& + \beta \times Squared\ distance_{i,t} + \rho \times Sensitivity_{i,t} + \gamma \times Covariates_{i,t-1} + \theta_{i,t} + \varepsilon_{i,t}
\end{aligned}
\tag{5}
$$

where i indexes mutual fund share classes and t indexes time in month. The dependent variable is share class i's percentage return in excess of S&P 500 on the last trading day of month t. *Squared distance*$_{i,t}$ is the squared distance between share class i's within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. The interaction term, *Sensitivity*$_{i,t}$, is (1) an indicator variable that takes the value of one if share class i's overall star ratings at the end of month t are to be completely determined by three-year star ratings and zero otherwise, or (2) an indicator variable that takes the value of one if share class i's within-category percentile rankings are closest to the four/five-star cutoff at the end of the second-to-last trading day of month t and zero otherwise. *Covariates*$_{i,t-1}$ are the same set of share class characteristics as in Equation (3). All regressions include category $\times$ month fixed-effects ($\theta_{i,t}$), consistent with Morningstar's within-category ranking procedure, and are estimated with the weighted least squares (WLS) estimation in which each share-class-month observation is weighted by the inverse of the number of share classes belonging to the same fund. Standard errors are double-clustered by fund and by month.

The regression results are presented in Table 6. In the first two columns, *Sensitivity*$_{i,t}$ is an indicator variable for three-year star ratings. Consistent with my prediction, the estimate $\hat{\delta}$ is negative and statistically significant at the 5% level. In addition, the estimate $\hat{\beta}$ is also negative and statistically significant at the conventional levels, and the magnitude of $\hat{\delta}$ is about two to three times as large as that of $\hat{\beta}$. Compared to young funds that are farther away (11.25^{th} to 17.5^{th} percentile), young funds with a return history of less than five years that are near rating thresholds on average earn 1.0 to 2.5 basis point higher returns on the last trading day of the month. This negative relation is weaker among older funds with a return history of at least five years.

[Insert Table 6]

In the last two columns of Table 6, *Sensitivity*$_{i,t}$ is an indicator variable for four/five-star cutoff. Consistent with my prediction, the estimate $\hat{\delta}$ is negative and statistically significant at the

5% level. In addition, the estimate $\hat{\beta}$ is also negative and statistically significant at the 5% level without controls in column (3), although it loses its statistical significance (t-statistic = -1.55) with controls for share class characteristics in column (4). The magnitude of $\hat{\delta}$ is about five to six times as large as that of $\hat{\beta}$. Overall, my results suggest that star rating manipulation through portfolio pumping is much more pronounced among funds around the four/five-star cutoff, consistent with the star rating effect on fund flows (Del Guercio and Tkac (2008), Reuter and Zitzewitz (2015)).

In the corresponding fund-level regression results presented in Table IA5 in the Internet Appendix, an indicator variable is replaced by the proportion of a fund's total net assets belonging to its share classes for which an indicator variable takes the value of one. Consistent with the share-class-level WLS results, the fund-level OLS results show that the negative relation between the distance to a rating threshold and month-end performance inflation is more pronounced among funds for which a greater fraction of their total net assets consist of share classes with a return history of less than five years and share classes around the four/five-star cutoff.

5.4 More Cross-sectional Tests

Prior studies on portfolio pumping make several cross-sectional predictions about the extent to which fund managers engage in portfolio pumping. Building on the prior literature, I test a set of cross-sectional predictions that portfolio pumping to manipulate star ratings should be more pronounced among funds with greater incentives and abilities to pump their portfolios.

First, Carhart et al. (2002) argue that if fund managers are indeed "marking up" their portfolio values, performance inflation should be more pronounced among small-cap funds because the closing prices of less liquid stocks would presumably be easier to influence. Second, Patel and Sarkissian (Forthcoming) argue that peer effects among teams such as the presence of peer monitoring and joint monetary incentives are effective in deterring fund managers from engaging in illegal trading activities such as portfolio pumping. Hence, the negative relation between the distance to a rating threshold and month-end performance inflation should be more pronounced among small-cap funds and single-managed funds, weakening as the size of management team increases.

To test the above cross-sectional predictions, I estimate the linear regression model in Equation (5) where for an interaction term, $Sensitivity_{i,t}$, I use (1) an indicator variable that takes the value of one if share class i belongs to one of the small-cap categories and zero otherwise, or (2) the logarithmic of the number of named managers of mutual fund share class i, all prior to the end of month t.

The regression results are presented in Table 7. In the first two columns, $Sensitivity_{i,t}$ is an indicator variable for small-cap funds. Consistent with Carhart et al. (2002), the estimate $\hat{\delta}$ is negative and statistically significant at the 5% level, with or without controls for share class characteristics. In addition, the estimate $\hat{\beta}$ is also negative and the magnitude of $\hat{\delta}$ is about three to six times as large as that of $\hat{\beta}$. Compared to small-cap funds that are farther away (11.25^{th} to 17.5^{th} percentile), small-cap funds near rating thresholds on average earn 1.1 to 2.6 basis point higher returns on the last trading day of the month. This negative relation is substantially weaker among mid- and large-cap funds.

In the last two columns of Table 7, $Sensitivity_{i,t}$ is the logarithmic of the number of named managers of mutual fund share class i prior to the end of month t. Consistent with Patel and Sarkissian (Forthcoming), the estimate $\hat{\delta}$ is positive. The estimate $\hat{\delta}$ is also statistically significant at the 10% level when share class characteristics are controlled for. In addition, the estimate $\hat{\beta}$ is negative and statistically significant at the 1% level. Compared to single-managed funds that are farther away (11.25^{th} to 17.5^{th} percentile), single-managed funds near rating thresholds on average earn 0.7 to 1.6 basis point higher returns on the last trading day of the month. This negative relation weakens as the size of management team increases, presumably due to peer effects among teams.

[Insert Table 7]

5.5 Has Portfolio Pumping Become More Evasive?

After the initial results of Carhart et al. (2002) drew a great deal of attention from regulators, academics, and practitioners, the U.S. Securities and Exchange Commission (SEC) began to investigate suspicious trading activities such as portfolio pumping (Duong and Meschke (2020)). Consistent with heightened regulatory attention, recent studies find that portfolio pumping has become more evasive (e.g., Hu et al. (2014), Wang (2019)). My results are also consistent with the notion that fund managers exercise caution when they engage in illegal trading activities such as portfolio pumping. Specifically, the extent to which fund managers inflate their month-end performance figures is greater when fund rankings are closer to the rating thresholds prior to monthly rating updates.

I conjecture that fund managers may pump their portfolios to manipulate star ratings when portfolio pumping is less likely to attract regulatory attention. Just like academic studies on portfolio pumping that have largely focused on quarter-ends (especially year-ends), the regulatory attention may also have been limited to quarter/year-ends that are naturally more important because reporting on a quarterly, semi-annual, or annual basis is common in the mutual fund industry. Duong and Meschke (2020) find that compared to the early period of 1992 to 2000, portfolio pumping has substantially declined at quarter-ends and almost disappeared at year-ends in the later period of 2001 to 2011. These findings are not inconsistent with my conjecture. Unlike prior studies, my paper focuses on all month-ends, allowing me to directly test the above conjecture that portfolio pumping may have migrated from quarter/year-ends to less prominent month-ends.

To test the above conjecture, I add an interaction term in Equation (3) and estimate the variants of the following linear regression model:

$$R_{i,t}^{\textit{Last day}} = \beta \times \textit{Squared distance}_{i,t} + \delta \times \textit{Squared distance}_{i,t} \times \textit{Quarter-end}_t + \gamma \times \textit{Covariates}_{i,t-1} + \theta_{i,t} + \varepsilon_{i,t} \tag{6}$$

where i indexes mutual fund share classes and t indexes time in month. The dependent variable is share class i's percentage return in excess of S&P 500 on the last trading day of month t. $\textit{Squared distance}_{i,t}$ is the squared distance between share class i's within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. The interaction term, $\textit{Quarter-end}_t$, is an indicator variable that takes the value of one if month t is March, June, September, or December, and zero otherwise. $\textit{Covariates}_{i,t-1}$ are the same set of share class characteristics as in Equation (3). All regressions include category $\times$ month fixed-effects ($\theta_{i,t}$), consistent with Morningstar's within-category ranking procedure, and are estimated with the weighted least squares (WLS) estimation in which each share-class-month observation is weighted by the inverse of the number of share classes belonging to the same fund. Standard errors are double-clustered by fund and by month.

The regression results are presented in Table 8. The results from the early period (January 1990 to May 2002) are reported in the first two columns. The estimates $\hat{\beta}$ and $\hat{\delta}$ are both negative and statistically significant at the conventional levels. Hence, my results suggest that the extent to which fund managers engage in portfolio pumping to manipulate star ratings was greater at quarter/year-ends than at less prominent month-ends in the early period, consistent with the prior literature's focus on quarter/year-ends (e.g., Carhart et al. (2002), Hu et al. (2014)).

The above calendar month pattern, however, reverses in the later period (June 2002 to December 2018), as reported in the last two columns of Table 8. The estimate $\hat{\beta}$ is negative and statistically significant at the conventional levels, suggesting that mutual fund managers still engage in portfolio pumping to manipulate star ratings at month-ends that are not quarter- or year-ends. The estimate $\hat{\delta}$, however, turns positive and is statistically significant at the conventional levels.

The sum of the estimates $(\hat{\beta} + \hat{\delta})$ is close to zero and statistically insignificant. Thus, portfolio pumping to manipulate star ratings has largely disappeared at quarter/year-ends, consistent with Duong and Meschke (2020).

Overall, my results in this subsection suggest that following heightened regulatory scrutiny prompted by Carhart et al. (2002), portfolio pumping to manipulate star ratings appears to have largely migrated from quarter/year-ends to less prominent month-ends. This calendar effect, which is novel to the literature on portfolio pumping, is consistent with the findings in recent studies that portfolio pumping has become more evasive (e.g., Hu et al. (2014), Wang (2019)).

[Insert Table 8]

5.6 Robustness Checks

In this subsection, I provide some robustness checks on my baseline results in Section 5.1. For the main identification, I exploit *cross-sectional* variation in the distance to a rating threshold prior to monthly rating updates. Alternatively, I could exploit time-series variation in percentile rankings and distances to rating thresholds because star ratings are based on the past performance on a rolling basis. For instance, a fund's rankings may sharply rise (or fall) as the fund "rolls" out of a bad month and "rolls" into a good month (or vice versa). Building on this observation, I exploit *time-series* variation in the distance to a rating threshold to explain the month-end performance inflation. Specifically, I replace category $\times$ month fixed-effects with fund fixed-effects and re-estimate the linear regression model in Equation (3). As reported in Panel A of Table 9, my results remain qualitatively similar. Funds tend to earn higher returns on the last trading day of the month when their rankings are closer to rating thresholds, compared to when their rankings are farther away from rating thresholds.

In Section 5.1, I use the *squared* distance to a rating threshold as the independent variable of interest to reflect the curvature in the relation between the distance to a rating threshold and month-end performance inflation, as shown in Figure 1. For a robustness check, I replace the *squared* distance with the distance and re-estimate the linear regression model in Equation (3). As reported in Panel B of Table 9, my results remain qualitatively similar. Compared to distant peers, mutual funds near rating thresholds tend to earn significantly higher returns on the last trading day of the month, which partially reverses on the first trading day of the next month.

[Insert Table 9]

6 The Effects of Star Rating Manipulation

Some may wonder what fund managers would gain from engaging in portfolio pumping because it only shifts a little bit of performance from the next month to the current month. In this section, I exploit the two-stage least squares (2SLS) estimation to show that portfolio pumping can temporarily inflate star ratings, thereby increasing future fund flows, especially in the month of a rating upgrade.

6.1 The Effect of Portfolio Pumping on Star Ratings

The results in Section 5 suggest that fund managers manipulate star ratings by inflating month-end portfolio values, especially when their funds are likely to finish the month near rating cutoffs. Portfolio pumping, however, could lower performance figures for the next month because because a large fraction of gains on the last trading day of the month dissipate immediately on the first trading day of the subsequent month. Theoretical studies on portfolio pumping also suggest that portfolio pumping, while improving a fund's short-term values, may hurt its long-term values (e.g., Bhattacharyya and Nanda (2013)). In this subsection, I examine the *net* effect of portfolio pumping on star ratings in the current and subsequent months as a first-step to examining the effects of star rating manipulation. To account for the adverse effect of portfolio pumping on performance figures for the next month, I use the turn-of-the-month return reversal, $\frac{R_{i,t}^{Last\ day} - R_{i,t+1}^{First\ day}}{2}$, instead of the return on the last day of the month, to measure the extent to which fund managers engage in portfolio pumping.

Specifically, I estimate the variants of the following linear regression model:

$$\mathbb{1}(\textit{Ratings change}_{i,t+s}) = \beta \times \frac{R_{i,t}^{\textit{Last day}} - R_{i,t+1}^{\textit{First day}}}{2} + \gamma \times \textit{Covariates}_{i,t-1} + \theta_{i,t+s} + \varepsilon_{i,t+s}, \quad s = 0, 1 \quad (7)$$

where i indexes mutual fund share classes and t indexes time in month. The dependent variable is (1) $\mathbb{1}(\textit{Upgrade}_t)$, which is an indicator variable that takes the value of one if share class i receives a rating upgrade at the end of month t and zero otherwise, or (2) $\mathbb{1}(\textit{Downgrade}_{t+1} \mid \textit{Upgrade}_t)$, which is an indicator variable that takes the value of one if share class i receives a rating downgrade at the end of month $t+1$ after receiving a rating upgrade at the end of month t and zero otherwise. The independent variable of interest, $(R_{i,t}^{\textit{Last day}} - R_{i,t+1}^{\textit{First day}})/2$, is share class i's return reversal around the turn of month t. Returns are in excess of S&P 500. $\textit{Covariates}_{i,t-1}$ are the same set of share class characteristics as in Equation (3). All regressions include category $\times$ month fixed-effects ($\theta_{i,t+s}$) to be consistent with Morningstar's within-category ranking procedure, and are estimated with the weighted least squares (WLS) estimation in which each share-class-month observation is weighted by the inverse of the number of share classes belonging to the same fund. Standard errors are double-clustered by fund and by month.

The regression results are presented in Table 10. In columns (1) and (2), the dependent variable is $\mathbb{1}(\textit{Upgrade}_t)$. In column (1), the estimate $\hat{\beta}$ is positive and statistically significant at the 1% level, suggesting that portfolio pumping is effective in inflating star ratings at the end of the month. The estimate $\hat{\beta}$ remains largely unchanged when share class characteristics are controlled for in column (2). One standard deviation increase in the return reversal around the turn of the month is associated with a 77 basis point increase in the probability of a rating upgrade at the end of the month. The economic magnitude is also meaningful given that the unconditional probability of a rating upgrade is about 7 percent.

In columns (3) and (4), I replace the dependent variable with $\mathbb{1}(Downgrade_{i,t+1} \mid Upgrade_{i,t})$. The estimate $\hat{\beta}$ is positive and statistically significant at the 1% level, suggesting that portfolio pumping also increases the conditional probability of an immediate rating downgrade at the end of the subsequent month following a rating upgrade. One standard deviation increase in the return reversal around the turn of the month is associated with a 2.97 percent increase in the probability of an immediate rating downgrade following an upgrade. The economic magnitude is also meaningful given that the conditional probability of an immediate rating downgrade following an upgrade is about 29 percent.

Overall, the results suggest that portfolio pumping is effective in inflating star ratings. Those inflated star ratings induced by portfolio pumping are more likely to revert back to the previous level in the subsequent month. These results are consistent with prior studies suggesting that portfolio pumping is effective only in the short run (e.g., Bhattacharyya and Nanda (2013)). Next, I turn to examining how portfolio pumping affects future fund flows by temporarily inflating star ratings.

[Insert Table 10]

6.2 The Effect of Star Rating Manipulation on Fund Flows

Examining the effect of star rating manipulation on fund flows poses an empirical challenge because changes in star ratings (especially upgrades) have a large impact on fund flows (Del Guercio and Tkac (2008)) and a rating upgrade is at most only partially attributable to portfolio pumping. To tease out the effect of a rating upgrade that can be attributable to portfolio pumping, I exploit the following two-stage least squares (2SLS) estimation: In the first stage, I estimate the effect of portfolio pumping on a rating upgrade as a linear probability model, as in Section 6.1. In the second stage, I estimate the effect of star rating manipulation on fund flows using the fitted value of the probability of a rating upgrade from the first-stage regression.

Specifically, I estimate the variants of the following 2SLS model:

$$\begin{aligned}\mathbb{1}(\mathit{Upgrade}_{i,t}) = \beta_1 \times \frac{R_{i,t}^{\mathit{Last\ day}} - R_{i,t+1}^{\mathit{First\ day}}}{2} + \gamma_1 \times \mathit{Covariates}_{i,t-1} \\ + \eta_1 \times \mathit{Additional\ controls}_{i,t} + \theta_{1,i,t} + \varepsilon_{1,i,t} \quad \text{(first stage)}\end{aligned} \tag{8}$$

$$\begin{aligned}\mathit{Flow}_{i,t+s} = \beta_2 \times \mathbb{1}(\widehat{\mathit{Upgrade}}_{i,t}) + \gamma_2 \times \mathit{Covariates}_{i,t-1} \\ + \eta_1 \times \mathit{Additional\ controls}_{i,t} + \theta_{2,i,t+s} + \varepsilon_{2,i,t+s}, \quad s = 1,2,3 \quad \text{(second stage)}\end{aligned} \tag{9}$$

where i indexes mutual fund share classes and t indexes time in month. The first-stage regression in Equation (8) is similar to that in Equation (7) in the previous subsection. In the second-stage, the dependent variable, $\mathit{Flow}_{i,t+s}$, is share class i' fund flows as percentage of the beginning-of-the-month TNA during month $t+s$, $s = 1,2,3$. The independent variable of interest, $\mathbb{1}(\widehat{\mathit{Upgrade}}_{i,t})$, is the fitted value of the probability of a rating upgrade at the end of month t from the corresponding first-stage regression. $\mathit{Covariates}_{i,t-1}$ include the same set of share class characteristics as in Equation (3). $\mathit{Additional\ controls}_{i,t}$ include contemporaneous and lagged fund flows ($\mathit{Flow}_{i,t-s}$) and returns ($R_{i,t-s}$), $s = 0,1,2$. The contemporaneous return, $R_{i,t}^{\text{ex Last Day}}$, is cumulative only up to the second-to-last trading day of month t. Returns are in excess of S&P 500. All regressions include category × month fixed-effects ($\theta_{1,i,t}, \theta_{2,i,t+s}$) to be consistent with Morningstar's within-category ranking procedure, and are estimated with the weighted least squares (WLS) estimation in which each share-class-month observation is weighted by the inverse of the number of share classes belonging to the same fund. Standard errors are double-clustered by fund and by month.

The 2SLS results are presented in Table 11. The first-stage regression in columns (1) and (2) is similar to the one in column (2) of Table 10, except for $\mathit{Additional\ controls}_{i,t}$ including contemporaneous fund flows and returns in column (1) and contemporaneous and lagged fund flows and returns in column (2). Consistent with the results in the previous subsection, the estimate $\hat{\beta}_1$ is positive and statistically significant at the 1% level, suggesting that portfolio pumping significantly increases the probability of a rating upgrade at the end of the month. The inclusion of contemporaneous and lagged returns and flows only strengthens the results. Not surprisingly, the contemporaneous return up to the second-to-last trading day of the month also significantly increases the probability of a rating upgrade at the end of the month. In contrast, lagged returns do not have any significant impact on a rating upgrade at the end of the month because these returns affect star ratings both at the end of month t and month $t-1$. That is, changes in star ratings are primarily driven by the exclusion of the oldest month's return and inclusion of the current month's return on a rolling basis in the computation of Morningstar Risk-Adjusted Returns (MRAR).

In the second-stage regression in columns (3) and (4), the dependent variable is $Flow_{i,t+1}$. In column (3), the estimate $\hat{\beta}_2$ is positive and statistically significant at the 1% level, suggesting that star rating manipulation leads to additional fund flows in the month of a rating upgrade. The estimate $\hat{\beta}_2$ remains qualitatively and quantitatively similar when I additionally control for lagged fund flows and returns in column (4). In the remaining columns, I replace the dependent variable with $Flow_{i,t+s}$, $s = 2, 3$. The estimate $\hat{\beta}_2$ is positive, albeit statistically insignificant, suggesting that portfolio pumping does not lower fund flows in the subsequent months. If anything, the gains in fund flows extend beyond the month of a rating upgrade.

Overall, the 2SLS results suggest that portfolio pumping increases the probability of a rating update at the end of the month (first-stage), thereby increasing fund flows, especially in the month of a rating upgrade (second-stage). As inflated star ratings revert to the previous level in the subsequent month, fund flows also tend to subside to the previous level in the following months. Nevertheless, the gains in fund flows driven by star rating manipulation through portfolio pumping are not offset by any significant reductions in fund flows in the subsequent months.

[Insert Table 11]

7 Conclusion

The idea that mutual fund investors use risk-adjusted returns in their capital allocation decision is appealing and has motivated some prominent financial economists to use mutual fund flows to test asset pricing models. Berk and van Binsbergen (2016), for instance, conclude that the capital asset pricing model (CAPM) is the "closest to the asset pricing model investors are actually using." Barber et al. (2016) independently reach the same conclusion. Evans and Sun (Forthcoming), however, argue that mutual fund investors actually follow simple heuristics such as star ratings that are strongly correlated with the CAPM alpha. Ben-David et al. (2019) further argue that star ratings explain mutual fund investors' behavior much better than any asset pricing models, concluding that star ratings are the main determinant of capital allocation across mutual funds.

Given that mutual fund investors rely heavily on star ratings, it is natural to ask whether and how star ratings distort the incentives of mutual fund managers. The incentive to inflate performance metrics is naturally greater when funds are closer to rating cutoffs because even a small increase in fund rankings (such as going from 89^{th} percentile to 90^{th} percentile) can make discrete changes in star ratings (such as going from four stars to five stars) and lead to a large jump in fund flows (Reuter and Zitzewitz (2015)). Consistent with this prediction, I find that U.S. equity mutual fund managers manipulate star ratings by inflating month-end portfolio values when they are likely to finish the month in the vicinity of rating thresholds.

Compared to their distant peers, mutual funds near rating thresholds experience substantially larger gains on the last trading day of the month, which partially dissipate on the next trading day. These results suggest that the closer fund rankings are to rating cutoffs, the greater the extent to which portfolio managers engage in portfolio pumping (Zweig (1997), Carhart et al. (2002)). Placebo tests exploiting the June 2002 change in Morningstar's rating methodology yield expected null effects, corroborating that month-end performance inflation is indeed specifically designed to inflate star ratings. In cross-sectional tests, I further show that portfolio pumping to manipulate star ratings is more pronounced among funds with greater incentives and abilities to pump their portfolios and manipulate star ratings. For instance, star rating manipulation through portfolio pumping is more pronounced among funds with a shorter return history and around the four/five star rating cutoff. Exploiting the two-stage least squares (2SLS) estimation, I show that portfolio pumping increases the probability of a rating update at the end of the month, thereby increasing future fund flows, especially in the month of a rating upgrade.

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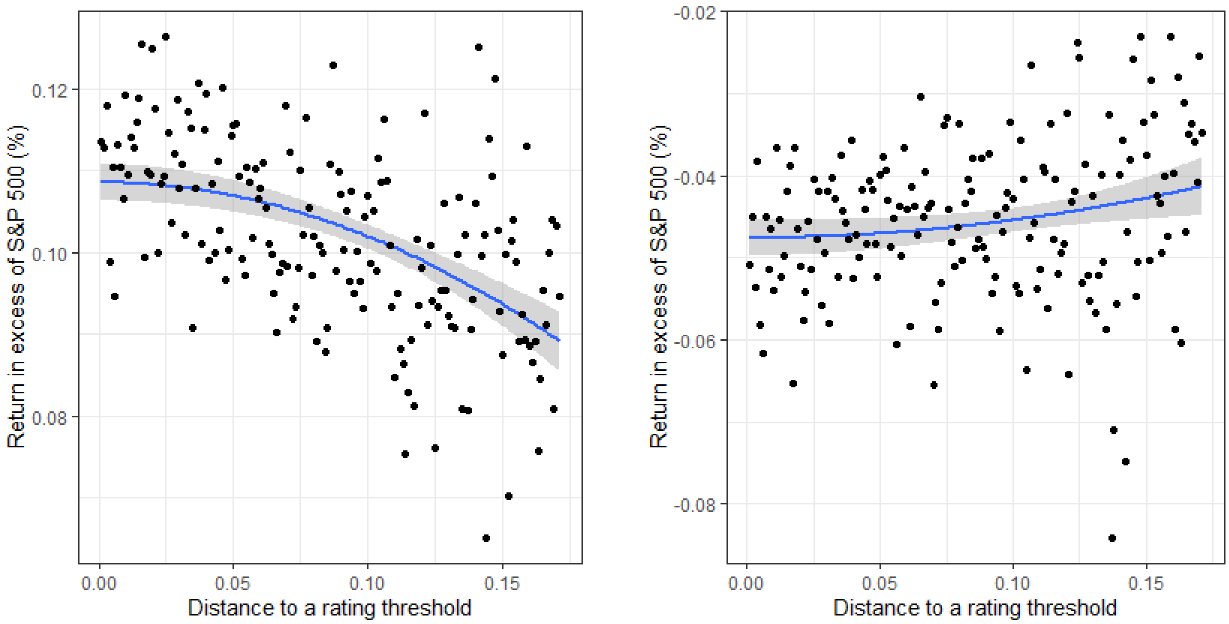
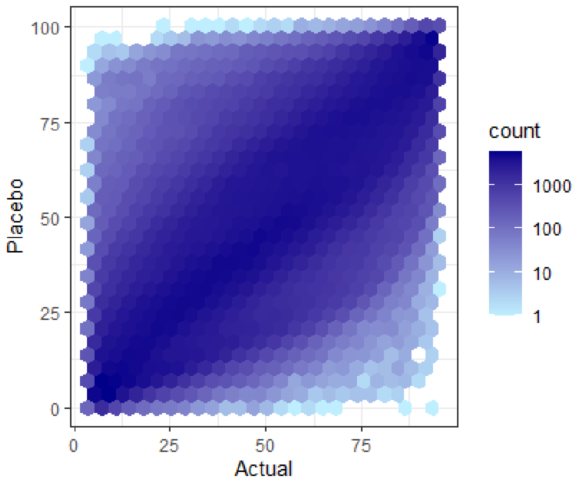


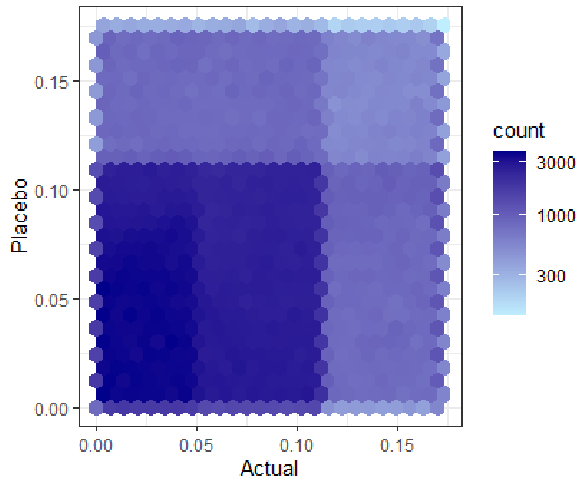
Panel A: On the last day of month t Panel B: On the first day of month $t+1$

Figure 1: Distance to a Rating Threshold and Month-End NAV Inflation

This figure plots the average fund returns in excess of the S&P 500 index on the last trading day of month t in Panel A and on the first trading day of month $t+1$ in Panel B across equally spaced bins of the distance to a rating threshold at the end of the second-to-last trading day of month t. For each bin with the equal length of one-tenth of a percentile (i.e., 0.001), I compute average daily returns of mutual fund share classes in excess of the S&P 500 index across each cross-section, weighted by the inverse of the number of share classes belonging to the same fund. Then, I compute the time-series averages of the cross-sectional average excess returns in the spirit of Fama and MacBeth (1973). In addition, I estimate the fitted curve from the regression of the excess return on the squared distance to a rating threshold and report a 95% confidence interval in the shaded area. The sample covers the period from 1990 to 2018.



Panel A: Within-category percentile rankings



Panel B: Distances to rating thresholds

Figure 2: Correlation between Actual vs. Placebo Rankings and Distances to Rating Thresholds

This figure shows the correlation between actual within-category percentile rankings and placebo within-category percentile rankings (correlation coefficient = 0.76) in Panel A and the correlation between actual distances to rating thresholds and placebo distances to rating thresholds (correlation coefficient = 0.10) in Panel B. *Actual* within-category percentile rankings and distances to rating thresholds are based on the actual Morningstar rating methodology. *Placebo* within-category percentile rankings and distances to rating thresholds are obtained by reversing the June 2002 change in Morningstar rating methodology. That is, I compute *placebo* within-category percentile rankings using the new rating methodology until May 2002 and the old one starting in June 2002. Then, I compute the *placebo* distance to a rating threshold as the distance between *placebo* within-category percentile rankings and the nearest rating threshold. The details on the construction of distance measures are provided in Section 4.

Table 1: Transition Matrix of Star Ratings

This table reports the transition matrix where each element in row i and column j represents the probability (in percent) of a mutual fund share class receiving star rating j at the end of month t conditional on its receiving star rating i at the end of month $t-1$. At the end of each month, mutual fund share classes are rated by Morningstar on an integer scale of one star (the lowest rating) to five stars (the highest rating) on the basis of Morningstar Risk-Adjusted Return (MRAR) over the prior three, five, and ten years, depending on data availability. On the basis of within-category rankings of MRAR, the top 10% of mutual fund share classes receive five stars, the next 22.5% four stars, the middle 35% three stars, the next 22.5% two stars, and the bottom 10% receive one star. Overall star ratings are determined by the weighted averages of three, five, and ten-year star ratings, depending on data availability, rounded to the nearest integer value. Share classes less than three years old are not rated. Share classes at least three years old but less than five years old are rated based only on three-year star ratings. Share classes at least five years old but less than ten years old are rated based on three-year star ratings (40 percent weight) and five-year star ratings (60 percent weight). Share classes at least ten years old are rated based on three-year star ratings (20 percent weight), five-year star ratings (30 percent weight), and ten-year star ratings (50 percent weight).

Panel A: Three-year star ratings

	At the end of month t				
At the end of month $t-1$	⋆	⋆⋆	⋆⋆⋆	⋆⋆⋆⋆	⋆⋆⋆⋆⋆
⋆	87.08	12.63	0.24	0.04	0.01
⋆⋆	5.20	83.82	10.82	0.15	0.01
⋆⋆⋆	0.05	8.21	84.10	7.54	0.10
⋆⋆⋆⋆	0.02	0.15	13.16	80.75	5.92
⋆⋆⋆⋆⋆	0.004	0.04	0.38	14.93	84.65

Panel B: Five-year star ratings

	At the end of month t				
At the end of month $t-1$	⋆	⋆⋆	⋆⋆⋆	⋆⋆⋆⋆	⋆⋆⋆⋆⋆
⋆	89.50	10.33	0.13	0.03	0.01
⋆⋆	4.39	86.69	8.80	0.10	0.02
⋆⋆⋆	0.03	6.73	87.18	6.00	0.06
⋆⋆⋆⋆	0.01	0.09	10.78	84.28	4.84
⋆⋆⋆⋆⋆	0.003	0.01	0.21	12.30	87.47

Table 1–*Continued*

Panel C: Ten-year star ratings

	At the end of month t				
At the end of month $t-1$	$\star$	$\star\star$	$\star\star\star$	$\star\star\star\star$	$\star\star\star\star\star$
$\star$	92.64	7.25	0.10	0.004	0.002
$\star\star$	3.39	90.03	6.52	0.05	0.01
$\star\star\star$	0.02	4.98	90.87	4.11	0.03
$\star\star\star\star$	0.002	0.04	7.61	88.90	3.45
$\star\star\star\star\star$	0	0.002	0.05	8.94	91.00

Panel D: Overall star ratings

	At the end of month t				
At the end of month $t-1$	$\star$	$\star\star$	$\star\star\star$	$\star\star\star\star$	$\star\star\star\star\star$
$\star$	87.55	12.18	0.23	0.03	0.01
$\star\star$	3.81	86.34	9.73	0.11	0.01
$\star\star\star$	0.04	6.72	86.87	6.32	0.05
$\star\star\star\star$	0.01	0.11	10.82	84.66	4.41
$\star\star\star\star\star$	0.001	0.02	0.29	14.16	85.53

Table 2: Summary Statistics

This table reports the summary statistics on the share-class-level variables. $R_t^{\text{Last Day}}$ and $R_{t+1}^{\text{First Day}}$ are a mutual fund share class's returns (in percent) on the last trading day of month t and on the first trading day of month $t+1$, respectively. Returns are in excess of the S&P 500 index. *Distance*, is the distance (in decimals) between a mutual fund share class's within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of the month. *Placebo distance* is the distance (in decimals) between a mutual fund share class's *placebo* within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of the month. *Placebo* within-category percentile rankings are obtained by reversing the June 2002 change in Morningstar rating methodology. The details on the construction of distance measures are provided in Section 4. Share class characteristics include total net assets (TNA) (in $ million), age (in years), turnover ratio, expense ratio (in percent), and an indicator variable for institutional share class. $\mathbb{1}$(Small-cap) is an indicator variable that takes the value of one if a mutual fund share class belongs to one of the small-cap categories and zero otherwise. *N Managers* is the number of named managers of a mutual fund share class. $\mathbb{1}$(Three-year rating) is an indicator variable that takes the value of one if a mutual fund share class's overall star ratings at the end of the month are to be completely determined by three-year star ratings and zero otherwise. $\mathbb{1}$(Four/five-star cutoff) is an indicator variable that takes the value of one if a mutual fund share class's within-category percentile rankings are closest to the four/five-star cutoff at the end of the second-to-last trading day of the month and zero otherwise. $\mathbb{1}$(Quarter-end) is an indicator variable that takes the value of one if a month is March, June, September, or December, and zero otherwise. $\mathbb{1}(\text{Upgrade}_t)$ is an indicator variable that takes the value of one if a mutual fund share class receives a rating upgrade at the end of month t and zero otherwise. $\mathbb{1}(\text{Downgrade}_{t+s} \mid \text{Upgrade}_t)$ is an indicator variable that takes the value of one if a mutual fund share class receives a rating downgrade at the end of month $t+s$ after receiving an upgrade at the end of month t and zero otherwise ($s = 1, 2$). Flow_{t+s} is a mutual fund share class's fund flows as percentage of the beginning-of-the-month TNA during month $t+s$ ($s = -2, -1, 0, 1, 2, 3$). R_{t+s} is a mutual fund share class's return during month $t-s$ ($s = 1, 2$). $R_t^{\text{ex Last Day}}$ is a mutual fund share class's return during month t cumulative up to the second-to-last trading day of month t. All continuous variables are winsorized at 1% and 99%. The sample covers the period from 1990 to 2018.

Variable	Obs.	Mean	St. Dev.	Q_1	Median	Q_3
$R_t^{\text{Last Day}}$ (%)	1,252,358	0.07	0.43	−0.14	0.05	0.26
$R_{t+1}^{\text{First Day}}$ (%)	1,252,358	−0.03	0.47	−0.24	−0.01	0.21
$(R_t^{\text{Last Day}} - R_{t+1}^{\text{First Day}})/2$ (%)	1,252,358	0.05	0.33	−0.12	0.03	0.20
Distance	1,252,358	0.07	0.05	0.03	0.06	0.10
Placebo distance	1,252,358	0.07	0.04	0.03	0.06	0.10
TNA (in $million)	1,141,114	467.33	1,295.58	12.48	65.81	301.41
Age (in years)	1,252,358	11.64	9.20	5.67	9.21	14.35
Turnover	1,218,346	0.77	0.63	0.34	0.61	1.01
Expense ratio (%)	1,218,613	1.33	0.49	0.98	1.25	1.65
$\mathbb{1}$(Institutional)	1,252,358	0.19	0.40	0	0	0
$\mathbb{1}$(Small-cap)	1,252,358	0.22	0.41	0	0	0
N Managers	1,239,838	2.66	2.03	1	2	3
$\mathbb{1}$(Three-year rating)	1,252,358	0.23	0.42	0	0	0
$\mathbb{1}$(Four/five-star cutoff)	1,252,358	0.14	0.35	0	0	0
$\mathbb{1}$(Quarter-end)	1,252,358	0.34	0.47	0	0	1

Table 2–*Continued*

Variable	Obs.	Mean	St. Dev.	Q_1	Median	Q_3
$\mathbb{1}(\text{Upgrade}_t)$	$1,241,336$	0.07	0.26	0.00	0.00	0.00
$\mathbb{1}(\text{Downgrade}_{t+1} \mid \text{Upgrade}_t)$	$86,391$	0.29	0.45	0.00	0.00	1.00
$\mathbb{1}(\text{Downgrade}_{t+2} \mid \text{Upgrade}_t)$	$85,911$	0.34	0.48	0.00	0.00	1.00
Flow_{t-2} (%)	$1,122,543$	0.06	8.12	-1.78	-0.50	0.76
Flow_{t-1} (%)	$1,122,543$	-0.04	7.68	-1.81	-0.51	0.74
Flow_{t} (%)	$1,126,532$	0.06	8.95	-1.81	-0.51	0.74
Flow_{t+1} (%)	$1,120,116$	-0.03	8.06	-1.82	-0.52	0.72
Flow_{t+2} (%)	$1,113,624$	-0.08	7.62	-1.82	-0.53	0.70
Flow_{t+3}(%)	$1,108,185$	-0.13	7.33	-1.83	-0.54	0.68
R_{t-2} (%)	$1,252,358$	0.13	2.12	-0.88	0.10	1.11
R_{t-1} (%)	$1,252,358$	0.13	2.11	-0.87	0.10	1.11
$R_t^{\text{ex Last Day}}$ (%)	$1,252,358$	0.05	2.07	-0.91	0.05	1.03

Table 3: Distance to a Rating Threshold and Month-End NAV Inflation

This table presents the results of the variants of the following linear regression model:

$$R_{i,t}^{Last\ day}\ (R_{i,t+1}^{First\ day}) = \beta \times Squared\ distance_{i,t} + \gamma \times Covariates_{i,t-1} + \theta_{i,t} + \varepsilon_{i,t}$$

where i indexes mutual fund share classes and t indexes time in month. The dependent variable is share class i's return (in percent) on the last trading day of month t or on the first trading day of month $t+1$. Returns are in excess of the S&P 500 index. The independent variable of interest, $Squared\ distance_{i,t}$, is the squared distance between share class i's within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. $Covariates_{i,t-1}$ are a vector of share class characteristics that include the logarithmic of total net assets (TNA) (in $ million), logarithmic of age (in years), turnover ratio, expense ratio (in percent), and an indicator variable for institutional share class. All regressions include category × month fixed-effects ($\theta_{i,t}$) and are estimated with the weighted least squares (WLS) estimation in which each share-class-month observation is weighted by the inverse of the number of share classes belonging to the same fund. Standard errors are double-clustered by fund and by month, and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. The sample covers the period from 1990 to 2018.

	$R_t^{\text{Last Day}}$		$R_{t+1}^{First\ day}$	
	(1)	(2)	(3)	(4)
Squared distance	−0.44***	−0.33***	0.24*	0.19*
	(−4.00)	(−3.31)	(1.95)	(1.76)
log(TNA)		0.004***		−0.001
		(4.30)		(−1.53)
log(Age)		−0.01***		0.003
		(−4.58)		(1.48)
Turnover		0.01**		0.003
		(2.47)		(0.64)
Expense ratio		0.02***		−0.02***
		(5.78)		(−5.49)
$\mathbb{1}$(Institutional)		0.01***		−0.01***
		(3.74)		(−4.38)
Category × Month FE	Yes	Yes	Yes	Yes
Observations	1,252,358	1,110,321	1,252,358	1,110,321
Adjusted R^2	0.45	0.46	0.45	0.46

Table 4: Placebo Tests: Reversing the June 2002 Change in Morningstar Rating Methodology

This table presents the results of the variants of the following linear regression model:

$$R_{i,t}^{Last\ day}\ (R_{i,t+1}^{First\ day}) = \beta \times Squared\ placebo\ distance_{i,t} + \gamma \times Covariates_{i,t-1} + \theta_{i,t} + \varepsilon_{i,t}$$

where i indexes mutual fund share classes and t indexes time in month. The dependent variable is share class i's return (in percent) on the last trading day of month t or on the first trading day of month $t+1$. Returns are in excess of the S&P 500 index. The independent variable of interest, $Squared\ placebo\ distance_{i,t}$, is the squared distance between share class i's *placebo* within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. *Placebo* within-category percentile rankings are obtained by reversing the June 2002 change in Morningstar rating methodology. That is, I compute *placebo* within-category percentile rankings using the new rating methodology until May 2002 and the old one starting in June 2002. $Covariates_{i,t-1}$ are the same set of share class characteristics as in Table 3. All regressions include category × month fixed-effects ($\theta_{i,t}$) and are estimated with the weighted least squares (WLS) estimation in which each share-class-month observation is weighted by the inverse of the number of share classes belonging to the same fund. Standard errors are double-clustered by fund and by month, and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. The sample covers the period from 1990 to 2018.

	$R_t^{\text{Last Day}}$		$R_{t+1}^{First\ day}$	
	(1)	(2)	(3)	(4)
Squared *placebo* distance	0.01	0.09	0.09	0.03
	(0.13)	(1.03)	(1.10)	(0.39)
log(TNA)		0.004***		−0.001
		(4.14)		(−1.47)
log(Age)		−0.01***		0.003
		(−4.45)		(1.47)
Turnover		0.01**		0.004
		(2.47)		(0.68)
Expense ratio		0.02***		−0.02***
		(5.69)		(−5.36)
$\mathbb{1}$(Institutional)		0.01***		−0.01***
		(3.80)		(−4.39)
Category × Month FE	Yes	Yes	Yes	Yes
Observations	1,252,358	1,095,824	1,252,358	1,095,824
Adjusted R^2	0.45	0.46	0.45	0.46

Table 5: Placebo Tests: Index Funds

This table presents the results of the variants of the following linear regression model in a sample of index funds:

$$R_{i,t}^{Last\ day}\ (R_{i,t+1}^{First\ day}) = \beta \times Squared\ distance_{i,t} + \gamma \times Covariates_{i,t-1} + \theta_{i,t} + \varepsilon_{i,t}$$

where i indexes mutual fund share classes and t indexes time in month. The dependent variable is share class i's return (in percent) on the last trading day of month t or on the first trading day of month $t+1$. Returns are in excess of the S&P 500 index. The independent variable of interest, $Squared\ distance_{i,t}$, is the squared distance between share class i's within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. $Covariates_{i,t-1}$ are the same set of share class characteristics as in Table 3. All regressions include category × month fixed-effects ($\theta_{i,t}$) and are estimated with the weighted least squares (WLS) estimation in which each share-class-month observation is weighted by the inverse of the number of share classes belonging to the same fund. Standard errors are double-clustered by fund and by month, and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. The sample covers the period from 1990 to 2018.

	$R_t^{\text{Last Day}}$		$R_{t+1}^{First\ day}$	
	(1)	(2)	(3)	(4)
Squared distance	0.01	0.01	−0.01	−0.04
	(0.04)	(0.05)	(−0.04)	(−0.20)
log(TNA)		−0.0003		0.001
		(−0.25)		(0.89)
log(Age)		−0.002		0.001
		(−0.20)		(0.23)
Turnover		0.002		−0.003
		(0.38)		(−0.76)
Expense ratio		−0.01		0.003
		(−1.11)		(0.43)
$\mathbb{1}$(Institutional)		−0.003		0.002
		(−0.45)		(0.42)
Category × Month FE	Yes	Yes	Yes	Yes
Observations	81,728	75,156	81,728	75,156
Adjusted R^2	0.72	0.72	0.74	0.75

Table 6: Are All Star Ratings Created Equal?

This table presents the results of the variants of the following linear regression model:

$$\begin{aligned} R_{i,t}^{Last\ day} &= \delta \times \mathit{Squared\ distance}_{i,t} \times \mathit{Sensitivity}_{i,t} \\ &+ \beta \times \mathit{Squared\ distance}_{i,t} + \rho \times \mathit{Sensitivity}_{i,t} + \gamma \times \mathit{Covariates}_{i,t-1} + \theta_{i,t} + \varepsilon_{i,t} \end{aligned}$$

where i indexes mutual fund share classes and t indexes time in month. The dependent variable is share class i's return (in percent) on the last trading day of month t. Returns are in excess of the S&P 500 index. $\mathit{Squared\ distance}_{i,t}$ is the squared distance between share class i's within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. $\mathit{Sensitivity}_{i,t}$ is (1) an indicator variable that takes the value of one if share class i's overall star ratings at the end of month t are to be completely determined by three-year star ratings and zero otherwise, or (2) an indicator variable that takes the value of one if share class i's within-category percentile rankings are closest to the four/five-star cutoff at the end of the second-to-last trading day of month t and zero otherwise. $\mathit{Covariates}_{i,t-1}$ are the same set of share class characteristics as in Table 3. All regressions include category × month fixed-effects ($\theta_{i,t}$) and are estimated with the weighted least squares (WLS) estimation in which each share-class-month observation is weighted by the inverse of the number of share classes belonging to the same fund. Standard errors are double-clustered by fund and by month, and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. The sample covers the period from 1990 to 2018.

	$R_t^{\text{Last Day}}$			
	(1)	(2)	(3)	(4)
Squared distance × 𝟙(Three-year rating)	−0.52**	−0.55**		
	(−2.21)	(−2.36)		
Squared distance × 𝟙(Four/five-star cutoff)			−1.38**	−1.10**
			(−2.48)	(−1.98)
Squared distance	−0.29***	−0.19**	−0.26**	−0.19
	(−2.85)	(−2.07)	(−2.07)	(−1.55)
𝟙(Three-year rating)	0.01**	−0.004		
	(2.17)	(−1.35)		
𝟙(Four/five-star cutoff)			0.02**	0.02*
			(2.08)	(1.79)
log(TNA)		0.004***		0.003***
		(4.04)		(3.82)
log(Age)		−0.01***		−0.01***
		(−4.48)		(−3.85)
Turnover		0.01**		0.01**
		(2.46)		(2.49)
Expense ratio		0.02***		0.02***
		(5.58)		(5.69)
𝟙(Institutional)		0.01***		0.01***
		(3.71)		(3.80)
Category × Month FE	Yes	Yes	Yes	Yes
Observations	1,252,358	1,095,824	1,252,358	1,095,824
Adjusted R^2	0.45	0.46	0.45	0.46

Table 7: More Cross-Sectional Tests

This table presents the results of the variants of the following linear regression model:

$$R_{i,t}^{Last\ day} = \delta \times Squared\ distance_{i,t} \times Sensitivity_{i,t} + \beta \times Squared\ distance_{i,t} + \rho \times Sensitivity_{i,t} + \gamma \times Covariates_{i,t-1} + \theta_{i,t}\ (\theta_t) + \varepsilon_{i,t}$$

where i indexes mutual fund share classes and t indexes time in month. The dependent variable is share class i's return (in percent) on the last trading day of month t. Returns are in excess of the S&P 500 index. $Squared\ distance_{i,t}$ is the squared distance between share class i's within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. $Sensitivity_{i,t}$ is (1) an indicator variable that takes the value of one if share class i belongs to one of the small-cap categories and zero otherwise, or (2) the logarithmic of the number of named managers of mutual fund share class i, prior to the end of month t. $Covariates_{i,t-1}$ are the same set of share class characteristics as in Table 3. All regressions include category × month fixed-effects ($\theta_{i,t}$) or month fixed-effects (θ_t) and are estimated with the weighted least squares (WLS) estimation in which each share-class-month observation is weighted by the inverse of the number of share classes belonging to the same fund. Standard errors are double-clustered by fund and by month, and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. The sample covers the period from 1990 to 2018.

	$R_t^{\text{Last Day}}$			
	(1)	(2)	(3)	(4)
Squared distance × 𝟙(Small-cap)	−0.63**	−0.68**		
	(−2.16)	(−2.35)		
Squared distance × log(N Managers)			0.16	0.16*
			(1.62)	(1.68)
Squared distance	−0.22*	−0.12	−0.52***	−0.44***
	(−1.85)	(−1.11)	(−3.55)	(−3.31)
𝟙(Small-cap)	0.09***	0.08***		
	(3.82)	(3.61)		
log(N Managers)			−0.0004	−0.001
			(−0.24)	(−0.30)
log(TNA)		0.004***		0.004***
		(4.18)		(4.24)
log(Age)		−0.01***		−0.01***
		(−3.77)		(−4.40)
Turnover		0.01**		0.01**
		(2.21)		(2.36)
Expense ratio		0.02***		0.02***
		(5.38)		(5.59)
𝟙(Institutional)		0.01***		0.01***
		(2.79)		(3.61)
Category × Month FE	No	No	Yes	Yes
Month FE	Yes	Yes	No	No
Observations	1,252,358	1,095,824	1,239,838	1,085,804
Adjusted R^2	0.29	0.30	0.46	0.47

Table 8: Has Portfolio Pumping Become More Evasive?

This table presents the results of the variants of the following linear regression model in sub-periods:

$$R_{i,t}^{Last\ day} = \beta \times Squared\ distance_{i,t} + \delta \times Squared\ distance_{i,t} \times Quarter\text{-}end_t + \gamma \times Covariates_{i,t-1} + \theta_{i,t} + \varepsilon_{i,t}$$

where i indexes mutual fund share classes and t indexes time in month. The dependent variable is share class i's return (in percent) on the last trading day of month t. Returns are in excess of the S&P 500 index. *Squared distance*$_{i,t}$ is the squared distance between share class i's within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. *Quarter-end*$_t$ is an indicator variable that takes the value of one if month t is March, June, September, or December, and zero otherwise. *Covariates*$_{i,t-1}$ are the same set of share class characteristics as in Table 3. All regressions include category $\times$ month fixed-effects ($\theta_{i,t}$) and are estimated with the weighted least squares (WLS) estimation in which each share-class-month observation is weighted by the inverse of the number of share classes belonging to the same fund. Standard errors are double-clustered by fund and by month, and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. The sample covers the period from 1990 to 2018 and is split around the June 2002 change in Morningstar rating methodology.

	$R_t^{\text{Last Day}}$			
	1990:01–2002:05		2002:06–2018:12	
	(1)	(2)	(3)	(4)
Squared distance × 𝟙(Quarter-end)	−1.34*	−1.51**	0.22*	0.24**
	(−1.79)	(−2.05)	(1.93)	(2.08)
Squared distance	−1.11**	−0.70*	−0.17**	−0.14*
	(−2.35)	(−1.70)	(−2.07)	(−1.86)
log(TNA)		0.004		0.002***
		(1.18)		(4.32)
log(Age)		−0.01***		−0.002
		(−3.14)		(−1.12)
Turnover		0.04***		0.002
		(2.64)		(0.57)
Expense ratio		0.06***		0.01***
		(4.86)		(3.23)
𝟙(Institutional)		0.04***		0.002
		(3.76)		(1.00)
Category × Month FE	Yes	Yes	Yes	Yes
Observations	160,944	151,052	1,091,414	944,772
Adjusted R^2	0.28	0.28	0.56	0.57

Table 9: Portfolio Pumping Induced by Star Ratings: Robustness Checks

This table presents the results of the variants of the following linear regression models:

$$R_{i,t}^{Last\ day}\ (R_{i,t+1}^{First\ day}) = \beta \times Squred\ distance_{i,t} + \gamma \times Covariates_{i,t-1} + \alpha_i + \varepsilon_{i,t}$$

and

$$R_{i,t}^{Last\ day}\ (R_{i,t+1}^{First\ day}) = \beta \times Distance_{i,t} + \gamma \times Covariates_{i,t-1} + \theta_{i,t} + \varepsilon_{i,t}$$

where i indexes mutual fund share classes and t indexes time in month. The dependent variable is share class i's return (in percent) on the last trading day of month t or on the first trading day of month $t+1$. Returns are in excess of the S&P 500 index. *Squared distance*$_{i,t}$ is the squared distance between share class i's within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. *Covariates*$_{i,t-1}$ are the same set of share class characteristics as in Table 3. All regressions include fund fixed-effects (α_i) or category × month fixed-effects ($\theta_{i,t}$), and are estimated with the weighted least squares (WLS) estimation in which each share-class-month observation is weighted by the inverse of the number of share classes belonging to the same fund. Standard errors are double-clustered by fund and time, and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. The sample covers the period from 1990 to 2018.

Panel A: Fund fixed-effects, instead of category × month fixed-effects

	$R_t^{\text{Last Day}}$		$R_{t+1}^{First\ day}$	
	(1)	(2)	(3)	(4)
Squared distance	-0.32^{***}	-0.19^{*}	0.11	0.05
	(−2.60)	(−1.73)	(0.83)	(0.41)
log(TNA)		0.01^{***}		-0.01^{**}
		(3.17)		(−2.09)
log(Age)		-0.06^{***}		0.03^{*}
		(−4.70)		(1.85)
Turnover		0.02^{**}		−0.003
		(2.10)		(−0.36)
Expense ratio		0.003		−0.004
		(0.45)		(−0.73)
Fund FE	Yes	Yes	Yes	Yes
Observations	1,252,358	1,095,824	1,252,358	1,095,824
Adjusted R^2	0.03	0.03	0.01	0.01

Table 9–*Continued*

Panel B: Distance, instead of squared distance

	$R_t^{\text{Last Day}}$		$R_{t+1}^{First\ day}$	
	(1)	(2)	(3)	(4)
Distance	-0.08^{***}	-0.06^{***}	0.03^{*}	0.03
	(-4.05)	(-3.58)	(1.68)	(1.44)
log(TNA)		0.004^{***}		-0.001
		(4.12)		(-1.46)
log(Age)		-0.01^{***}		0.003
		(-4.40)		(1.46)
Turnover		0.01^{**}		0.004
		(2.46)		(0.69)
Expense ratio		0.02^{***}		-0.02^{***}
		(5.67)		(-5.40)
$\mathbb{1}$(Institutional)		0.01^{***}		-0.01^{***}
		(3.80)		(-4.40)
Category × Month FE	Yes	Yes	Yes	Yes
Observations	1,252,358	1,095,824	1,252,358	1,095,824
Adjusted R^2	0.45	0.46	0.45	0.46

Table 10: The Effect of Portfolio Pumping on Star Ratings

This table presents the results of the variants of the following linear regression model:

$$\mathbb{1}(\textit{Ratings change}_{i,t+s}) = \beta \times \frac{R_t^{\text{Last Day}} - R_{t+1}^{\text{First Day}}}{2} + \gamma \times \textit{Covariates}_{i,t-1} + \theta_{i,t+s} + \varepsilon_{i,t+s}, \quad s = 0, 1$$

where i indexes mutual fund share classes and t indexes time in month. The dependent variable is (1) $\mathbb{1}(\textit{Upgrade}_{i,t})$, which is an indicator variable that takes the value of one if share class i receives an upgrade in star ratings at the end of month t and zero otherwise, or (2) $\mathbb{1}(\textit{Downgrade}_{i,t+1} \mid \textit{Upgrade}_{i,t})$, which is an indicator variable that takes the value of one if share class i receives a downgrade in star ratings at the end of month $t+1$ after receiving an upgrade at the end of month t and zero otherwise. The independent variable of interest, $(R_{i,t}^{\textit{Last day}} - R_{i,t+1}^{\textit{First day}})/2$, is share class i's daily return reversal (in percent) around the turn of month t. Returns are in excess of the S&P 500 index. $\textit{Covariates}_{i,t-1}$ are the same set of share class characteristics as in Table 3. All regressions include category $\times$ month fixed-effects ($\theta_{i,t+s}$) and are estimated with the weighted least squares (WLS) estimation in which each share-class-month observation is weighted by the inverse of the number of share classes belonging to the same fund. Standard errors are double-clustered by fund and time, and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. The sample covers the period from 1990 to 2018.

Dependent variable:	$\mathbb{1}$(Upgrade$_t$)		$\mathbb{1}$(Downgrade$_{t+1}$ | Upgrade$_t$)	
	(1)	(2)	(3)	(4)
$(R_t^{\text{Last Day}} - R_{t+1}^{\text{First Day}})/2$	0.02***	0.02***	0.09***	0.08***
	(3.74)	(3.63)	(6.25)	(6.08)
log(TNA)		−0.001***		0.003***
		(−2.74)		(2.66)
log(Age)		−0.01***		0.01*
		(−15.33)		(1.96)
Turnover		0.004***		0.002
		(3.73)		(0.60)
Expense ratio		0.01***		0.01
		(4.06)		(1.63)
$\mathbb{1}$(Institutional)		0.002*		−0.0002
		(1.77)		(−0.03)
Category × Month FE	Yes	Yes	Yes	Yes
Observations	1,241,336	1,087,734	86,391	75,597
Adjusted R^2	0.01	0.01	0.06	0.06

Table 11: The Effect of Star Rating Manipulation on Fund Flows

This table presents the results of the variants of the following two-stage least squares (2SLS) model:

$$\mathbb{1}(\mathit{Upgrade}_{i,t}) = \beta_1 \times \frac{R_t^{\text{Last Day}} - R_{t+1}^{\text{First Day}}}{2} + \gamma_1 \times \mathit{Covariates}_{i,t-1} + \eta_1 \times \mathit{Additional\ controls}_{i,t} + \theta_{1,i,t} + \varepsilon_{1,i,t} \quad \text{(first stage)}$$

$$\mathit{Flow}_{i,t+s} = \beta_2 \times \mathbb{1}(\widehat{\mathit{Upgrade}}_{i,t+1}) + \gamma_2 \times \mathit{Covariates}_{i,t-1} + \eta_1 \times \mathit{Additional\ controls}_{i,t} + \theta_{2,i,t+s} + \varepsilon_{2,i,t+s}, \quad s = 1,2,3 \quad \text{(second stage)}$$

where i indexes mutual fund share classes and t indexes time in month. In the first stage, the dependent variable is an indicator variable that takes the value of one if share class i receives a rating upgrade at the end of month t and zero otherwise. The independent variable of interest in the first stage is share class i's daily return reversal (in percent) around the turn of month t. Returns are in excess of the S&P 500 index. In the second stage, the dependent variable is share class i' fund flows as percentage of the beginning-of-the-month TNA during month $t+s$, $s = 1,2,3$. The independent variable of interest in the second stage is the fitted value of the dependent variable in the first stage. $\mathit{Covariates}_{i,t-1}$ are the same set of share class characteristics as in Table 3. $\mathit{Additional\ controls}_{i,t}$ include contemporaneous and lagged fund flows ($\mathit{Flow}_{i,t-s}$), lagged returns ($R_{i,t-s}$), $s = 1,2$, and contemporaneous returns ($R_t^{\text{ex Last Day}}$) cumulative up to the second-to-last trading day of month t. All regressions include category $\times$ month fixed-effects (θ) and are estimated with the weighted least squares (WLS) estimation in which each share-class-month observation is weighted by the inverse of the number of share classes belonging to the same fund. Standard errors are double-clustered by fund and time, and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. The sample covers the period from 1990 to 2018.

Table 11–*Continued*

Dependent variable:	First-stage		Second-stage					
	$\mathbb{1}(\text{Upgrade}_t)$		Flow_{t+1}		Flow_{t+2}		Flow_{t+3}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}(\widehat{\text{Upgrade}_t})$			8.54^{***}	8.43^{***}	2.87	2.97	3.27	3.52
			(3.48)	(3.60)	(1.10)	(1.16)	(1.24)	(1.39)
$(R_t^{\text{Last Day}} - R_{t+1}^{\text{First Day}})/2$	0.03^{***}	0.03^{***}						
	(7.90)	(8.01)						
Flow_t	-0.0000	0.0002	0.16^{***}	-0.35^{***}	0.14^{***}	-0.31^{***}	0.12^{***}	-0.30^{***}
	(-0.31)	(0.94)	(26.47)	(-17.58)	(30.12)	(-18.51)	(29.94)	(-23.04)
Flow_{t-1}		-0.0003		0.57^{***}		0.50^{***}		0.47^{***}
		(-1.10)		(24.64)		(25.62)		(29.96)
Flow_{t-2}		0.0001		0.13^{***}		0.11^{***}		0.09^{***}
		(1.53)		(31.50)		(32.15)		(30.17)
$R_t^{\text{ex Last Day}}$	0.03^{***}	0.03^{***}	-0.07	-0.09	0.10	0.08	0.09	0.06
	(30.76)	(30.64)	(-0.90)	(-1.23)	(1.22)	(1.03)	(1.07)	(0.83)
R_{t-1}		0.001		0.12^{***}		0.14^{***}		0.12^{***}
		(0.91)		(8.69)		(10.08)		(8.97)
R_{t-2}		0.001		0.12^{***}		0.11^{***}		0.13^{***}
		(1.11)		(10.42)		(8.54)		(9.10)
log(TNA)	-0.0003	-0.0003	-0.16^{***}	-0.17^{***}	-0.16^{***}	-0.18^{***}	-0.17^{***}	-0.18^{***}
	(-1.43)	(-1.38)	(-14.47)	(-17.98)	(-15.71)	(-18.85)	(-16.41)	(-19.05)
log(Age)	-0.01^{***}	-0.01^{***}	-0.57^{***}	-0.38^{***}	-0.63^{***}	-0.46^{***}	-0.60^{***}	-0.45^{***}
	(-16.27)	(-16.24)	(-12.24)	(-8.94)	(-13.14)	(-10.43)	(-12.85)	(-10.38)
Turnover	0.004^{***}	0.004^{***}	-0.07^{*}	-0.07^{**}	-0.04	-0.05	-0.05	-0.05^{*}
	(4.01)	(3.98)	(-1.93)	(-2.38)	(-1.28)	(-1.57)	(-1.37)	(-1.66)
Expense ratio	0.01^{***}	0.01^{***}	-0.86^{***}	-0.78^{***}	-0.84^{***}	-0.77^{***}	-0.88^{***}	-0.82^{***}
	(6.55)	(6.54)	(-16.62)	(-17.50)	(-16.14)	(-16.87)	(-16.45)	(-16.87)
$\mathbb{1}$(Institutional)	0.002^{**}	0.002^{*}	-0.29^{***}	-0.24^{***}	-0.29^{***}	-0.24^{***}	-0.31^{***}	-0.26^{***}
	(2.02)	(1.96)	(-6.20)	(-5.76)	(-6.18)	(-5.80)	(-6.48)	(-6.17)
Category × Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,075,491	1,071,857	1,069,355	1,066,029	1,063,102	1,059,987	1,057,854	1,054,814
Adjusted R^2	0.05	0.05	-0.03	0.01	0.04	0.07	0.03	0.05

Internet Appendix for
"Do Mutual Funds Manipulate Star Ratings? Evidence from Portfolio Pumping"

Sanghyun (Hugh) Kim

This Internet Appendix provides fund-level results that are equivalent to the share-class-level results presented in the main text. The fund-level results are obtained by aggregating share-class-level variables to the fund-level and using the ordinary least squares (OLS) estimation.

Table IA1: Summary Statistics

This table reports the summary statistics on the fund-level variables. $R_{i,t}^{\text{Last Day}}$ and $R_{i,t+1}^{\text{First Day}}$ are mutual fund i's returns (in percent) on the last trading day of month t and on the first trading day of month $t+1$, respectively. Returns are in excess of category benchmark returns, computed as average returns across mutual funds belonging to the same Morningstar category starting in June 2002 and across all U.S. equity funds as a single category group prior to June 2002. $Distance_{i,t}$, is the distance (in decimals) between fund i's within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. *Placebo* $distance_{i,t}$ is the distance (in decimals) between fund i's *placebo* within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. *Placebo* within-category percentile rankings are obtained by reversing the June 2002 change in Morningstar's rating methodology when it refined its peer groups used to rank mutual funds. The details on the construction of distance measures are provided in Section 4 of the main text. Fund characteristics include total net assets (TNA) (in $ million), age (in years), turnover ratio, and expense ratio (in percent). Month-end $TNA_{i,t}$ is deflated by $1 + R_{i,t}^{Last\ day}$ to estimate its value at the end of the second-to-last trading day of month t. For mutual funds with multiple share classes, share-class-level variables are aggregated to the fund level by computing the sum of TNAs, the maximum of ages, and the value-weighted averages for the rest of the share-class-level variables. *% Institutional* $TNA_{i,t}$ is the proportion of TNAs from institutional share classes of mutual fund i. $\mathbb{1}$(*Small-cap*$_{i,t}$) is an indicator variable that takes the value of one if fund i belongs to one of the small-cap categories and zero otherwise. *N* $Managers_{i,t}$ is the number of named managers of mutual fund i. *% Three-year* $TNA_{i,t}$ is the proportion of TNAs from share classes of mutual fund i for which overall star ratings at the end of month t are to be completely determined by three-year star ratings. $\mathbb{1}$(*Four/five-star cutoff*$_{i,t}$) is an indicator variable that takes the value of one if fund i's within-category percentile rankings are closest to the four/five-star cutoff at the end of the second-to-last trading day of month t and zero otherwise. $\mathbb{1}$(*Quarter-end*$_t$) is an indicator variable that takes the value of one if month t is March, June, September, or December, and zero otherwise. All continuous variables are winsorized at 1% and 99%. The sample covers the period from 1990 to 2018.

Variable	Obs.	Mean	St. Dev.	Q_1	Median	Q_3
$R_t^{\text{Last Day}}$ (%)	466,078	0.09	0.47	−0.14	0.06	0.30
$R_{t+1}^{\text{First Day}}$ (%)	466,078	−0.04	0.50	−0.26	−0.01	0.22
Distance	466,078	0.07	0.04	0.03	0.06	0.10
Placebo distance	466,078	0.07	0.04	0.03	0.06	0.10
TNA (in $million)	466,078	1,141.11	2,839.99	68.70	253.21	941.11
Age (in years)	466,078	14.96	11.92	6.69	11.49	18.75
Turnover	446,445	0.76	0.65	0.32	0.59	1.00
Expense ratio (%)	450,524	1.17	0.41	0.92	1.13	1.39
% Institutional TNA	466,078	0.26	0.38	0	0	0.5
$\mathbb{1}$(Small-cap)	466,078	0.23	0.42	0	0	0
N Managers	458,059	2.51	2.02	1	2	3
% Three-year rating TNA	466,078	0.27	0.43	0	0	1
$\mathbb{1}$(Four/five-star cutoff)	466,078	0.17	0.36	0	0	0
$\mathbb{1}$(Quarter-end)	466,078	0.33	0.47	0	0	1

Table IA2: Distance to a Rating Threshold and Month-End NAV Inflation

This table presents the results of the following linear regression model:

$$R_{i,t}^{Last\ day}\ (R_{i,t+1}^{First\ day}) = \beta \times Squared\ distance_{i,t} + \gamma \times Covariates_{i,t} + \theta_t + \varepsilon_{i,t}$$

where i indexes mutual funds and t indexes time in month. The dependent variable is fund i's return (in percent) on the last trading day of month t or on the first trading day of month $t+1$. Returns are in excess of category benchmark returns, computed as average returns across mutual funds belonging to the same Morningstar category starting in June 2002 and across all U.S. equity funds as a single category group prior to June 2002. The independent variable of interest, $Squared\ distance_{i,t}$, is the squared distance between fund i's within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. $Covariates_{i,t}$ are a vector of fund characteristics that include the logarithmic of total net assets (TNA) (in $ million), logarithmic of age (in years), turnover ratio, expense ratio (in percent), and the proportion of TNAs from institutional share classes. Month-end $TNA_{i,t}$ is deflated by $1 + R_{i,t}^{Last\ day}$ to estimate its value at the end of the second-to-last trading day of month t. All regressions include time fixed-effects (θ_t) and are estimated with the ordinary least squares (OLS) estimation. Standard errors are double-clustered by fund and time, and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. The sample covers the period from 1990 to 2018.

	$R_t^{\text{Last Day}}$		$R_{t+1}^{First\ day}$	
	(1)	(2)	(3)	(4)
Squared distance	-0.54^{***}	-0.40^{***}	0.23	0.15
	(-4.24)	(-3.58)	(1.59)	(1.18)
log(TNA)		0.004^{***}		-0.0001
		(3.17)		(-0.05)
log(Age)		-0.01^{***}		0.003
		(-4.05)		(1.40)
Turnover		0.01^{**}		0.004
		(2.27)		(0.84)
Expense ratio		0.03^{***}		-0.03^{***}
		(6.15)		(-5.03)
% Institutional TNA		0.01^{**}		-0.01^{***}
		(2.28)		(-3.19)
Category × Month FE	Yes	Yes	Yes	Yes
Observations	466,078	445,756	466,078	445,756
Adjusted R^2	0.46	0.46	0.45	0.46

Table IA3: Placebo Tests: Reversing the June 2002 Change in Morningstar's Rating Methodology

This table presents the results of the following linear regression model:

$$R_{i,t}^{Last\ day}\ (R_{i,t+1}^{First\ day}) = \beta \times Squared\ placebo\ distance_{i,t} + \gamma \times Covariates_{i,t} + \theta_t + \varepsilon_{i,t}$$

where i indexes mutual funds and t indexes time in month. The dependent variable is fund i's return (in percent) on the last trading day of month t or on the first trading day of month $t+1$. Returns are in excess of category benchmark returns, computed as average returns across mutual funds belonging to the same Morningstar category starting in June 2002 and across all U.S. equity funds as a single category group prior to June 2002. The independent variable of interest, $Squared\ placebo\ distance_{i,t}$, is the squared distance between fund i's *placebo* within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. *Placebo* within-category percentile rankings are obtained by reversing the June 2002 change in Morningstar's rating methodology when it refined its peer groups used to rank mutual funds. To accomplish this, I rank mutual funds within Morningstar categories until May 2002, while ranking all U.S. equity mutual funds against each other as a single category group starting in June 2002. $Covariates_{i,t}$ are the same set of fund characteristics as in Table IA2. All regressions include time fixed-effects (θ_t) and are estimated with the ordinary least squares (OLS) estimation. Standard errors are double-clustered by fund and time, and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. The sample covers the period from 1990 to 2018.

	$R_t^{\text{Last Day}}$		$R_{t+1}^{First\ day}$	
	(1)	(2)	(3)	(4)
Squared *placebo* distance	−0.02	0.10	0.14	0.06
	(−0.25)	(1.01)	(1.53)	(0.69)
log(TNA)		0.004***		−0.0001
		(3.20)		(−0.06)
log(Age)		−0.01***		0.003
		(−4.10)		(1.40)
Turnover		0.01**		0.004
		(2.28)		(0.84)
Expense ratio		0.03***		−0.03***
		(6.17)		(−4.97)
% Institutional TNA		0.01**		−0.01***
		(2.27)		(−3.19)
Category × Month FE	Yes	Yes	Yes	Yes
Observations	466,078	445,756	466,078	445,756
Adjusted R^2	0.46	0.46	0.45	0.46

Table IA4: Placebo Tests: Index Funds

This table presents the results of the following linear regression model in a sample of *index funds*:

$$R_{i,t}^{Last\ day}\ (R_{i,t+1}^{First\ day}) = \beta \times \textit{Squared distance}_{i,t} + \gamma \times \textit{Covariates}_{i,t} + \theta_t + \varepsilon_{i,t}$$

where i indexes mutual funds and t indexes time in month. The dependent variable is share class i's return (in percent) on the last trading day of month t or on the first trading day of month $t+1$. Returns are in excess of category benchmark returns, computed as average returns across mutual funds belonging to the same Morningstar category starting in June 2002 and across all U.S. equity funds as a single category group prior to June 2002. $\textit{Squared distance}_{i,t}$ is the squared distance between fund i's within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. $\textit{Covariates}_{i,t}$ are the same set of fund characteristics as in Table IA2. All regressions include time fixed-effects (θ_t) and are estimated with the ordinary least squares (OLS) estimation. Standard errors are double-clustered by fund and time, and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. The sample covers the period from 1990 to 2018.

	$R_t^{\text{Last Day}}$		$R_{t+1}^{First\ day}$	
	(1)	(2)	(3)	(4)
Squared distance	0.003	0.03	−0.07	−0.09
	(0.01)	(0.15)	(−0.29)	(−0.36)
log(TNA)		−0.0003		0.002
		(−0.16)		(1.18)
log(Age)		0.0001		−0.0001
		(0.01)		(−0.03)
Turnover		0.001		−0.002
		(0.12)		(−0.54)
Expense ratio		−0.01		0.01
		(−0.68)		(0.61)
% Institutional TNA		−0.01		0.005
		(−1.04)		(0.86)
Category × Month FE	Yes	Yes	Yes	Yes
Observations	36,077	34,999	36,077	34,999
Adjusted R^2	0.71	0.72	0.74	0.74

Table IA5: Are All Star Ratings Created Equal?

This table presents the results of the following linear regression model:

$$R_{i,t}^{Last\ day} = \delta \times Squared\ distance_{i,t} \times Sensitivity_{i,t} + \beta \times Squared\ distance_{i,t} + \rho \times Sensitivity_{i,t} + \gamma \times Covariates_{i,t} + \theta_t + \varepsilon_{i,t}$$

where i indexes mutual funds and t indexes time in month. The dependent variable is fund i's return (in percent) on the last trading day of month t. Returns are in excess of category benchmark returns, computed as average returns across mutual funds belonging to the same Morningstar category starting in June 2002 and across all U.S. equity funds as a single category group prior to June 2002. $Squared\ distance_{i,t}$ is the squared distance between fund i's within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. $Sensitivity_{i,t}$ is (1) the proportion of TNAs from share classes of mutual fund i for which overall star ratings at the end of month t are to be completely determined by three-year star ratings, or (2) an indicator variable that takes the value of one if fund i's within-category percentile rankings are closest to the four/five-star cutoff at the end of the second-to-last trading day of month t and zero otherwise. $Covariates_{i,t}$ are the same set of fund characteristics as in Table IA2. All regressions include time fixed-effects (θ_t) and are estimated with the ordinary least squares (OLS) estimation. Standard errors are double-clustered by fund and time, and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. The sample covers the period from 1990 to 2018.

	$R_t^{\text{Last Day}}$			
	(1)	(2)	(3)	(4)
Squared distance × % Three-year rating TNA	-0.71^{**}	-0.73^{***}		
	(-2.49)	(-2.60)		
Squared distance × % Four/five-star cutoff TNA			-1.53^{**}	-1.15^{*}
			(-2.57)	(-1.96)
Squared distance	-0.34^{***}	-0.21^{*}	-0.34^{**}	-0.23^{*}
	(-2.87)	(-1.94)	(-2.33)	(-1.66)
% Three-year rating TNA	0.01^{**}	-0.005		
	(2.22)	(-1.38)		
% Four/five-star cutoff TNA			0.02^{**}	0.02^{*}
			(2.05)	(1.76)
log(TNA)		0.004^{***}		0.003^{***}
		(3.15)		(2.83)
log(Age)		-0.01^{***}		-0.01^{***}
		(-4.24)		(-3.50)
Turnover		0.01^{**}		0.01^{**}
		(2.28)		(2.32)
Expense ratio		0.03^{***}		0.03^{***}
		(6.12)		(6.15)
% Institutional TNA		0.01^{**}		0.01^{**}
		(2.22)		(2.34)
Category × Month FE	Yes	Yes	Yes	Yes
Observations	466,078	445,756	466,078	445,756
Adjusted R^2	0.46	0.46	0.46	0.46

Table IA6: Cross-Section of Mutual Funds and the Star Rating Effect on Portfolio Pumping

This table presents the results of the following linear regression model:

$$R_{i,t}^{Last\ day} = \delta \times Squared\ distance_{i,t} \times Sensitivity_{i,t} + \beta \times Squared\ distance_{i,t} + \rho \times Sensitivity_{i,t} + \gamma \times Covariates_{i,t} + \theta_t + \varepsilon_{i,t}$$

where i indexes mutual funds and t indexes time in month. The dependent variable is fund i's return (in percent) on the last trading day of month t. Returns are in excess of category benchmark returns, computed as average returns across mutual funds belonging to the same Morningstar category starting in June 2002 and across all U.S. equity funds as a single category group prior to June 2002. $Squared\ distance_{i,t}$ is the squared distance between fund i's within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. $Sensitivity_{i,t}$ is (1) an indicator variable that takes the value of one if fund i belongs to one of the small-cap categories and zero otherwise, or (2) the logarithmic of the number of named managers of mutual fund i, all prior to the end of month t. $Covariates_{i,t}$ are the same set of fund characteristics as in Table IA2. All regressions include time fixed-effects (θ_t) and are estimated with the ordinary least squares (OLS) estimation. Standard errors are double-clustered by fund and time, and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. The sample covers the period from 1990 to 2018.

	$R_t^{\text{Last Day}}$			
	(1)	(2)	(3)	(4)
Squared distance × $\mathbb{1}$(Small-cap)	−0.46	−0.58*		
	(−1.43)	(−1.81)		
Squared distance × log(N Managers)			0.20*	0.21*
			(1.74)	(1.89)
Squared distance	−0.33**	−0.17	−0.66***	−0.54***
	(−2.28)	(−1.28)	(−3.99)	(−3.55)
$\mathbb{1}$(Small-cap)	0.08***	0.08***		
	(3.75)	(3.53)		
log(N Managers)			−0.001	−0.0004
			(−0.28)	(−0.20)
log(TNA)		0.004***		0.004***
		(3.29)		(3.23)
log(Age)		−0.01***		−0.01***
		(−3.43)		(−4.05)
Turnover		0.01**		0.01**
		(2.06)		(2.18)
Expense ratio		0.03***		0.03***
		(5.90)		(6.04)
% Institutional TNA		0.002		0.01**
		(0.69)		(2.00)
Category × Month FE	No	No	Yes	Yes
Month FE	Yes	Yes	No	No
Observations	466,078	445,756	458,059	439,236
Adjusted R^2	0.30	0.30	0.46	0.46

Table IA7: The Fall of Portfolio Pumping? Quarter/Year-Ends vs. Other Month-Ends

This table presents the results of the following linear regression model:

$$R_{i,t}^{Last\ day} = \beta \times Squared\ distance_{i,t} + \delta \times Squared\ distance_{i,t} \times Quarter\text{-}end_t + \gamma \times Covariates_{i,t} + \theta_t + \varepsilon_{i,t}$$

where i indexes mutual funds and t indexes time in month. The dependent variable is fund i's return (in percent) on the last trading day of month t. Returns are in excess of category benchmark returns, computed as average returns across mutual funds belonging to the same Morningstar category starting in June 2002 and across all U.S. equity funds as a single category group prior to June 2002. $Squared\ distance_{i,t}$ is the squared distance between fund i's within-category percentile rankings and its nearest rating threshold at the end of the second-to-last trading day of month t. $Quarter\text{-}end_t$ is an indicator variable that takes the value of one if month t is March, June, September, or December, and zero otherwise. $Covariates_{i,t}$ are the same set of fund characteristics as in Table IA2. All regressions include time fixed-effects (θ_t) and are estimated with the ordinary least squares (OLS) estimation. Standard errors are double-clustered by fund and time, and the resulting t-statistics are reported in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. The sample covers the period from 1990 to 2018 and is split around the June 2002 change in Morningstar's rating methodology.

	$R_t^{\text{Last Day}}$			
	1990:01–2002:05		2002:06–2018:12	
	(1)	(2)	(3)	(4)
Squared distance × 𝟙(Quarter-end)	−1.51*	−1.58**	0.31**	0.34**
	(−1.94)	(−2.05)	(2.07)	(2.30)
Squared distance	−1.22**	−0.75*	−0.24**	−0.20**
	(−2.43)	(−1.71)	(−2.36)	(−2.11)
log(TNA)		0.003		0.003***
		(0.90)		(3.39)
log(Age)		−0.02***		−0.001
		(−3.57)		(−0.83)
Turnover		0.04**		0.002
		(2.58)		(0.48)
Expense ratio		0.07***		0.01***
		(5.09)		(3.99)
% Institutional TNA		0.04***		−0.002
		(3.33)		(−0.80)
Time fixed-effects	Yes	Yes	Yes	Yes
Observations	110,665	104,657	355,413	341,099
Adjusted R^2	0.28	0.29	0.56	0.57