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ADVICE-DRIVEN DEMAND AND SYSTEMATIC PRICE FLUCTUATIONS

Itzhak Ben-David
Jiacui Li
Andrea Rossi
Yang Song

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ABSTRACT

We show that advice in the form of mutual fund ratings generates correlated demand that creates systematic price fluctuations. Mutual fund investors chase fund performance via Morningstar ratings. Until June 2002, funds pursuing the same investment style had highly correlated ratings. Therefore, rating-chasing investors directed capital into winning styles, generating style-level price pressures that reverted over time. In June 2002, Morningstar reformed its methodology to equalize ratings across styles. Style-level correlated demand via mutual funds immediately became muted, significantly altering the time-series and cross-sectional variation of style returns. Advice-driven demand also explains substantial variation in the size and value factors.

Itzhak Ben-David
The Ohio State University
Fisher College of Business
606A Fisher Hall
Columbus, OH 43210-1144
and NBER
ben-david.1@osu.edu

Andrea Rossi
University of Arizona
Eller College of Management
Department of Finance
1130 E. Helen St.
Tucson, AZ 85721
rossi2@email.arizona.edu

Jiacui Li
David Eccles School of Business
University of Utah
SFEBB 8123, 1655 Campus Center Dr
Salt Lake City, UT 84112
jiacui.li@eccles.utah.edu

Yang Song
Foster School of Business
University of Washington
Seattle, WA 98195
songy18@uw.edu

1 Introduction

Stock ownership by retail-owned mutual funds in the U.S. has been steadily rising since the 1980s, reaching about 25% of the entire market capitalization in the early 2000s. With such a high ownership rate, the financial advice that guides households' capital investments could play a central role in driving flows and shaping financial markets. Indeed, previous studies have found that mutual fund flows respond to past performance in the form of external ratings (Del Guercio and Tkac, 2008; Reuter and Zitzewitz, 2015; Kaniel and Parham, 2017; Evans and Sun, 2021) and that mutual fund flows can generate large price pressure in the underlying stocks (Coval and Stafford, 2007; Lou, 2012). Hence, it is important to test how the content of the advice consumed by households filters into security prices and, more importantly, whether this advice translates into systematic price patterns.

Among the different types of financial advice that U.S. mutual fund investors follow, Morningstar star ratings are perhaps the most prominent and consequential. Soon after introducing the ratings in 1985, Morningstar became the industry leader in rating mutual funds, with millions of subscribed investors either directly or through investment advisors. Moreover, investment platforms and fund families prominently feature Morningstar ratings as part of the information they display to investors. While ratings are a "backward-looking measure of a fund's past performance"[1] and therefore are not necessarily useful for forward-looking guidance, they are important inputs in households' investment decisions. Discrete changes in Morningstar star ratings drive mutual fund flows (Del Guercio and Tkac, 2008; Reuter and Zitzewitz, 2015), and Morningstar ratings are the prime determinant of flows in the cross-section of equity mutual funds (Ben-David, Li, Rossi, and Song, 2019).

In this study, we test whether advice-driven demand causes *systematic* price fluctuations in the stock market. Investors rely heavily on Morningstar ratings throughout our sample period (1991–2018). As a consequence, stocks experience price pressures based on the rat-

[1] From Morningstar's website (`https://www.morningstar.com/company/morningstar-ratings-faq`), retrieved December 20, 2020.

ing changes of the mutual funds that own them. Because Morningstar reformed its rating methodology in June 2002, we can trace changes in systematic price patterns back to advice-driven mutual fund flows. Our analysis shows that the 2002 Morningstar reform dramatically changed the allocation of investors' capital across styles, which in turn significantly altered the time-series and cross-sectional variation of style returns. Overall, our results show that financial advice to households can cause systematic and persistent price fluctuations in the stock market.

The key mechanism by which Morningstar influences capital flows is best explained through the lens of its rating methodology. Prior to June 2002, Morningstar ratings were broadly aligned with mutual funds' past performance. In that period, Morningstar rated all mutual funds—regardless of their style tilts—based on their performance ranking across the *entire universe* of U.S. equity funds, with minor adjustments for loads and volatility. Because a significant fraction of fund performance is determined by style exposure (e.g., small-cap or growth-oriented), funds that pursued similar investment style mandates had highly correlated ratings. Under Morningstar's pre-June 2002 methodology, investing in high-rated funds was broadly equivalent to chasing funds' past returns.

In June 2002, Morningstar implemented a simple yet impactful revision of its rating methodology. Instead of ranking all equity funds against each other, Morningstar began benchmarking funds against peer funds *within* their style. The style-peer groups are based on the well-known Morningstar three-by-three "style box" (value/blend/growth $\times$ small/mid/large cap). By design, the revised methodology removes the style-performance component from the fund ranking, and therefore fund ratings immediately became balanced across styles. Panel (a) of Figure 1 shows how the dispersion of average ratings across styles suddenly collapsed in June 2002 as a consequence of the reform.

Our paper analyzes the systematic impact of this reform on the stock market. The empirical analysis has four parts.

In the first part, we demonstrate that the key elements of the mechanism exist in the

Figure 1. Morningstar Rating Methodology Change and Style Price Pressures

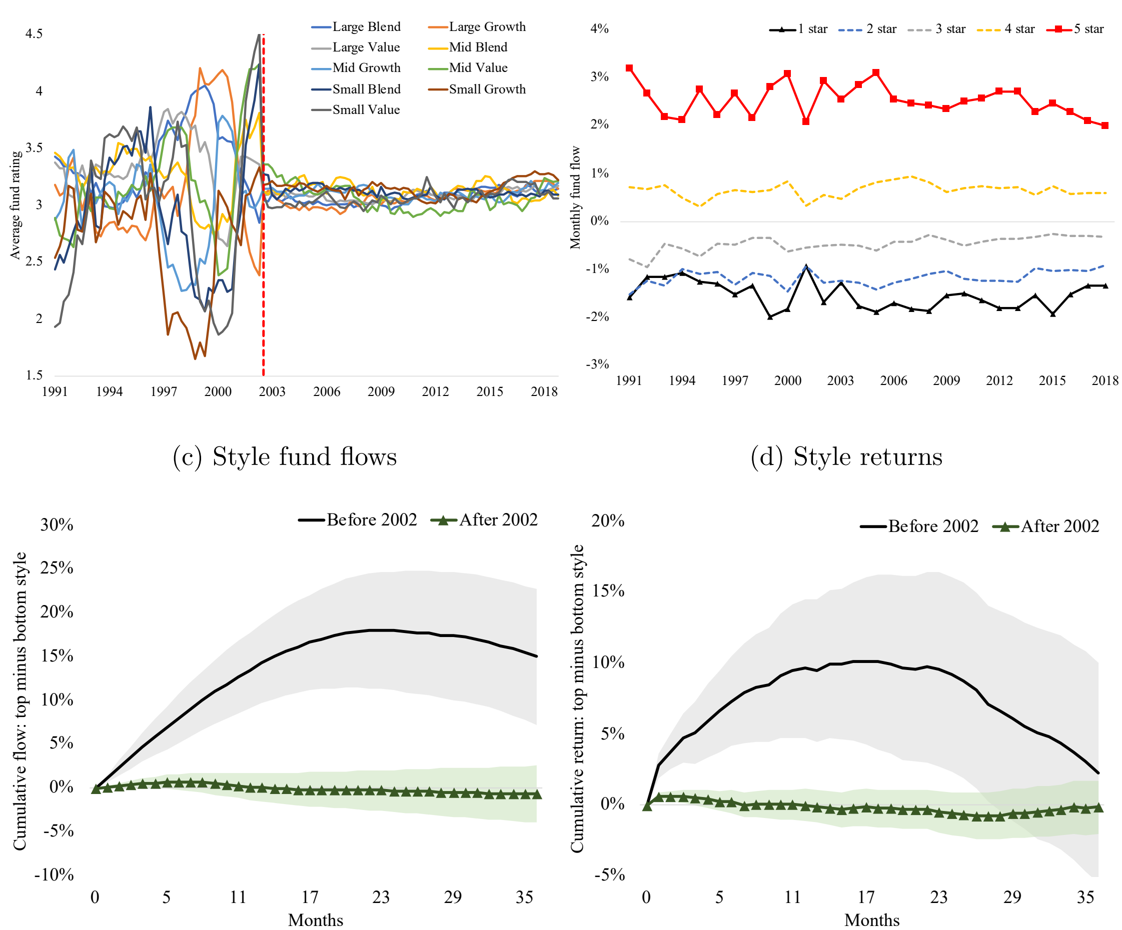
This figure highlights the main results in the paper. Panel (a) plots the average mutual fund rating by the 3×3 size-value Morningstar styles. The vertical dashed line marks the June 2002 methodology change event. Panel (b) plots the average monthly fund flow by one- to five-star Morningstar ratings. In Panels (c) and (d), we sort the 3×3 style portfolios by their lagged rating changes (ExpSum(ΔRating), defined in Section 4.2). We then plot the cumulative differences in flows and returns between the top and bottom styles for the subsequent three years. The shaded areas are 95% bootstrapped confidence intervals.

(a) Morningstar fund rating by style

(b) Fund flow by Morningstar rating

(c) Style fund flows

(d) Style returns



data: (*i*) investor flows respond to ratings, and (*ii*) flow-induced trades create price pressures. First, we document that investors chase ratings *regardless* of the rating methodology.[2] This finding is evident in Panel (b) of Figure 1: Monthly fund flows to mutual funds strongly depend on Morningstar ratings, and the dependence magnitude is stable over the 28 years

[2]Ben-David et al. (2019) and Evans and Sun (2021) make similar observations. These findings are most consistent with the explanation that investors view Morningstar's ratings as a recommendation about the best funds from a trusted advisor (e.g., as in the "money doctors" model proposed by Gennaioli, Shleifer, and Vishny, 2015).

in our sample.[3] Second, we use an impulse-response analysis to show that a rating increase results in a surge in mutual fund flows, and that flow increases lead to contemporaneous stock price appreciation and subsequent reversals.

We also formally analyze the magnitude of this advice-driven effect in the cross-section of monthly stock returns. To do so, we regress stock returns on the average lagged rating changes of the funds holding the stock as of the previous month, while controlling for those funds' past return history, for the stock's past returns, and for prominent stock return predictors. In this case, lagged rating changes proxy for expected rating-induced mutual fund flows. This specification allows us to measure the *marginal* impact of rating-induced price pressure on stock returns. We find that the effect of ratings on stock returns is economically large and statistically significant. In fact, the marginal effect of rating-induced flows on stock return predictability is even larger than that of many prominent return predictors, such as value, momentum, and profitability.

The fact that expected flow-induced trading exerts price pressure on stocks is not a novel contribution of this paper (e.g., see Lou, 2012). Rather, this evidence serves as a premise for our main contribution on the influence of advice-driven mutual fund flows on systematic price fluctuations, because it demonstrates that changes in ratings have an independent causal effect on stock returns.

In the second part of our analysis, we examine the implications of advice-driven demand on systematic return patterns. Morningstar's reform impacted styles; hence, our analysis is at the style level. Before the reform, ratings clustered at the style level, leading to correlated style-level flows. Consequently, inflows hit a small subset of winning styles, forming concentrated price pressures in those styles. Indeed, before June 2002, the most upgraded styles (i.e., styles with the highest recent changes in ratings) drew large fund inflows, and

[3]Over a typical two-year period, five-star funds receive inflows equal to more than 75% of their initial AUM (assets under management), while one-star funds shrink by over one-third due to outflows.

their returns exhibited momentum and subsequent reversals.[4] Opposite patterns can be observed for the most downgraded styles. After June 2002, ratings became evenly distributed across styles, and therefore rating-chasing flows were distributed across the entire spectrum of styles. Because rating-chasing investors unknowingly stopped applying price pressure on a small subset of winning styles, the rating-induced style-level momentum and reversal effects became muted.

These results are illustrated in Panels (c) and (d) of Figure 1. Panel (c) shows that, before 2002, the most upgraded style attracted approximately 15% more flows than the most downgraded style over the subsequent 12 months. Once the reform was enacted and ratings became evenly distributed across styles, the spread in flows to the most upgraded versus downgraded styles disappeared, demonstrating the power of Morningstar ratings in driving flows. Panel (d) shows that the return difference between upgraded and downgraded styles mirrors the pattern observed for rating-induced flows. In fact, the rating-driven style momentum strategy (long/short) generated a considerable return of about 90 to 100 bps per month before June 2002 and became unprofitable afterward. We show later that these price pressure effects are stronger in stocks with higher mutual fund ownership, consistent with our fund flow channel.

In addition, the 2002 reform altered the dispersion of style flows and style returns. As ratings became more homogeneous across styles due to the reform, so did flows and returns. The average monthly style-level flow spread (top flow minus bottom flow) dropped from 3.3% before June 2002 to 1.4% after June 2002, and the return spread dropped from 5.5% to 3.0%. The general finding that return and flow dispersion collapsed after the rating reform is robust to using alternative dispersion measures or shorter time windows around the reform event.

In the third part of our analysis, we focus on a short period around June 2002. Because

[4] As we discuss in Section 4, we focus on rating changes (upgrading and downgrading), rather than rating levels. These empirical measures allow us to identify *changes* in flows and hence changes in *prices*, avoiding reversals due to earlier price pressures caused by earlier flows.

we are concerned that other factors (e.g., stock market decimalization) may have caused the effects we find, focusing on the months surrounding the event allows for a sharper identification of the reform-induced effects. In the months leading up to June 2002, funds in top-rated styles gathered inflows and the underlying stocks performed well. By the same token, funds in bottom-rated styles experienced outflows and the underlying stocks performed poorly. The methodology reform caused rating dispersion across styles to sharply collapse, and so did flow dispersion. As predicted, the style return patterns also immediately halted and even slightly reversed. We also carry out a battery of tests to tackle possible alternative explanations for the event study results. The results are all supportive of our interpretation that the rating reform causally impacted style-level flows and returns.

In the final part of our empirical analysis, we explore further implications of advice-driven flows. Specifically, we study the explanatory power of rating-induced demand on fluctuations in the common risk factors related to size and value (Fama and French, 1993). These factors are defined as long-short portfolios along the two style dimensions, size and book/market, and are considered by many financial economists as only reflecting fundamental risk. To quantify the impact of rating-induced demand, we first use the Morningstar reform as an instrument to estimate the price pressure coefficient of style ratings on future style returns over a short window around June 2002. Focusing on this window allows us to cleanly isolate variation in ratings that is caused by the methodology change, thereby mitigating endogeneity concerns. We then apply the estimate to quantify the effect of style ratings on style returns for our sample period of 1991–2018. Admittedly, this is a crude estimate, but it is informative about the size of the potential impact of rating-induced demand. Our analysis shows that rating-induced price pressure can explain 10% to 30% of the variation in monthly factor returns before 2002. As expected, the explanatory power dropped precipitously after June 2002.[5]

To summarize, we document that a seemingly innocuous reform implemented by a sin-

[5]Because ratings are persistent, in untabulated results, we find that the explanatory power of rating-induced price pressure for the size and value factor returns before 2002 rises to an average of 40% at the quarterly frequency.

gle rating firm created a long-lasting impact on the allocation of investors' capital across styles. This reallocation of capital flows altered the time-series and cross-sectional variation of style returns and widely used return factors. These findings highlight the importance of nonfundamental demand in shaping systematic returns.

Our paper is related to the literature on demand-effects in asset prices. Unlike traditional asset pricing, which assumes that price movements are only explained by cash flow and discount rate variation (Cochrane, 2011), studies in this field have also found effects of demand in index additions and deletions (Harris and Gurel, 1986; Shleifer, 1986; Wurgler and Zhuravskaya, 2002; Chang, Hong, and Liskovich, 2015), mutual fund flows (Coval and Stafford, 2007; Lou, 2012; Li, 2020), exchange-traded fund flows (Ben-David, Franzoni, and Moussawi, 2018; Brown, Davies, and Ringgenberg, 2021), and other sources of institutional investor demand (Koijen and Yogo, 2019; Ben-David, Franzoni, Moussawi, and Sedunov, 2021; Parker, Schoar, and Sun, 2020). Consistent with the model in Barberis and Shleifer (2003), the pioneering work of Teo and Woo (2004) and Froot and Teo (2008) showed evidence that institutional demand can drive style-level returns. Most recently, Gabaix and Koijen (2020b) show that the demand-induced price impact coefficient at the aggregate level is larger than that at the idiosyncratic level, a finding that is corroborated in our study.

The rest of the paper is organized as follows. Section 2 introduces the data set. Section 3 describes the Morningstar rating methodology change in June 2002. Section 4 shows that investors chase Morningstar ratings to a similar extent after June 2002 and that rating-induced flows to funds indeed exert a large price impact on the underlying stocks. Section 5 demonstrates that style return dynamics have changed dramatically since 2002. Section 6 examines ratings, flows, and returns around June 2002 using an event study approach. In Section 7, we quantify the influence of correlated demand on the size and value factors. Section 8 concludes. Additional results and robustness checks are provided in the appendices.

2 Data and Variable Construction

In this section, we describe the data set and explain how we construct the rating and flow variables.

2.1 Mutual Fund Sample

Mutual funds are one of the largest classes of equity investors in the U.S. and a prime investment vehicle for retail investors. When our sample begins in 1991, U.S. equity mutual funds held a total AUM of $326 billion, which was 8.9% of the entire market capitalization. Their ownership fraction grew steadily, reaching about 30% in 2005 and has remained steady since then. By the end of our sample period in 2018, equity mutual funds owned $10,849 billion, which represented 29.3% of the entire market capitalization (Panel (a) of Figure 2).

We obtain monthly fund returns and total net assets (TNA) from the Center for Research in Security Prices (CRSP) survivorship-bias-free mutual fund data set. We use all U.S. domestic equity mutual funds. While funds are often marketed to different clients through different share classes, they invest in the same portfolio and typically only differ in the fee structure. Therefore, we aggregate all share classes at the fund level using Russ Wermer's MFLINKS (Wermers, 2000). We also obtain quarterly fund holdings from Thomson Reuters' S12 data. We augment the holdings data with stock returns and characteristics from the CRSP/Compustat merged database.

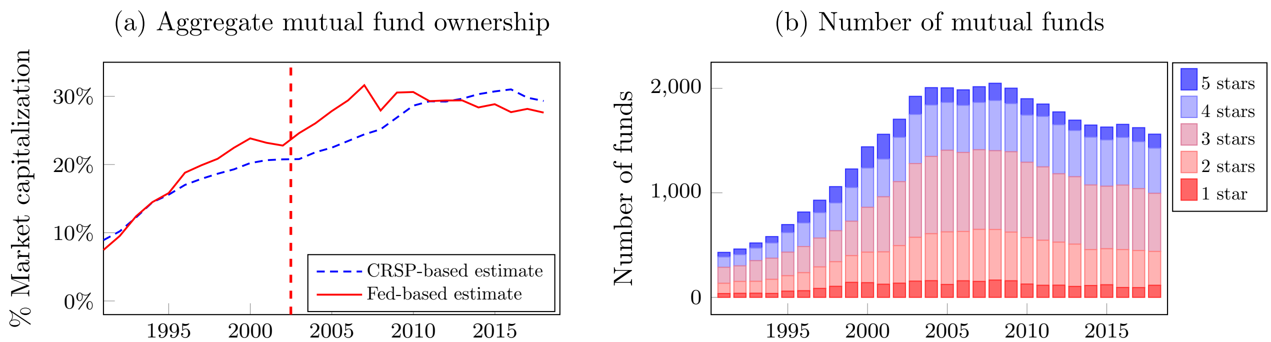
Our monthly sample starts in January 1991 and ends in December 2018. The starting date is based on data availability: Monthly AUM (which is required to calculate monthly flows) from CRSP starts in 1990, and some measures require one year of lagged data to construct. Following the mutual fund literature (e.g., Coval and Stafford, 2007), the fund flow for fund j in month t is defined as the net flow into the fund divided by lagged TNA:

$$\text{Flow}_{j,t} = \frac{\text{TNA}_{j,t}}{\text{TNA}_{j,t-1}} - (1 + \text{Ret}_{j,t}). \tag{1}$$

We obtain Morningstar ratings and style categories from Morningstar Direct and merge them with the CRSP mutual fund data using the matching table from Pastor, Stambaugh, and Taylor (2020).[6] Morningstar assigns ratings at the share class level. We follow Barber, Huang, and Odean (2016) and aggregate them at the fund level by TNA-weighting different share classes. We restrict our analysis to mutual funds with at least \$1 million TNA and winsorize fund flows at the 0.5% and 99.5% levels within each month. We require the existence of 12 lags of monthly flows, returns, and ratings. The resulting sample comprises a total of 3,305 funds with 454,787 fund-month observations.

Figure 2. Summary Statistics of Mutual Funds

Panel (a) shows the aggregate domestic mutual fund holding of U.S. stocks as a fraction of the overall market. The blue line is based on the CRSP mutual fund database, and the red line is based on Federal Reserve Board flow of fund reports (L.223). Panel (b) shows the number of funds in each Morningstar star rating classification during our sample period of 1991–2018. Appendix Table A.1 further summarizes the mutual fund sample used in this paper.



Panel (b) of Figure 2 summarizes the time series of the number of funds per Morningstar rating. The number of funds quadrupled from 1991 to 2005, and then plateaued before slightly declining from 2009 onward. Additional summary statistics are provided in Appendix A.1.

2.2 Stock- and Style-Level Ratings

As the main focus of this study is the effects of rating-induced demand on stocks and style portfolios, we summarize ratings and changes in ratings at both the stock and style

[6] We thank the authors for kindly providing the matching table.

levels.

We define the level of and change in the Morningstar rating of stock i in month t as the holdings-weighted average rating of all funds J that hold the stock i as of the end of the prior month:[7]

$$\text{Rating}^{\text{stock}}_{i,t} = \frac{\sum_{\text{fund} j \in J} \text{SharesHeld}_{i,j,t-1} \cdot \text{Rating}_{j,t}}{\sum_{\text{fund} j \in J} \text{SharesHeld}_{i,j,t-1}}, \tag{2}$$

$$\Delta\text{Rating}^{\text{stock}}_{i,t} = \frac{\sum_{\text{fund} j \in J} \text{SharesHeld}_{i,j,t-1} \cdot (\text{Rating}_{j,t} - \text{Rating}_{j,t-1})}{\sum_{\text{fund} j \in J} \text{SharesHeld}_{i,j,t-1}}. \tag{3}$$

We now define ratings and rating changes at the style level. For a given style π, we aggregate up the stock-level ratings:

$$\text{Rating}^{\text{style}}_{\pi,t} = \sum_{i \in \text{style } \pi} w^{\pi}_{i,t-1} \cdot \text{Rating}^{\text{stock}}_{i,t}, \tag{4}$$

$$\Delta\text{Rating}^{\text{style}}_{\pi,t} = \sum_{i \in \text{style } \pi} w^{\pi}_{i,t-1} \cdot \Delta\text{Rating}^{\text{stock}}_{i,t}, \tag{5}$$

where $w^{\pi}_{i,t-1}$ is the portfolio weight of stock i in the corresponding style, based on the aggregate holdings of mutual funds that are classified by Morningstar as investing in the style π.

To measure style-level flows, we compute the TNA-weighted average flows to all funds in that style. We later drop the superscripts "stock" and "style" when unambiguous. Appendix Table A.2 presents summary statistics of ratings, flows, and returns for styles.

3 Morningstar Ratings: Background and 2002 Reform

In this section, we describe the simple, yet radical, methodological reform in the popular Morningstar star rating system that took place in June 2002. In later sections, we demonstrate that this exogenous reform had a far-reaching impact on style return dynamics.

[7] We use the latest holdings available in the past three months. We normalize by total shares held by mutual funds to be consistent with the specification in Lou (2012).

After launching its mutual fund rating system in 1985, Morningstar quickly became the industry leader in guiding investors' mutual fund selection. Since its early days, Morningstar's methodology has been transparent and publicly available. To assign ratings, Morningstar first summarizes the recent past returns of funds and conducts minor adjustments for return volatility and expenses. Depending on a fund's age, the lookback horizon for past performance can be three, five, or 10 years, and more weight is applied to the most recent three years of returns. Then, Morningstar ranks funds by their performance and assigns a rating of one to five stars with fixed proportions (10%, 22.5%, 35%, 22.5%, and 10%).

Morningstar's rating methodology changed abruptly in June 2002. The reason behind the change is related to the fact that many funds pursue specific investment styles (e.g., large-cap growth) by mandate.[8] Since its inception and until June 2002, Morningstar ranked all U.S. equity funds against each other. Because style performance is a significant part of fund performance, fund ratings were highly dependent on style performance. Following the dot-com crash, many fund managers specializing in large-cap growth stocks complained that their fund ratings dropped sharply. These managers argued that ratings barely reflected their own contributions and mostly echoed style-level returns outside of their control. As a result, the research team at Morningstar, spearheaded by the economist Dr. Paul Kaplan, redesigned the rating system.[9]

The main modification in the post-June 2002 methodology was that funds were ranked *within* style categories,[10] as opposed to across the entire universe. Morningstar classifies

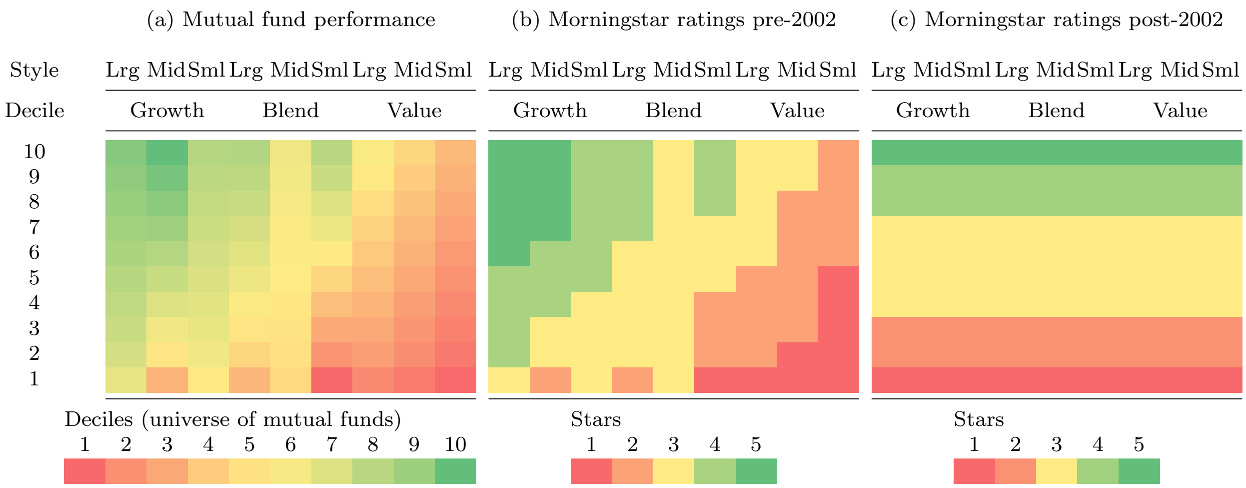
[8] Historically, mutual funds have followed different investment philosophies in identifying investment opportunities ("styles"). For example, managers following Graham and Dodd (1934) look for undervalued firms ("value"), while those following Fisher (1958) search for firms with substantial unrealized growth potential ("growth"). Funds therefore are often classified as value or growth. Funds that invest in the same style have more overlapping holdings.

[9] We learned this information during phone conversations with Morningstar management. Making ratings more balanced across styles was also one of the stated objectives for the methodology reform. For instance, in a *New York Times* interview, Don Phillips, a managing director of Morningstar, said, "Two years ago, every growth fund looked wonderful... Now, none does." See Floyd Norris, Morningstar to Grade on a Curve, *New York Times*, April 23, 2002.

[10] The modified methodology also ranked sector funds within their industrial sectors (e.g., financial, utilities). For simplicity, our analysis focuses on ratings and flows of diversified U.S. equity funds, which constitute 87% of all equity mutual funds in our sample period.

Figure 3. Illustration of Morningstar Methodology Pre- and Post-June 2002

The figure presents a hypothetical example of the mapping of mutual fund performance into Morningstar ratings pre- and post-June 2002. The columns represent different investment styles (large-growth, midcap-growth, small-growth, large-blend, midcap-blend, small-blend, large-value, midcap-value, small-value). In Panel (a), the rows represent three-year performance deciles of funds *within* each style. The colors represent the performance decile across the *entire* mutual fund universe: Green indicates top-ranked performance, and red indicates bottom-ranked performance across the entire mutual fund universe. Panel (b) shows ratings by Morningstar based on the pre-2002 methodology. Panel (c) shows ratings by Morningstar based on the post-June 2002 methodology.



diversified U.S. equity funds into the well-known 3×3 style matrix based on funds' holdings: combinations of small/midcap/large and value/blend/growth. Since June 2002, the distribution of star ratings has been the same for funds within each of the 3×3 styles for diversified funds. The modified methodology was announced as early as April 2002[11] and was implemented at the end of June 2002. Appendix B provides additional technical details about the rating methodology.

Figure 3 illustrates the relation between fund performance and Morningstar ratings. Before June 2002, Morningstar's mutual fund ratings closely mapped past overall fund performance into star ratings. Panel (a) shows a snapshot of mutual funds' past hypothetical performance (colors) for funds within styles. The columns represent the different styles, and the rows represent past fund performance deciles within each style. Funds in the top rows performed the best within their styles.

The pre-reform rating methodology largely mapped past performance into star ratings.

[11]See `http://news.morningstar.com/pdfs/FactSheet_StyleBox_Final.pdf`.

As Panel (a) shows, in this hypothetical example, large-growth funds had the best performance. Panel (b) shows that the best-performing funds were ranked the highest by Morningstar. In other words, before 2002, Morningstar ratings were highly correlated with raw past returns.

Since June 2002, Morningstar has ranked funds *within* style; hence, rankings are independent of style performance (Panel (c)). The demand from rating-chasing investors, therefore, became more evenly spread over all styles.

Discussion: Timing of the methodology reform. While the reform was prompted by the dot-com crash and therefore did not occur on a random date, its *exact timing* is exogenous—a fact that we will exploit in Section 6. While the dot-com peak was in March 2000, the designer of the reform, Dr. Paul Kaplan, was only appointed as the head of Morningstar research in February 2001.[12] While we do not observe the decision process within Morningstar, it likely took significant work and deliberation before the reform was finalized and approved, as Morningstar rarely changes its methodology and this reform is arguably the most significant change to date.

Furthermore, as shown in Section 4, investors' rating-chasing behavior did not change around the dot-com bust or the 2002 reform. Therefore, even though the reform timing is not entirely exogenous, it appears unrelated to the specific channel of rating-induced flows and price pressures that we are interested in.

4 Rating-Chasing Behavior and Price Impact

In this section, we examine the mechanism that links ratings to flows and then to returns. First, we present evidence that investors rely strongly on ratings throughout the sample period. Second, we use an impulse-response analysis to investigate the impact of

[12] See "Morningstar Appoints Paul Kaplan, Ph.D., CFA, as Director of Research, Vahid Fathi Named Director of Stock Research" from the Morningstar news archive.

rating changes on flows and returns. Finally, we show that rating changes lead to robust cross-sectional predictability in stock returns. The effect of rating-induced demand on stock return predictability is even stronger than that of some prominent predictors, such as value, momentum, and profitability.

4.1 Investors Chase Ratings Regardless of Rating Methodology

Because our identification relies on the reform in the Morningstar rating methodology, it is important to examine whether mutual fund investors continued to rely on Morningstar ratings after June 2002.

We begin by examining simple summary statistics. Panel (b) of Figure 1 plots the average flows to mutual funds with different Morningstar ratings. Throughout our sample period, five-star funds receive flows that amount to +2% to +3% of their AUM per month on average. This is economically large as it implies that the AUM of five-star funds increases by about 25% to 40% over one year. In contrast, one-star funds experience outflows of −1.5% to −2% of their AUM per month on average. Importantly, these patterns do not appear to differ before and after June 2002.

More formally, we estimate the response of fund flows to lagged fund ratings using three-year rolling-window TNA-weighted Fama-MacBeth regressions (Fama and MacBeth, 1973), controlling for 36 lags of monthly fund returns. The results are plotted in Panel (b) of Figure 4. The coefficient estimate varies only slightly over the sample, and there is no material drop around or following the 2002 reform. For example, the average flow-to-rating response was 0.37% before June 2002 and 0.48% after June 2002.[13]

In summary, these results indicate that, historically, mutual fund investor capital allocation chased Morningstar ratings regardless of the rating methodology. However, the rating reform led to significant changes in style-level fund flows. Because ratings are constructed within styles after June 2002, style-level fund flow dispersion dropped significantly after the

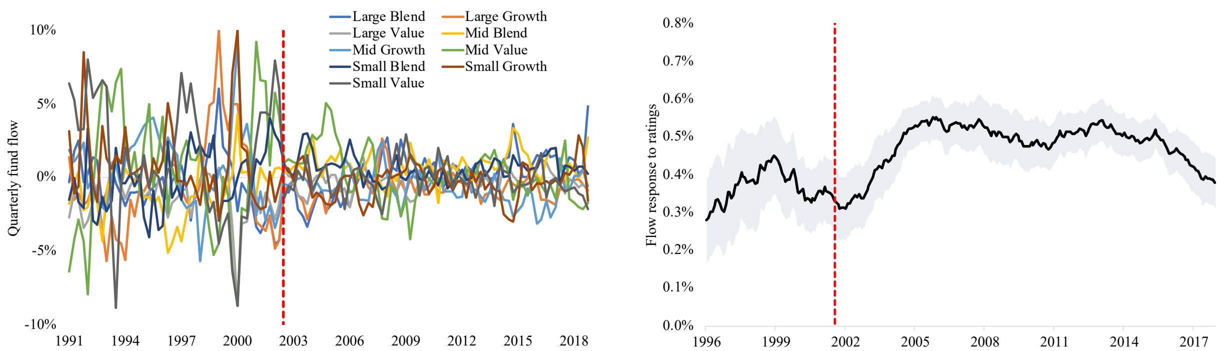
[13]See further analysis indicating that investors did not change their rating-chasing behavior in Ben-David et al. (2019) and Evans and Sun (2021).

Figure 4. The June 2002 Morningstar Methodology Reform

This figure examines the relation between Morningstar ratings and fund flows over the sample period. The vertical dashed red lines mark the June 2002 methodology change event. Panel (a) plots the TNA-weighted average quarterly fund flow by Morningstar 3×3 styles. Flows are demeaned cross-sectionally to focus on the dispersion. Panel (b) explores the stability of the relation between ratings and flows at the fund level. Specifically, it plots the regression coefficient of fund flows on lagged ratings estimated using three-year rolling windows. Because the regression controls for 36 lags of monthly fund returns and because it takes three years to compute a rolling average, the graph starts in 1996. (Raw monthly data are available from 1991.) The shaded area indicates the two standard error bands.

(a) Fund flow, by style

(b) Regression coefficient of fund flows on ratings



methodology reform, as is easily visible in Panel (a) of Figure 4. As we see later in Section 5.1, the style-level correlated demand due to rating-chasing behavior mostly disappeared after the reform.

4.2 Stock-Level Rating-Induced Price Pressures

Next, we confirm that Morningstar ratings substantially impact stock prices through flow-induced trading. This step is necessary before we explore the influence of rating-induced style demand on style returns in the subsequent analysis.

We assess the price impact of ratings on stock returns by first separately estimating the two chained effects: (*i*) the response of fund flows to Morningstar rating changes, and (*ii*) the response of stock returns to flow-induced trading.

First, we estimate the fund flow response to lagged fund rating changes:

$$\text{Flow}_{j,t} = a + b_1 \cdot \Delta\text{Rating}_{j,t-1} + \ldots + b_{36} \cdot \Delta\text{Rating}_{j,t-36} + X_{j,t} + u_{j,t}, \tag{6}$$

where $\Delta\text{Rating}_{j,t}$ is the month t rating change of fund j, and controls $X_{j,t}$ include 36 monthly lags of fund flows and returns. The cumulative response coefficients $(b_1, b_1+b_2, \ldots)$ are plotted in Panel (a) of Figure 5. In response to a one-star change in rating, funds experience an average of 6% additional flows, most of which take place over the first 24 months. This result is consistent with prior research showing that, when controlling for past fund performance, discrete changes in ratings cause sizeable differences in fund flows that last for several months (Del Guercio and Tkac, 2008; Reuter and Zitzewitz, 2015).

Second, we estimate the response of stock returns to stock-level flow-induced trading. To measure the amount of stock-level trading caused by fund flows, we follow Lou (2012) to calculate flow-induced trading (FIT) for each stock i in each month t:[14]

$$\text{FIT}_{i,t} = \frac{\sum_{\text{fund} j \in J} \text{SharesHeld}_{i,j,t-1} \cdot \text{Flow}_{j,t}}{\sum_{\text{fund} j \in J} \text{SharesHeld}_{i,j,t-1}}. \tag{7}$$

In short, FIT is the amount of mutual fund trading in stock i that is mechanically caused by fund flows. As explained in Lou (2012), whereas discretionary trading can reflect managers' information about fundamentals, FIT isolates the nondiscretionary trading that is only attributable to fund flows and thus likely does not contain fundamental information.[15]

We then estimate the response of stocks returns to FIT,

$$\text{Ret}_{i,t} = a + c_0 \cdot \text{FIT}_{i,t} + c_1 \cdot \text{FIT}_{i,t-1} + \ldots + c_{36} \cdot \text{FIT}_{i,t-36} + u_{i,t}, \tag{8}$$

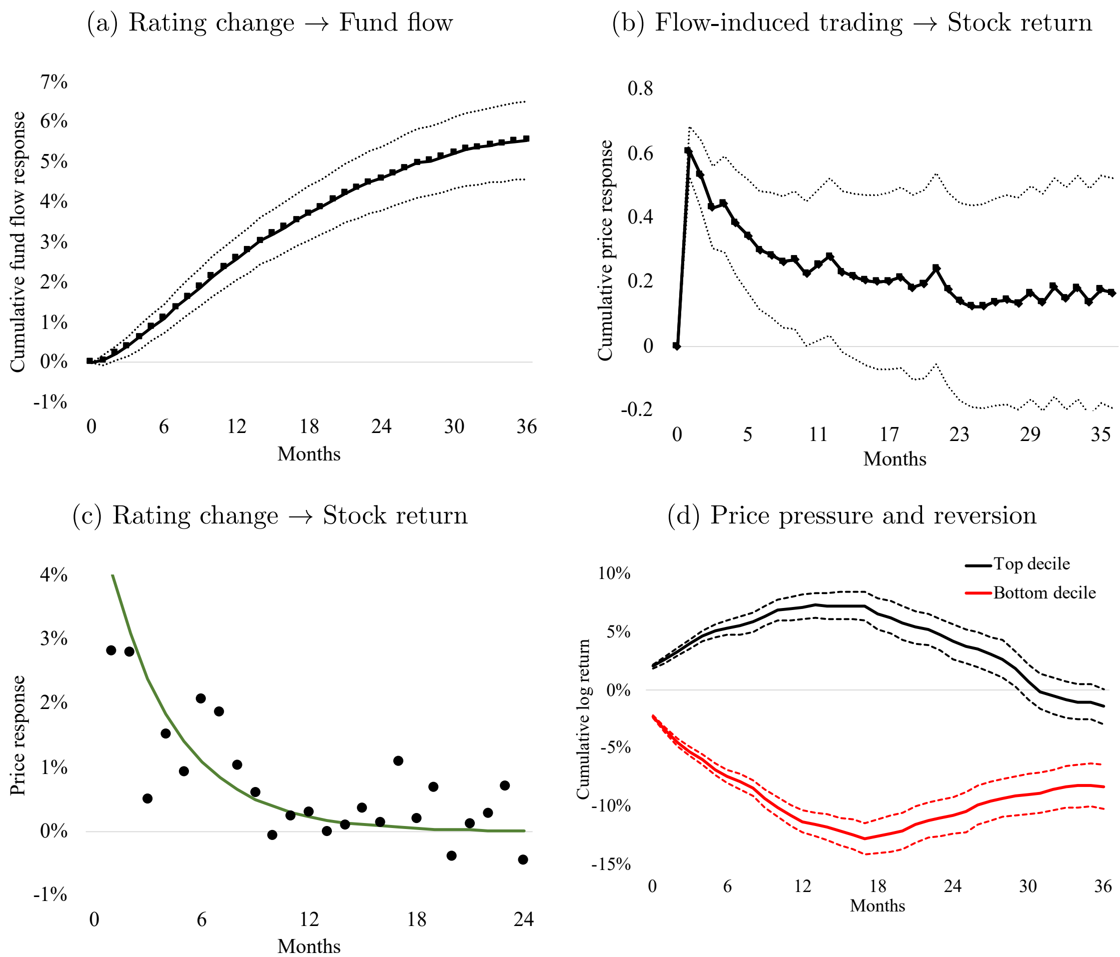
and plot the cumulative response $(c_0, c_0 + c_1, ...)$ in Panel (b) of Figure 5. An increase of 1% in mutual fund ownership through FIT (i.e., expected trading due to flows) leads to immediate price pressure of approximately 0.6% in the contemporaneous month, and a

[14] Lou (2012) also applies different scaling factors to inflows and outflows. We omit this scaling for simplicity, but our results are robust to using his scaling factors.

[15] Consistent with this interpretation, Lou finds that FIT leads to price pressures that revert over time. Wardlaw (2020) recently argued that some flow measures, such as that in Edmans, Goldstein, and Jiang (2012), inadvertently include contemporaneous stock returns. This does not apply to our flow measure, which is constructed following Lou (2012) and does not use price information.

Figure 5. Price Impact of Ratings and Flows

Panel (a) shows the cumulative response of fund flows to changes in fund ratings. Panel (b) shows the cumulative response of stock returns to flow-induced trading (FIT), defined as the nondiscretionary trading induced by mutual fund managers proportionally adjusting existing portfolio holdings in response to fund flows. Panel (c) shows the *noncumulative* response of stock returns to changes in ratings as well as the fitted exponential response (green line). Panel (d) plots the cumulative value-weighted price path of stocks with top and bottom deciles of the lagged exponential sum of rating changes ($\text{ExpSum}(\Delta\text{Rating})_{i,t-1}$). The sorting decile breakpoints are based on NYSE stocks. In Panels (a), (b), and (d), the dashed lines show two standard errors bands.



complete reversion in the subsequent one to two years. This result is consistent with the findings related to FIT in Lou (2012).

Combining these two effects, we predict that rating changes (especially recent changes) should impact stock returns. We expect the impact to come from rating changes rather than rating levels. This is because while a higher rating level in the more distant past also generates flows (Figure 5, Panel (a)), the price pressures created by their initial impact are already embedded in the later part of the "price pressure cycle" and are already reverting (Figure 5, Panel (b)). For this reason, we use rating changes in the rest of our analysis.[16]

To facilitate our later analysis of rating-induced price impact, it is convenient to summarize recent rating changes into a weighted average sum such that the weights correspond to how much each lag impacts returns. We obtain such a weighting scheme by directly estimating the response of stock returns on the past 24 lags of stock-level rating changes (defined in Equation (3)) with the same controls in Equation (10) discussed later.[17] We plot the coefficients in Panel (c) of Figure 5. As expected, more recent rating changes are more impactful, and the coefficients on more distant rating changes converge toward zero.

Because the impact primarily takes place over the first 12 months, we summarize past rating changes using the following weighted sum:

$$\text{ExpSum}(\Delta\text{Rating})_{i,t-1} = \sum_{k=1}^{12} \tau_k \cdot \Delta\text{Rating}_{i,t-k}, \tag{9}$$

where $\tau_k = \frac{12\cdot(1-\delta)}{1-\delta^{12}} \cdot \delta^{k-1}$ and $\sum_{k=1}^{12} \tau_k = 12$. The weights decay with factor $\delta = 0.76$, which is estimated from a least-squares fit to the response (Panel (c) of Figure 5).[18] Because the weights sum to 12 (months), in terms of units, ExpSum(ΔRating) should be interpreted as the rating change over one year. The estimated decay factor $\delta = 0.76$ implies a half-life of $-\ln(2)/\ln(\delta) \approx 2.58$ months. As we show in the next subsection, our results are not sensitive to reasonable variations in the choice of rating change horizon or weighting scheme.

The results presented so far indicate that recent rating changes cause price pressures. To

[16] Consistent with the patterns discussed here, in unreported results we find that rating levels also tend to positively predict future stock returns. However, the effect is statistically significant only if we also control for rating levels lagged by several months—which implies that the effect is better specified by using rating changes.

[17] Requiring the existence of 36 lags of ratings and controls leads to a significantly smaller sample size, so we use 24 lags here. We obtained nearly identical results when using 36 lags, despite the smaller sample.

[18] The estimate of δ is robust to the regression methodology in estimating the dependence of stock returns on rating changes. The estimate in our paper is based on a panel regression with market cap-weighted observations ($\delta = 0.764$). An equal weighted panel regression yields $\delta = 0.814$. If we use a Fama-MacBeth regression, δ becomes 0.793 if market-cap weighted and 0.815 if equal-weighted. All of our subsequent results are robust to much larger variation in estimates of δ.

further validate the price pressure interpretation, we examine whether the price movements revert. In Panel (d) of Figure 5, for each month, we sort stocks into decile portfolios based on $\text{ExpSum}(\Delta\text{Rating})_{i,t-1}$ and track the performance over the following three years. Stocks in the top decile of past rating changes outperform stocks in the bottom decile by about 20% over the subsequent 12 to 18 months. Importantly, the cumulative return difference between the two groups of stocks indeed reverts over the 36-month horizon.[19]

4.3 Return Predictability in the Cross-Section of Stock Returns

The results presented above suggest that rating-induced flows create price pressure at the stock level. To put the rating-induced stock return predictability into perspective, in this section, we compare rating changes and some of the most prominent return predictors.

Specifically, we estimate the following model:

$$\text{Return}_{j,t} = d_1 \Delta\text{Rating}_{j,t-1-h\to t-1} + \gamma^s X^s_{j,t} + \gamma^f X^f_{j,t} + u_{j,t}, \tag{10}$$

where the dependent variable is the return of stock j in month t; $\Delta\text{Rating}_{j,t-1-h\to t-1}$ is the share-weighted average change in ratings from month $t-1-h$ to month $t-1$ for the funds that hold stock j as of the end of month $t-1$; $X^s_{j,t}$ is a vector of stock-based controls that include known predictors of stock returns, i.e., the lagged one-month return, momentum (i.e., the stock return from month $t-12$ to month $t-2$ as in Jegadeesh and Titman, 1993), long-term reversal (i.e., the stock return from month $t-36$ to month $t-13$ as in De Bondt and Thaler, 1985), size (Banz, 1981), value (Fama and French, 1993), profitability (i.e., gross profitability as in Novy-Marx, 2013), and investment (i.e., asset growth as in Cooper, Gulen, and Schill, 2008); and $X^f_{j,t}$ is a vector of fund–stock-based controls that includes the

[19]The bootstrapped standard errors are obtained via randomly permuting stocks in each year. That is, in each year and for each stock, we assign the decile ranking of another randomly chosen stock to it. We repeat this procedure 1,000 times to measure the variation of the subsequent price paths of these randomly sorted stocks. Our approach amounts to a randomization test to sample from the null hypothesis that $\text{ExpSum}_{i,t-1}$ does not impact stock returns.

the fraction of stock j's outstanding shares held by funds and the share-weighted average three-year return of the funds that hold stock j as of the end of month $t-1$.

To allow for an easy comparison of rating changes and other return predictors, we standardize the within-month mean and standard deviation of the right-hand side variables to zero and one, respectively (the approach is similar to that of Green, Hand, and Zhang, 2017, and other studies that present coefficients as z-scores). Only stocks held by at least one fund as of the end of the previous month are included in the analysis. Following literature standards, the regression is estimated via the Fama-MacBeth procedure with the Newey-West standard error correction of 12 lags.

Note that this analysis implicitly builds on the discontinuity approach of Del Guercio and Tkac (2008) and Reuter and Zitzewitz (2015). A key difference is that our analyses are carried out at the stock level rather than at the fund level. In our setting, stock-level ratings are weighted averages of individual fund ratings and are therefore not a discrete variable. For this reason, unlike in Del Guercio and Tkac (2008) and Reuter and Zitzewitz (2015), it is not possible to perform an exact discontinuity-design regression here.

Panel A of Table 1 presents baseline results with rating changes summarized using the exponential decay function described in Section 4.2. That is, lagged rating changes are measured as ExpSum(ΔRating) over the prior 12 months. The first column shows how stock returns are related to characteristics, without including rating changes or any fund-level control. Overall, the results are broadly consistent with those reported in recent literature (Fama and French, 2015; Hou, Xue, and Zhang, 2015). That is, there is no significant size premium (the sample period is 1994–2018), and investment and profitability are robust predictors of stock returns.

We estimate Equation (10) using three different samples: all stocks, stocks held by at least three mutual funds as of the end of the previous month,[20] and all stocks excluding

[20]Dropping stocks held by less than three funds from the sample is intended to reduce the noise in the relation between rating changes and expected rating-induced trading. The same data requirement is imposed in Table 9 of Lou (2012).

microcaps.[21] The results are reported in Columns (2), (4), and (6), respectively. Across the three specifications, the effect of rating changes is stronger than the effect of size, value, profitability, momentum, and long-term reversal in terms of both magnitude and statistical significance. Only investment is a stronger predictor than rating changes.

In Columns (3), (5), and (7), we modify Equation (10) by multiplying rating changes and lagged three-year fund returns by the fraction of a stock's market cap held by mutual funds as of the end of the previous month. The key results from the analysis are robust to

[21]Microcaps are defined as stocks with lagged market capitalization below the 20th percentile of NYSE market capitalization.

Table 1. Rating-Induced Price Pressures in the Cross-Section of Stocks

Panel A presents coefficient estimates for Equation (10) estimated via the Fama-MacBeth (Fama and MacBeth, 1973) procedure. Panel B provides robustness tests with respect to the length of the rating change measurement horizon, weighting method of observations, nonlinear fund return controls, and taking into account heterogeneity in flow response to ratings. Specifically, *nonlinear control* refers to specifications in which the past three-year fund returns of the funds holding each stock are controlled for by using decile indicators instead of a continuous variable. *Heterogeneous response* refers to specifications in which rating changes are weighted by the relative magnitude of their threshold effect (e.g., 4 to 5 star upgrades may produce different effects relative to 1 to 2 star upgrades). Independent variables are transformed into z-scores (mean = 0, standard deviation = 1) within each cross-section. The t-statistics presented in parentheses are computed based on standard errors with Newey-West corrections of 12 lags.

Panel A: Return Predictability from Ratings and Stock Characteristics

	All stocks			Min 3 funds		Ex. microcaps	
ExpSum(ΔRating)		0.15***		0.16***		0.15***	
		(3.06)		(3.13)		(2.63)	
ExpSum(ΔRating) × %Held			0.14***		0.15***		0.13**
			(2.74)		(2.92)		(2.28)
Size	−0.03	−0.02	−0.04	−0.02	−0.04	−0.03	−0.05
	(−0.66)	(−0.38)	(−0.82)	(−0.46)	(−0.81)	(−0.62)	(−0.99)
Value	0.11	0.11*	0.12*	0.08	0.09	0.02	0.02
	(1.58)	(1.76)	(1.78)	(1.34)	(1.40)	(0.34)	(0.39)
Profitability	0.13**	0.13**	0.12**	0.12**	0.11**	0.07*	0.05
	(2.51)	(2.45)	(2.27)	(2.23)	(2.01)	(1.71)	(1.21)
Investment	−0.19***	−0.19***	−0.20***	−0.17***	−0.18***	−0.15***	−0.15***
	(−4.38)	(−4.41)	(−4.58)	(−4.12)	(−4.32)	(−3.19)	(−3.32)
Momentum	0.13	0.11	0.09	0.09	0.07	−0.03	−0.04
	(0.86)	(0.75)	(0.61)	(0.59)	(0.44)	(−0.18)	(−0.26)
Reversal	−0.03	−0.04	−0.06	−0.05	−0.07	−0.09*	−0.11**
	(−0.62)	(−0.78)	(−1.13)	(−0.94)	(−1.32)	(−1.95)	(−2.37)
Fund-Level Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	945,706	945,706	945,706	860,340	860,340	455,308	455,308
Average R^2	0.040	0.045	0.048	0.047	0.050	0.071	0.072

$^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$

Table 1. Continued

Panel B: Robustness with Respect to Specification						
	ΔRating, linear control			ΔRating $\times$ %Held, linear control		
	All stocks	Min 3 funds	Ex. microcaps	All stocks	Min 3 funds	Ex. microcaps
ExpSum(ΔRating)	0.15***	0.15***	0.15***	0.14***	0.15***	0.13**
	(3.06)	(2.92)	(2.92)	(2.74)	(2.63)	(2.28)
3-Month ΔRating	0.11***	0.13***	0.13***	0.12***	0.13***	0.12***
	(2.73)	(3.37)	(3.37)	(3.11)	(3.21)	(2.95)
6-Month ΔRating	0.12**	0.14***	0.14***	0.13***	0.15**	0.13**
	(2.50)	(2.68)	(2.68)	(2.63)	(2.55)	(2.24)
9-Month ΔRating	0.13***	0.16***	0.16***	0.14***	0.13**	0.14**
	(2.60)	(2.85)	(2.85)	(2.79)	(2.32)	(2.23)
12-Month ΔRating	0.09*	0.15**	0.15**	0.13**	0.13**	0.14**
	(1.84)	(2.34)	(2.34)	(2.23)	(2.02)	(2.04)
	ΔRating, nonlinear control			ΔRating $\times$ %Held, nonlinear control		
	All stocks	Min 3 funds	Ex. microcaps	All stocks	Min 3 funds	Ex. microcaps
ExpSum(ΔRating)	0.16***	0.17***	0.15***	0.16***	0.17***	0.15**
	(3.31)	(3.34)	(2.64)	(2.95)	(3.07)	(2.51)
3-Month ΔRating	0.12***	0.13***	0.13***	0.14***	0.15***	0.14***
	(2.96)	(3.09)	(3.17)	(3.37)	(3.53)	(3.08)
6-Month ΔRating	0.13***	0.14***	0.15**	0.15***	0.16***	0.15**
	(2.76)	(2.87)	(2.50)	(2.67)	(2.73)	(2.45)
9-Month ΔRating	0.13***	0.15***	0.13**	0.16***	0.17***	0.16**
	(2.71)	(2.83)	(2.32)	(2.86)	(2.91)	(2.48)
12-Month ΔRating	0.10**	0.11*	0.13**	0.15**	0.16**	0.16**
	(1.96)	(1.95)	(2.03)	(2.34)	(2.44)	(2.27)
	ΔRating, heterogeneous response			ΔRating $\times$ %Held, heterogeneous response		
	All stocks	Min 3 funds	Ex. microcaps	All stocks	Min 3 funds	Ex. microcaps
ExpSum(ΔRating)	0.15***	0.16***	0.14**	0.13***	0.14***	0.12**
	(2.94)	(2.97)	(2.56)	(2.59)	(2.79)	(2.21)
3-Month ΔRating	0.12***	0.13***	0.12***	0.11***	0.12***	0.11***
	(2.80)	(3.00)	(3.21)	(2.98)	(3.22)	(2.90)
6-Month ΔRating	0.12***	0.14***	0.14**	0.12***	0.13***	0.12**
	(2.60)	(2.73)	(2.48)	(2.58)	(2.65)	(2.18)
9-Month ΔRating	0.13***	0.14***	0.13**	0.13**	0.15***	0.13**
	(2.80)	(2.82)	(2.43)	(2.81)	(2.88)	(2.30)
12-Month ΔRating	0.10**	0.10*	0.12**	0.13**	0.14**	0.13**
	(1.98)	(1.90)	(2.05)	(2.19)	(2.32)	(2.06)

$^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$

this specification change.

In Panel B of Table 1, we show that rating-induced return predictability is not sensitive to reasonable variations in the choice of rating change horizon or weighting scheme. Specifically, we report estimates for the coefficient on $\Delta\text{Rating}_{j,t-1-h\rightarrow t-1}$ with h equal to three, six, nine, and 12 months and where each lagged rating change is weighted equally. The results are presented in the upper part of the panel. Consistent with the patterns presented in Figure 5(c), the effect is particularly strong over the first six months and tends to weaken after the initial nine months.

In the middle part of Panel B, we also verify that the results are robust to controlling for potential nonlinearity in the relation between past fund returns and fund flows.[22] In most studies, this relation is found to be convex (e.g., Chevalier and Ellison, 1997). However, Spiegel and Zhang (2013) argue that the relation may actually be linear, especially when studying size-weighted flows. We take an agnostic approach and simply modify Equation (10) to allow for a nonlinear effect. Specifically, we change the fund–stock-based control for the lagged average three-year fund return from a continuous variable into 10 indicator variables representing lagged fund return deciles. All the results are robust to this specification.

Finally, in the bottom part of Panel B, we verify the robustness of the results after taking into account differential fund flow response to different rating change thresholds. As documented in Del Guercio and Tkac (2008) and Reuter and Zitzewitz (2015), at the fund level, the fund flow response is larger around the 4/5 and 3/4 star rating thresholds relative to the 2/3 and 1/2 star thresholds. We confirm this empirical fact in our data. Because the vast majority of stocks are held by multiple funds, it is not clear whether this heterogeneity would matter at the stock level, but we again take an agnostic approach and simply modify the specification to allow for heterogeneous rating change effects. We estimate the following marginal effects: 0.120, 0.340, 0.620, and 0.623 for the 1/2, 2/3, 3/4, and 4/5 star rating thresholds, respectively.[23] We then use these estimates as weights when aggregating fund-level rating changes at the stock level. The results are virtually unchanged.

Notably, the patterns described here are obtained while controlling for the past returns of the funds that hold the stock and the past returns of the stock itself. Thus, the effect

[22] We thank Motohiro Yogo for suggesting this test.

[23] Similar to Reuter and Zitzewitz (2015), these threshold effects are estimated using four threshold regressions of fund flows on lagged rating changes and past fund return controls.

we document should be interpreted as evidence that discrete changes in Morningstar ratings cause flow-induced trading that has a significant *marginal* impact on the cross-section of stock returns. This evidence serves as a premise for our main contribution in the next few sections because it demonstrates that changes in ratings have an independent causal effect on stock returns. We now show that rating-driven demand strongly influences the time-series and cross-sectional variation of style returns.

5 Impact of Rating-Chasing Demand on Style Performance

So far, we have presented evidence that ratings impact returns at the stock level. In this section, we move up a level and examine the impact of the Morningstar reform on style portfolios. To be better aligned with the definition of Morningstar ratings—the key driver of results—we use Morningstar's fund style classifications to define styles portfolios. For instance, the large-cap growth style portfolio is defined by the aggregate holdings of all funds in the Morningstar Large-Cap Growth category.[24] Specifically, for each stock i, its weight in style π is given by[25]

$$w^{\pi}_{i,t-1} = \frac{\sum_{\text{fund } j \in \text{ style } \pi} \text{Price}_{i,t-1} \cdot \text{SharesHeld}_{i,j,t-1}}{\sum_{\text{fund } j \in \text{ style } \pi} \text{TNA}_{j,t-1}}. \tag{11}$$

In the subsections that follow, we document our main results. We start by showing the existence of robust style-level rating-induced price pressures as well as style-level momentum and reversal patterns before the June 2002 reform. Consistent with the idea that these

[24] We use this classification because it is the basis for the style-level adjustments in Morningstar ratings. Lettau, Ludvigson, and Manoel (2019) document that fund-based style classification in the financial industry does not map exactly to the size and value definitions used by academics, which are based on market capitalization and book-to-market ratios (Fama and French, 1993). Appendix A.2 shows that the industry classification is a "smoothed" version of the academic style definitions. In Appendix A.3, we present results repeating the main analyses for styles based on the academic definitions. The results generally extend to the academic-based styles qualitatively, though with weaker magnitudes, as expected.

[25] Because $\text{TNA}_{j,t-1} = \sum_{\text{stock } i} \text{Price}_{i,t-1} \cdot \text{SharesHeld}_{i,j,t-1}$, we have $\sum_{\text{stock } i} w^{\pi}_{i,t-1} = 1$.

patterns were due to correlated rating-induced trading at the style level, the effects dissipated after the reform. Moreover, style return dispersion declined dramatically following the rating methodology change. To provide sharper identification, in Section 6, we conduct an event study using a short window to focus exclusively on the reform-induced rating movements in June 2002.

5.1 Style-Level Rating-Induced Price Pressures

We start by examining the effects of the Morningstar reform on style-level demand and return dynamics. To this end, we first calculate the style-level changes in Morningstar ratings. We aggregate the stock-level rating changes for each style portfolio π:

$$\text{ExpSum}(\Delta\text{Rating})_{\pi,t-1} = \sum_{\text{stock } i \in \text{ style } \pi} w^{\pi}_{i,t-1} \cdot \text{ExpSum}(\Delta\text{Rating})_{i,t-1}, \tag{12}$$

where the stock-level lagged 12-month rating change, $\text{ExpSum}(\Delta\text{Rating})_{\pi,t-1}$, is as defined in Equation (9), and $w^{\pi}_{i,t-1}$ is the portfolio weight of stock i in style π.

To examine the effects of rating changes on style flows and returns, we rank the nine style portfolios by $\text{ExpSum}(\Delta\text{Rating})_{\pi,t-1}$ within each month and track average cumulative flows and returns over the following months. The results, which are also presented graphically in Panels (c) and (d) of Figure 1, are tabulated in Table 2. Panel A shows statistics for the top- versus bottom-ranked styles over horizons of up to 36 months, and Panel B repeats the analysis for the three top-ranked versus three bottom-ranked styles. The standard errors are bootstrapped by randomly permuting the style portfolios in each year.[26]

Before 2002, the top style experienced approximately 1% higher flows per month relative to the bottom style over the next 12 months. As expected, the spread in flows between the top three and the bottom three styles is smaller, at about 0.7%. Following the rating reform of June 2002, which mechanically shrunk the dispersion of ratings across styles, the spread

[26] In other words, we conduct a randomization test to sample from the null hypothesis that ratings do not impact style returns at all.

Table 2. Rating-Induced Price Pressures in Style Portfolios

We sort style portfolios using the lagged exponential sum of rating changes ($\text{ExpSum}(\Delta\text{Rating})_{\pi,t-1}$) and tabulate their average monthly fund flow and return over the subsequent 36 months. Panel A shows the difference between the top and bottom styles. Panel B shows the difference between the averages of the top three and the bottom three styles. Bootstrapped standard errors are reported in parentheses.

Panel A: Top 1 Minus Bottom 1

	Months:	1–6	7–12	13–24	25–36
Monthly Flow (%)	Before June 2002	1.14***	0.92***	0.38*	−0.25
		(0.33)	(0.28)	(0.23)	(0.19)
	After June 2002	0.09	−0.09*	−0.04	−0.02
		(0.07)	(0.05)	(0.05)	(0.05)
	Before − After	1.05***	1.01***	0.42*	−0.22
		(0.34)	(0.29)	(0.23)	(0.19)
Monthly Return (%)	Before June 2002	0.76**	0.39	−0.04	−0.58***
		(0.31)	(0.35)	(0.22)	(0.22)
	After June 2002	−0.07*	−0.04	−0.05	0.04
		(0.04)	(0.06)	(0.05)	(0.04)
	Before − After	0.83***	0.43	0.02	−0.62***
		(0.32)	(0.36)	(0.23)	(0.23)

Panel B: Top 3 Minus Bottom 3

	Months:	1–6	7–12	13–24	25–36
Monthly Flow (%)	Before June 2002	0.81***	0.66***	0.14	−0.14
		(0.22)	(0.19)	(0.16)	(0.09)
	After June 2002	0.10**	−0.08**	−0.04	−0.05**
		(0.04)	(0.03)	(0.02)	(0.02)
	Before − After	0.71***	0.74***	0.17	−0.09
		(0.23)	(0.20)	(0.16)	(0.10)
Monthly Return (%)	Before June 2002	0.47**	0.28	−0.10	−0.39***
		(0.21)	(0.22)	(0.17)	(0.13)
	After June 2002	−0.08***	−0.04	−0.05	0.03
		(0.03)	(0.03)	(0.03)	(0.03)
	Before − After	0.55**	0.31	−0.05	−0.42***
		(0.22)	(0.22)	(0.17)	(0.13)

$^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$

in flows over the 12 months after sorting styles became about 10 times smaller.

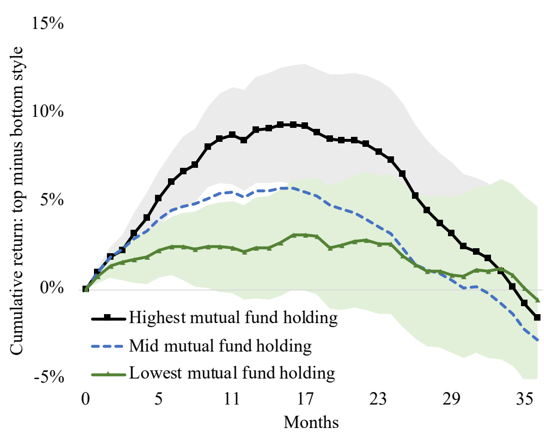
Table 2 also shows that the patterns observed in style flows are mirrored in style returns. Before June 2002, the top style outperformed the bottom style by about 10% in total over the next 12 to 18 months, and the return spread reverted subsequently. Strikingly, the return spread is effectively zero after June 2002. Again, we find similar patterns when comparing the top-three and bottom-three styles (Panel B). Overall, these results are consistent with style-level ratings creating flow-induced price pressures and subsequent reversals before June 2002 but not after that date as flows spread out across styles after the reform.

Heterogeneous exposure to Morningstar ratings within styles. To further sharpen the test, we make use of the fact that stocks more heavily held by mutual funds within a given style portfolio should experience larger rating-induced price pressures. In each style portfolio, we further sort stocks into three equal-stock-count terciles based on the lagged fraction of shares held by all mutual funds. On average, mutual funds hold 30.6% of the stocks in the top tercile, followed by 18.8% and 11.6% for the next two terciles.

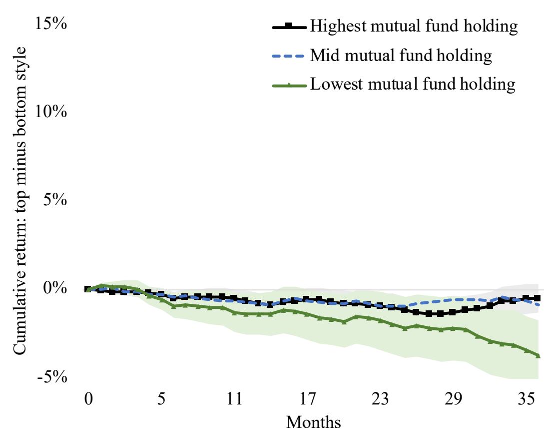
Figure 6. Rating-Induced Style Returns: Splitting on Mutual Fund Ownership

As in Panel (d) in Figure 1, we sort the 3 × 3 style portfolios by their lagged rating changes (ExpSum(ΔRating)) and plot the cumulative differences in returns between the top and bottom styles for the subsequent 36 months. Both bottom- and top-ranked styles are split into three subsets of stocks, based on the fraction of total shares held by mutual funds. The shaded areas are based on bootstrapped two-standard-error bands.

(a) Before June 2002



(b) After June 2002



We then repeat the same exercise—sorting styles using ExpSum_{t-1} and examining the difference between the top and bottom styles. for each of the three mutual-fund-holding terciles. The results are plotted in Figure 6. As predicted, the price effect before June 2002 is stronger in the style portfolios consisting of stocks with higher mutual fund ownership than in those consisting of stocks with low mutual fund ownership.[27] There is no effect in any of the terciles after June 2002.

5.2 Profitability of the Rating-Driven Style Momentum Strategy

These price pressure results suggest that a rating-based style momentum strategy would be profitable before June 2002, but not afterward. This is indeed the case. In Table 3, we examine the monthly returns of style portfolios sorted by the lagged exponential sum of rating changes ($\text{ExpSum}(\Delta\text{Rating})_{\pi,t-1}$). Panels A and B show that, prior to June 2002, styles with high past rating changes generally have better performance than other styles and that that difference shrank significantly after June 2002. As a consequence, a trading strategy that goes long the top ranked style and short the bottom style was profitable, with about a 1% monthly return and CAPM alpha before June 2002. As we predicted, the strategy became unprofitable after June 2002.

5.3 Cross-Sectional Dispersion in Style Returns

As a result of the reform, the dispersion in average Morningstar ratings across fund styles declined sharply after June 2002 (Panel (a) of Figure 1). Therefore, if our hypothesis — that ratings drive flows and then lead to price impact — is correct, we should observe a decline in the dispersion in style flows and returns after the reform.

To test this prediction, we use two definitions of dispersion: the spread between the styles with highest and lowest realizations, and the standard deviation across all styles. We calculate style-level dispersion in ratings, flows, and returns. We then regress these dispersion measures on an indicator that equals one after June 2002. In addition to using

[27] The style portfolios with higher mutual-fund-holding stocks in fact have *more* overlap in their portfolio constituents. As higher overlap mechanically leads to less return dispersion (100% overlap means zero return dispersion), this goes against us finding a result. To examine this, we compute the pairwise overlap of each pair of portfolios j and k, defined as $\sum_{\text{stock } i} |\min(w_{i,\text{portfolio } j}, w_{i,\text{portfolio } k})|$, where $w_{i,\text{portfolio } l}$ is the weight of portfolio l in stock i. We then take an average across all pairs of style portfolios within each tercile. The average overlap for the highest, mid, and lowest mutual fund holding terciles are 24.2%, 17.0%, and 11.9%, respectively.

Table 3. Rating-Induced Style Momentum Strategy Around June 2002

This table shows monthly flows and returns of 3 × 3 Morningstar style portfolios sorted each month by the lagged exponential sum of rating changes ($\text{ExpSum}(\Delta\text{Rating})_{\pi,t-1}$). Panels A and B, respectively, show the average monthly return and CAPM alpha as percentages. The last column is the difference between the top- and bottom-ranking styles. In Panel A, style returns are demeaned in each month to focus on the cross-sectional difference. The standard errors are reported in parenthesis. Results that are statistically significant at 10%, 5%, and 1% levels are denoted as *, **, and ***, respectively.

	Bot	2	3	4	5	6	7	8	Top	Top − Bot
Panel A: Return (Demeaned)										
Before 2002	−0.42*	−0.45**	−0.25	0.00	−0.08	0.21	−0.06	0.49**	0.54**	0.96**
	(0.22)	(0.22)	(0.18)	(0.17)	(0.11)	(0.15)	(0.16)	(0.23)	(0.24)	(0.44)
After 2002	−0.02	0.08	−0.06	0.08	−0.07	0.04	−0.07	0.04	−0.01	0.01
	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.09)	(0.15)
Panel B: CAPM Alpha										
	Bot	2	3	4	5	6	7	8	Top	Top − Bot
Before 2002	−0.24	−0.29	−0.11	0.23	0.13	0.46**	0.20	0.71***	0.82***	1.06***
	(0.23)	(0.23)	(0.18)	(0.18)	(0.16)	(0.19)	(0.23)	(0.27)	(0.29)	(0.37)
After 2002	−0.01	0.09	−0.02	0.12	−0.05	0.05	−0.06	0.08	0.04	0.05
	(0.11)	(0.11)	(0.10)	(0.09)	(0.11)	(0.10)	(0.10)	(0.10)	(0.10)	(0.15)

the full sample, to account for the impact of the dot-com bust, we also use a four-year window centered on the methodology change event, as well as a full sample window that excludes the four years surrounding the event. Standard errors are adjusted using the Newey-West procedure.

The regression coefficients on the post-June-2002 dummy variable are shown in Table 4. As predicted, regardless of the dispersion measures used, we find that ratings, flows, and returns of styles became less dispersed after June 2002. Columns (1) to (4) show that the dispersion in ratings and flows declined dramatically regardless of the time window.

Columns (5) and (6) show that style return dispersion also dropped precipitously after June 2002. Over the entire sample, the monthly return spread between the top and bottom styles dropped by 2.54% after June 2002 (from 5.5% to 2.9%).When excluding the sample period from 2000Q3 to 2004Q2 to alleviate the concern about the dot-com bust, the monthly return spread between the top and bottom styles dropped by 2.1% (from 5.0% to 2.9%). The result are qualitatively similar when dispersion is measured using the standard deviation of

Table 4. Dispersion of Style Ratings, Flows, and Returns

We regress dispersion measures of monthly ratings, flows, and returns of style portfolios on a dummy that equals one after June 2002. We report the coefficient on the dummy variable in this table. In Columns (1), (3), and (5), we measure dispersion using the spread between the styles with the highest and lowest realizations. In Columns (2), (4), and (6), we measure dispersion using the standard deviation of those variables. Across the different rows, we vary the sample size used in the regressions. Newey-West standard errors are reported in parentheses.

Regression coefficient on the post-June 2002 dummy						
Dependent variables:	Rating		Flow (%)		Return (%)	
	Spread	Std Dev	Spread	Std Dev	Spread	Std Dev
	(1)	(2)	(3)	(4)	(5)	(6)
Full sample	-0.61^{***}	-0.22^{**}	-1.88^{***}	-0.60^{***}	-2.54^{***}	-0.90^{***}
	(0.22)	(0.11)	(0.23)	(0.08)	(0.68)	(0.25)
2000Q3–2004Q2	-0.53^{***}	-0.20^{***}	-1.74^{***}	-0.63^{***}	-4.45^{***}	-1.53^{***}
	(0.19)	(0.06)	(0.45)	(0.17)	(0.85)	(0.31)
Exclude 2000Q3–2004Q2	-0.62^{**}	-0.22^{*}	-1.91^{***}	-0.59^{***}	-2.11^{***}	-0.76^{***}
	(0.26)	(0.13)	(0.27)	(0.09)	(0.73)	(0.25)

$^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$

returns.[28]

Overall, the results in this section suggest that Morningstar ratings have had a noticeable impact on style flow and return dynamics over the sample period studied. We now conduct an event study around the 2002 shock to further zoom in on the event.

6 Event Study Around the Morningstar Reform

The style-level price pressure results documented so far build on the evidence that rating-induced fund flows have a causal effect on stock returns (see Section 4 and especially Table 1).

In this section, we provide an additional and independent test of rating-induced demand effects on style returns. To do so, we conduct an event study using a one-year window (January to December 2002) around the reform implementation date. By focusing on a short window and by relying on the degree of exposure of the various styles to the Morningstar reform, we can ensure that the rating changes are primarily caused by the methodology change

[28]Moreover, in untabulated tests, we find that the results presented in Table 4 are robust to the inclusion of a time trend control, indicating that they are not driven by a general decline in style-level dispersion.

(as opposed to by managerial skill, for instance). Focusing on a narrow window reduces the chance that our findings are confounded by other events such as NYSE decimalization in early 2001 and the introduction of NYSE auto quoting in 2003 (Hendershott, Jones, and Menkveld, 2011). In addition, we examine other variables around that date to verify that the effects we document do not stem from shocks to the fundamentals of the stocks forming the style portfolios or from the trading behavior of market participants other than mutual funds.

6.1 Performance of Styles, by Predicted Rating Impact

Our analysis tracks style ratings, flows, and returns in 2002; the styles are sorted by their exposure to Morningstar's methodology reform. The reform caused the style ratings to converge on three stars. Thus, styles that had ratings greater than three stars as of May 2002 experienced a drop in their ratings due to the methodology reform. In contrast, styles that had ratings lower than three stars experienced an increase. The objective of our analysis is to compare the ratings, flows, and returns of the styles that experience the largest changes in ratings due to the reform.

Our ranking of the exposure of styles to the Morningstar reform relies on pre-window information.[29] Specifically, since the change in ratings between May and June includes components that are related both to the methodology reform and to style performance, we rank styles by the *predicted* rating change due to the reform, computed using December 2001 data. We calculate the predicted rating changes in the following fashion. For each fund j, we compute

$$\widehat{\Delta \text{Rating}}_j = \text{Rating}^{\text{counterfactual}}_{j,\text{Dec 2001}} - \text{Rating}^{\text{actual}}_{j,\text{Dec 2001}}, \tag{13}$$

where $\text{Rating}^{\text{counterfactual}}_{j,\text{Dec 2001}}$ is our estimate of what its December 2001 rating would have been

[29] Ranking on pre-window information alleviates concerns about mean-reversion in returns, which would be an issue, for instance, if we rank styles based on their average performance during January to June 2002.

under the post-2002 methodology.[30] $\widehat{\Delta\text{Rating}}_j$ thus measures how the fund's rating would have changed in December 2001 had the reform happened then. We then aggregate up these fund-level predictions at the style level.

When we sort the nine styles by the predicted rating change, we find that this procedure correctly predicts which style portfolios experienced the largest changes in June 2002. Specifically, the small-value style enjoyed the highest rating in December 2001 and is therefore predicted to experience the largest reform-driven decline; the large-growth style had the lowest rating in December 2001 and is predicted to experience the largest increase. The reason why we can successfully predict the exposure of different styles to the reform using data from six months before the reform is that ratings are slow-moving.[31]

In Figure 7, we present the evolution of style ratings, flows, and returns in 2002. Panel (a), which plots average style ratings (demeaned cross-sectionally), shows a sharp methodology-induced rating collapse exactly at the event. The style most negatively affected by the reform suffered a drop of about 0.4 stars, while the most positively affected style experienced an increase of about 0.4 stars. Similar patterns can be observed when comparing the flows to the second-most positively and negatively affected styles.

Next, we look at flows. Panel (c) shows that in the months leading up to the event, the top-rated style (expected to be most negatively affected by the reform) experienced approximately 23% additional flows relative to the bottom-rated style. As a result of the reform, the average star rating across styles became approximately 3 at the end of June 2002. Thus, as expected, the divergence in cumulative flows between styles disappeared.

Finally, we examine cumulative style returns in Panel (e). Pre-event style returns lined up with pre-event ratings and flows. Following the June 2002 event, return differences leveled off with a slight reversal. The most negatively affected style had returns of 2.6% per month during the pre-event period and reverted to -0.5% after the event. The most positively

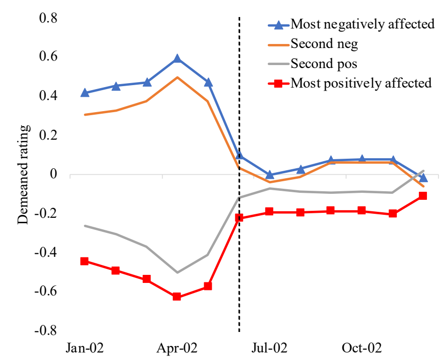
[30] Appendix A.6 provides more details about how the counterfactual ratings are computed in a bottom-up fashion using past fund returns.

[31] As explained in Appendix B, ratings are slow-moving because they are based on three, five, and 10 years of past fund returns.

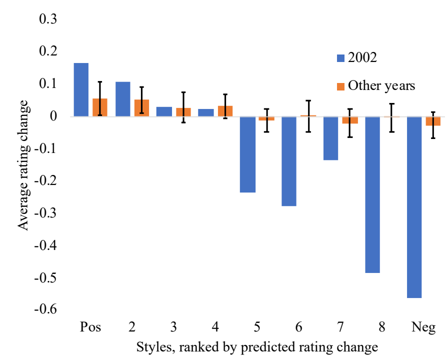
Figure 7. Event Study Around June 2002

We perform event studies on the 3 × 3 size-value Morningstar style portfolios during the six months before and after the June 2002 methodology change. In the left panels, we sort styles by their *predicted* rating change at the June 2002 event using December 2001 data, and then plot the evolution of their ratings in Panel (a), cumulative flows in Panel (c), and cumulative returns in Panel (e). The dashed vertical line is the June 2002 event. The right panels conduct the same exercises in years other than 2002 as a placebo test. The blue bars plot the average rating, flow, and return changes after June 2002 (average of July to December 2002 minus average of January to June 2002), while the orange bars plot the corresponding results for years other than 2002. The whiskers represent two-standard-error bands. To focus on cross-sectional dispersion, all variables—ratings, returns, and flows—are demeaned cross-sectionally.

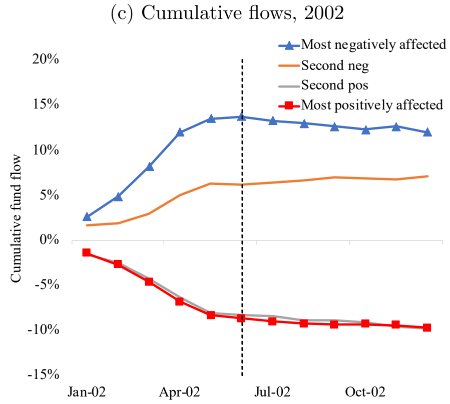
(a) Ratings, 2002



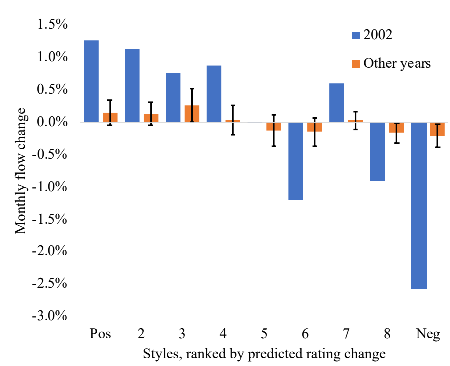
(b) Ratings change: 2002 vs. placebo



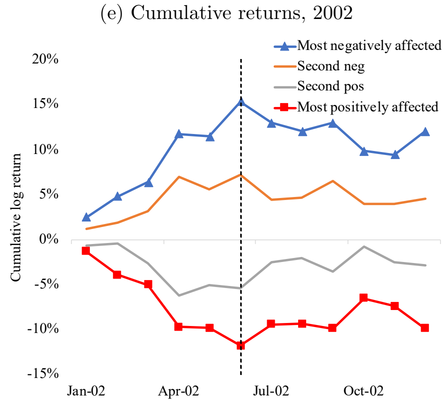
(c) Cumulative flows, 2002



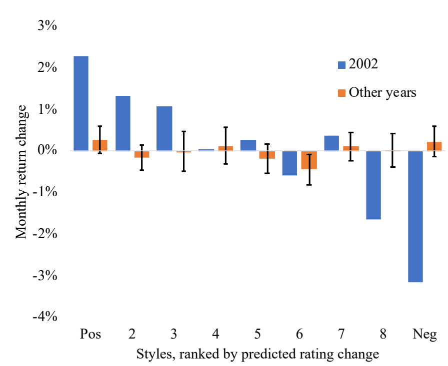
(d) Flow change: 2002 vs. placebo



(e) Cumulative returns, 2002



(f) Return change: 2002 vs. placebo



affected style had a −1.9% monthly return before the event and 0.3% after.

Similar to this style-level exercise, we also perform this event study using individual stocks and obtain similar results. The benefit of repeating the exercise using stocks is that doing so allows us to study a cross-section of thousands of observations (stocks), each of which has a different degree of ex-ante "exposure" to the Morningstar reform. Specifically, we follow the same procedure described above to estimate the predicted stock-level methodology-induced rating change using data as of December 2001 and sort stocks into quintiles. Appendix Figure A.5 plots the evolution of the ratings and cumulative returns of these stocks. The results are consistent with the style-level exercise.

To put the size of the price impact (reciprocal of demand elasticity) into perspective, a back-of-the-envelope exercise shows that the style-level price impact coefficient in our results is approximately 5.3. That is, buying 1% of the market cap outstanding creates a price impact of 5.3%.[32] This magnitude is consistent with the existing literature. Because the 2002 shock generated less diversifiable style-level flows, we expect our estimate to be higher than estimates based on stock-level shocks but smaller than those based on market-level shocks. Using a demand system approach, Koijen and Yogo (2019) estimate the coefficient to be between 2 to 4 at the stock level. Using the granular instrument approach of Gabaix and Koijen (2020a), Gabaix and Koijen (2020b) estimate the market-level coefficient to be between 5.28 and 7.08. Our estimate lies between these two.

6.2 Testing for Alternative Explanations

The fact that the reform happened at the end of June 2002 alleviates the concern about other contaminating events. For instance, one may worry about the NYSE decimalization and auto-quoting introduction, both of which increased market liquidity. However, the former happened in early 2001 and the latter in 2003 (Hendershott et al., 2011). The accel-

[32] In our exercise, the cumulative fund flow difference between the top and bottom-ranked styles is 22.4% in the six months leading up to the event (Panel (c) of Figure 7). The return difference is 27.2%. As mutual funds held approximately 22.8% of the U.S. stock market in 2002, this implies a style-level price impact coefficient of $\frac{27.2\%}{22.5\%} \times \frac{1}{22.8\%} \approx 5.3$.

eration of 10K filings by the Securities and Exchange Commission (SEC) became effective in November 2002 and can only have had an impact when companies filed their 10Ks, i.e., not before early 2003 (Securities and Exchange Commission, 2002). The Sarbane-Oxley Act was passed in July 2002, but it is unlikely to have driven our results for two reasons. First, the Sarbane-Oxley Act is concerned with regulating the financial reporting of firms and thus should not have had large impacts on mutual fund flows. Second, while some studies have found that the Sarbane-Oxley Act event had differential price impacts on different stocks, the findings are unrelated to style differences across firms and are much smaller in magnitude than the effects we document (for instance, Table 3 in Jain and Rezaee (2006) and Table 6 in Li, Pincus, and Rego (2008)).[33]

In addition, we conduct three further tests around the June 2002 event window to examine alternative explanations. The results do not support any of the alternative hypotheses.

Placebo test: Other years. First, to alleviate the concern that the style flow and return patterns occur mechanically due to regression to the mean, we conduct a placebo test by rerunning an identical exercise in all years other than 2002. Panels (b), (d), and (f) of Figure 7 show that the patterns observed in 2002 did not take place in other years. The orange bars show the same exercise in other years together with two-standard-error bands. The sharp changes in style ratings, flows, and returns are unique to 2002.

Other factors that may have impacted style returns around 2002. Our event study methodology assumes that no other sudden style-level shocks occurred around June 2002 that could have caused the patterns we observe. Such shocks would need to impact flows and returns of styles in a manner that is aligned with how the Morningstar reform impacted ratings across styles. While we are not aware of similar shocks around June 2002, this is a key assumption that merits further validation.

[33]This discussion is motivated by the conjectures put forth in Green et al. (2017) about what is different before and after 2002.

For this purpose, in Figure 8 we examine whether there are sudden changes in a number of other variables. Theoretically speaking, asset prices can move due to changes in fundamentals or due to trading behaviors,[34] and thus we investigate these two possibilities separately.

To investigate changes in fundamentals, we compute return on assets (ROA) and return on equity (ROE) using quarterly Compustat data and plot their evolution at the style-level (value-weighted) in Panels (a) and (b). While the fundamentals of different styles do differ and fluctuate, there is no discernible sudden change around June 2002 that is correlated with the style-level return movements.

To investigate trading behaviors of institutions, we examine trades by 13F institutions at the style level. We obtain quarterly 13F holdings data from Thomson Reuters and aggregate by the legal types of institutions obtained from Brian Bushee's website.[35] We then plot the cumulative trading by different types of institutions as a fraction of market capitalization in Panels (c) to (e).

Panel (c) plots the combined trading by investment companies and independent investor advisors, a category that includes the mutual fund sector. Consistent with our argument, these institutions indeed trade in a manner aligned with the flow patterns depicted in Figure 7(a): They traded into (out of) styles with high (low) pre-2002 ratings, before halting suddenly right after June 2002. Panel (d) plots the trading of banks, insurance companies, and pension funds. Panel (e) plots the trading of endowment funds and other institutions. There is no discernible "kink" in the trading of any of those non-mutual-fund institutions. Finally, because 13F data only records long positions, we also examine the evolution of aggregate short interest in Panel (f). While there is a general slow rise in short interest across all styles over the window, there is no clear change around the event.

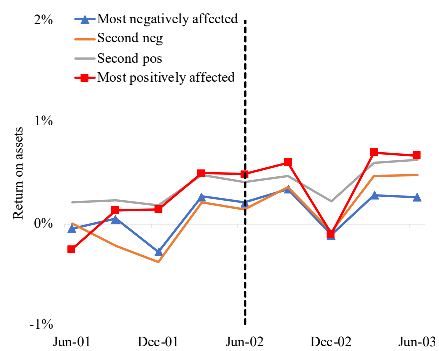
[34] It is unlikely that a rationally determined discount rate can vary so much in a short period of time, so we do not investigate this possibility. Note that 2002 is not a recession period; the U.S. economy was already out of the dot-com-related recession by November 2001, according to the National Bureau of Economic Research.

[35] See `https://accounting-faculty.wharton.upenn.edu/bushee/`.

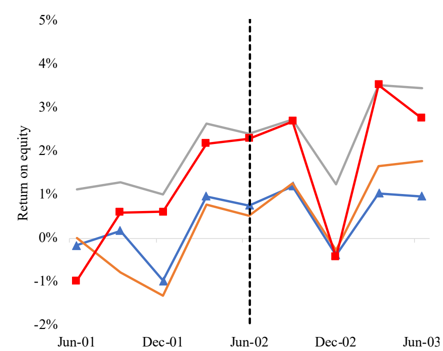
Figure 8. Event Study Around June 2002: Alternative Explanations

We perform event studies on the 3×3 Morningstar style portfolios around the June 2002 methodology change. As in Figure 7, we sort styles by their *predicted* rating change at the June 2002 event using December 2001 data, and then plot the evolution of various variables. To assess changes in fundamentals, Panels (a) and (b) plot the evolution of return on assets and return on equity. Panels (c) to (e) plot the cumulative trading (as a fraction of overall market capitalization) by different types of 13F institutions. Panel (c) plots trading by investment companies and advisors, which include the mutual fund sector. Panel (d) plots trading by banks, insurance companies, and pension funds; Panel (e) plots trading by endowment funds and other institutions. To focus on cross-sectional dispersion, the trading measures in Panels (c) to (e) are demeaned by period. Panel (f) plots the evolution of aggregate short interest. The vertical dashed line indicates the June 2002 methodology change event.

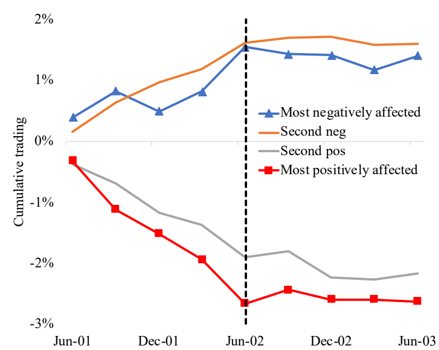
(a) Return on assets (ROA)



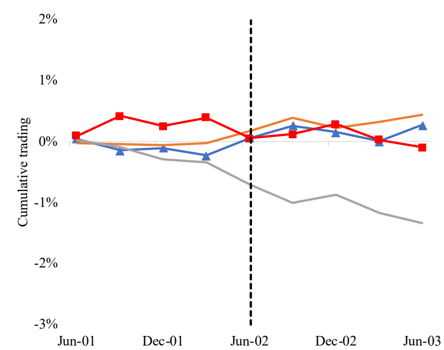
(b) Return on equity (ROE)



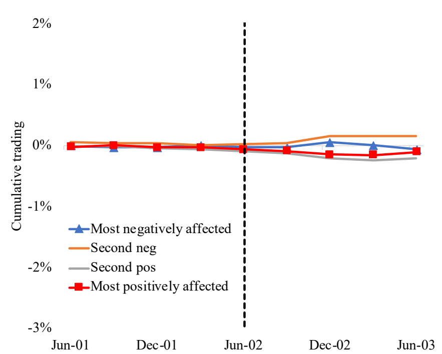
(c) Trading: Investment companies and advisors



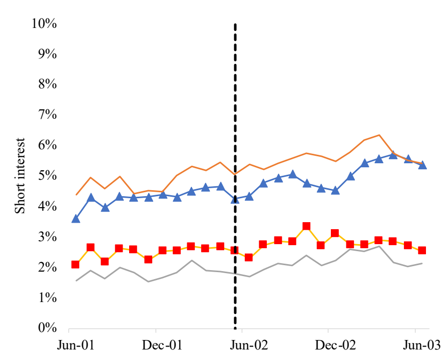
(d) Trading: Banks, insurance, pension funds



(e) Trading: Endowment funds and others



(f) Short interest



Controlling for stock characteristics. The previous two tests show that there were no sudden changes in fundamentals or trading behaviors of non-mutual-fund institutions around 2002. However, one might still argue that our results could be driven by sudden characteristics-related return changes that happened for other reasons. For example, one might hypothesize that investor sentiment suddenly decreased for small-value stocks after June 2002, causing returns to decrease for those stocks.

To further alleviate this concern, we show that our results—that predicted rating changes explain return changes—also take place at the stock level after controlling for size and book/market. Specifically, for each stock i, we define

$$\text{Rating}_{i,t}^{\text{idiosyncratic}} = \text{Rating}_{i,t} - \text{Rating}_{\text{size-book/market portfolio } p,t}, \tag{14}$$

$$\text{Ret}_{i,t}^{\text{idiosyncratic}} = \text{Ret}_{i,t} - \text{Ret}_{\text{size-book/market portfolio } p,t}, \tag{15}$$

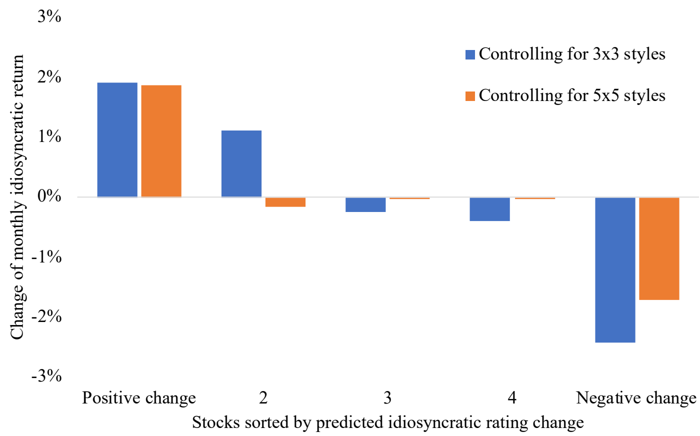
where p is the 3×3 or 5×5 size and book/market sorted portfolio (constructed using NYSE cutoffs) to which stock i belongs. We compute the rating and return of those portfolios by aggregating from the underlying stocks using market cap weights. We choose size and book/market because they are the most commonly used characteristics in the literature and because they are the most parsimonious way to "mimic" the size-value style box used by Morningstar. Thus, $\text{Rating}_{i,t}^{\text{idiosyncratic}}$ and $\text{Ret}_{i,t}^{\text{idiosyncratic}}$ measure the components of rating and return that are *not* explained by realized characteristics-related returns.

We then sort on the predicted idiosyncratic rating change (using December 2001 data)[36] and examine the change in idiosyncratic stock returns after the event in Figure 9. Note that our mechanism—that rating changes impact returns—works both at the characteristic-spanned and characteristic-orthogonal (idiosyncratic) levels. Therefore, even after controlling for characteristics, we should still expect to see an effect. Consistent with this ex-

[36] Specifically, we first compute counterfactual ratings for each fund in December 2001 under the post-reform Morningstar methodology. We then aggregate those at the stock and portfolio levels and subtract the latter from the former to get the counterfactual *idiosyncratic* rating at the stock level. The difference between this counterfactual idiosyncratic rating and the actual idiosyncratic rating in December 2001 is our prediction of the change.

Figure 9. Return Change Around June 2002: Controlling for Characteristics

We first subtract value-weighted average ratings and returns of 3×3 or 5×5 size-book/market portfolios to obtain *idiosyncratic* ratings and returns for each stock (see Equations (14) and (15)). Then, we sort stocks into quintiles based on their *predicted* idiosyncratic rating changes at the June 2002 event using December 2001 data. The top (bottom) quintile comprises stocks expected to experience the largest decline (increase) of idiosyncratic ratings. The figure plots the difference between the average six-month idiosyncratic return after the event (July to December 2002) and the average six-month idiosyncratic return before the event (January to June 2002).



pectation, stocks predicted to experience large upgrades (downgrades) in *idiosyncratic* rating (Equation (14)) experience positive (negative) changes in *idiosyncratic* returns (Equation (15)). The quantitative relation between rating changes and return changes is also comparable to that found at the style level (Panel (f) in Figure 7). These results further suggest that our style-level findings around June 2002 are unlikely to be driven by unspecified characteristics-level return movements.

7 Advice-Driven Demand and Asset Pricing Factors

So far, we have seen that rating-induced demand creates large price pressures on style returns. In this section, we explore the relation between rating-chasing demand and the size and value factors, which are defined as long-short portfolios on styles. Here, we ask, to what extent can the returns of the size and value factors be explained by rating-induced correlated demand? To be consistent with the earlier sections, we present findings based on Morningstar-based styles, but note that the results based on styles in academic studies (following Fama and French, 1993) are similar (Appendix A.3).

To answer this question, we first use the 12-month short window around June 2002 to estimate the price impact coefficient of Morningstar ratings on style returns—the building blocks of the size and value factors. We choose a short window for two reasons. First, we want to ensure that rating changes primarily come from the methodology change.[37] Second, we want to avoid the impact of other market-level changes, such as the dot-com bubble burst in early 2000, the decimalization event in 2001 (Chordia, Subrahmanyam, and Tong, 2014), the "momentum crash" period in 2008 (Daniel and Moskowitz, 2016), or an increase in the efficiency or liquidity of the market (e.g., Chordia et al., 2014).

Formally, we estimate a forecasting panel regression using the 12 months around the event (January 2001 to December 2001):

$$\mathrm{Ret}_{\pi,t} = \lambda \cdot \mathrm{ExpSum}(\Delta\mathrm{Rating})_{\pi,t-1} + \mathrm{Controls}_{\pi,t-1} + \epsilon_{\pi,t}, \tag{16}$$

where the controls include style returns over $t-1$, $t-2$ to $t-6$, and $t-7$ to $t-12$ months as well as style and time fixed effects. By controlling for past returns, we can better capture the marginal effect of rating changes in addition to possible style momentum effects (Ehsani and Linnainmaa, 2019; Gupta and Kelly, 2019). Standard errors are clustered by month.

The estimation results are shown in Table 5. For each star rating change, the style-level price impact is 2.89% per month with a t-statistic of 2.50 (Column (1)). To account for cross-sectional style return correlation, in Columns (3) and (4), we also adjust the standard

[37] This is not true if we use a longer sample as ratings are (albeit complex) functions of past returns. Recent studies find that return factors can exhibit momentum (Arnott, Clements, Kalesnik, and Linnainmaa, 2019; Gupta and Kelly, 2019); earlier papers found that returns tend to exhibit long-term reversion (De Bondt and Thaler, 1985). Thus, running a regression of style returns on lagged ratings may be picking up both momentum and reversal effects.

Table 5. Estimating the Price Impact of Ratings (λ) Around June 2002

We estimate the rating price impact coefficient λ through a forecasting panel regression of monthly returns of the 3×3 styles on lagged ratings changes (ExpSum(ΔRating)$_{\pi,t-1}$). We also control for past style returns over $t-1$, $t-2$ to $t-6$, and $t-7$ to $t-12$ months, as well as style and time fixed effects in some specifications. The sample spans the six months before to six months after the methodology change. Columns (1) and (2) are estimated in a panel regression, and standard errors are clustered by month. Columns (3) and (4) are estimated using feasible general least squares (FGLS), where we use the empirically estimated covariance matrix of style returns to adjust for cross-sectional correlations. Standard errors are shown in parentheses.

Dependent variable:	Monthly style return $\mathrm{Ret}_{\pi,t}$(%)			
	Panel regression		FGLS	
	(1)	(2)	(3)	(4)
ExpSum(ΔRating)$_{\pi,t-1}$	2.89**	2.63**	2.49***	1.76***
	(1.16)	(1.17)	(0.71)	(0.67)
Past Return Controls	Yes	Yes	Yes	Yes
Style FE	Yes	No	Yes	No
Time FE	Yes	Yes	Yes	Yes
Observations	108	108	108	108
Adjusted R^2	93.0%	93.2%	80.6%	78.9%

$^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$

errors using a feasible generalized least squares (FGLS) approach.[38] When using FGLS, the estimated price impact is 2.49% (t = 3.50). The estimates are both statistically and economically significant. Our estimates do not change materially if we use shorter or longer event-time windows, and we present those robustness checks in Appendix Table A.3.

[38] We use the full sample of style returns to estimate the covariance matrix of style returns and incorporate it into the estimation. Specifically, let y be the vector of style returns stacked together so that the first nine entries are the first month, the next nine entries are the second month, and so forth. Then, we estimate the covariance matrix of y to be

$$\hat{\Omega} = \begin{pmatrix} \hat{C} & 0 & \dots & 0 \\ 0 & \hat{C} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \hat{C} \end{pmatrix},$$

where $\hat{C}$ is the estimated contemporaneous return variance-covariance matrix of the nine styles. Let X denote the matrix of independent variables. Then, we estimate the regression coefficients and variance-covariance matrix using

$$\hat{b} = (X'\hat{\Omega}^{-1}X)^{-1}X'\hat{\Omega}^{-1}y,$$
$$\widehat{Var}(\hat{b}) = (X'\hat{\Omega}^{-1}X)^{-1}.$$

We now use the estimated $\lambda = 2.89\%$ in Column (1) to quantify the influence of ratings on style and factor returns. Specifically, we use the following price-impact specifications:

$$\text{Ret}_{\text{SMB},t} = \underbrace{\lambda \cdot \text{ExpSum}(\Delta\text{Rating})_{\text{SMB},t-1}}_{\text{Rating-induced price pressure}} + \text{Ret}^{\text{counterfactual}}_{\text{SMB},t} \tag{17}$$

$$\text{Ret}_{\text{HML},t} = \underbrace{\lambda \cdot \text{ExpSum}(\Delta\text{Rating})_{\text{HML},t-1}}_{\text{Rating-induced price pressure}} + \text{Ret}^{\text{counterfactual}}_{\text{HML},t}, \tag{18}$$

where

$$\text{ExpSum}(\Delta\text{Rating})_{\text{SMB},t-1} \equiv \left(\sum_{\pi\in\mathcal{S}} - \sum_{\pi\in\mathcal{B}}\right) \text{ExpSum}(\Delta\text{Rating})_{\pi,t-1}$$

$$\text{ExpSum}(\Delta\text{Rating})_{\text{HML},t-1} \equiv \left(\sum_{\pi\in\mathcal{V}} - \sum_{\pi\in\mathcal{G}}\right) \text{ExpSum}(\Delta\text{Rating})_{\pi,t-1}.$$

In the equations above, we use $\mathcal{S}$, $\mathcal{B}$, $\mathcal{V}$, and $\mathcal{G}$ to denote the three small-cap styles, the three large-cap styles, the three value styles, and the three growth styles, respectively. For example, $\mathcal{S}$ combines the value-small, blend-small, and growth-small portfolios.

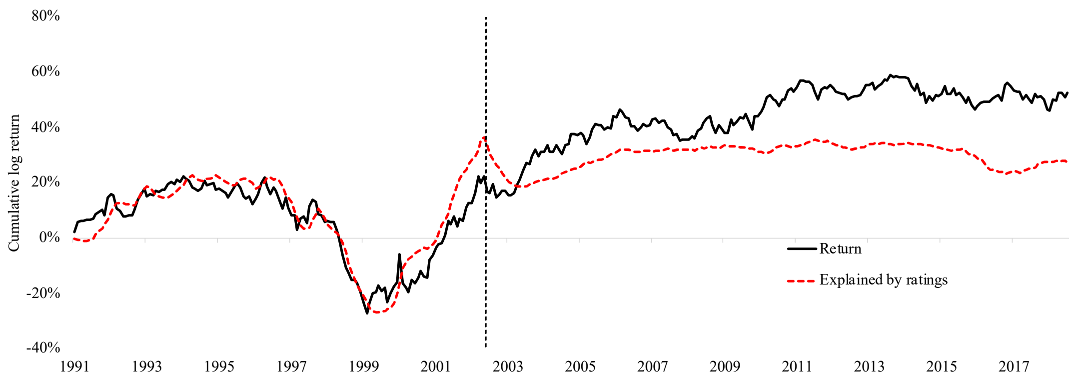
To visualize the influence of rating-induced price pressure on the factors, in Panels (a) and (b) of Figure 10, we plot the cumulative returns of factors against the cumulative rating-induced returns ($\lambda \cdot \text{ExpSum}(\Delta\text{Rating})_{t-1}$). To capture value and size premia in one single strategy, in Panel (c), we also plot the returns of the "diagonal" portfolio (SVMBG) that is long the small-value style and short the large-growth style. The plots suggest that rating-induced price pressures can explain a large portion of factor return variation before 2002. After June 2002, rating-induced demand largely loses explanatory power, as expected.

To quantify the explanatory power of rating-driven flows on factor return variation, we compute the modified "R-squared" of rating-induced price pressures by using the cleanly

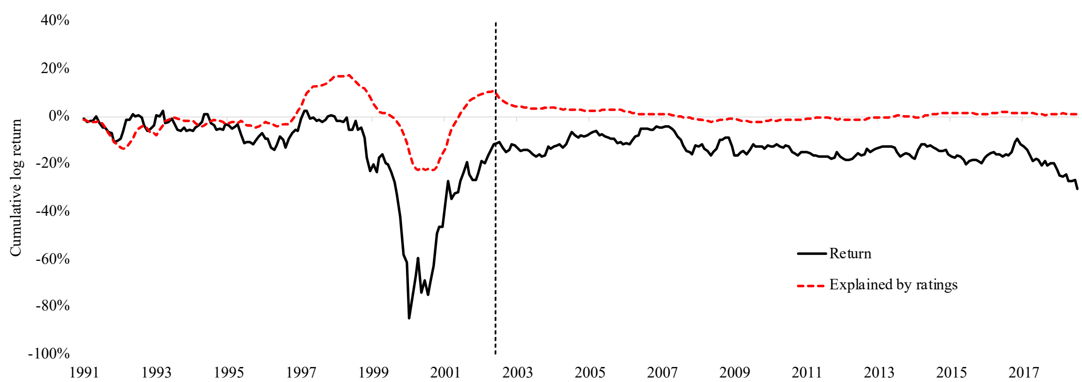
Figure 10. Explanatory Power of Ratings on Size and Value Factors

We quantify the explanatory power of rating pressures on long-short factor portfolios based on the 3×3 styles. Panel (a) plots the average returns of the three small capitalization styles minus the three large capitalization styles ("small-minus-big"). Panel (b) plots the average of the three value styles minus the average of the three growth styles ("high-minus-low"), while Panel (c) plots the small-value style minus the large-growth style. The solid black lines are the actual cumulative log returns, and the red dashed lines are the returns explained by ratings ($\lambda \cdot \text{ExpSum}(\Delta\text{Rating})_{\pi,t-1}$), where λ is estimated in Column (1) of Table 5.

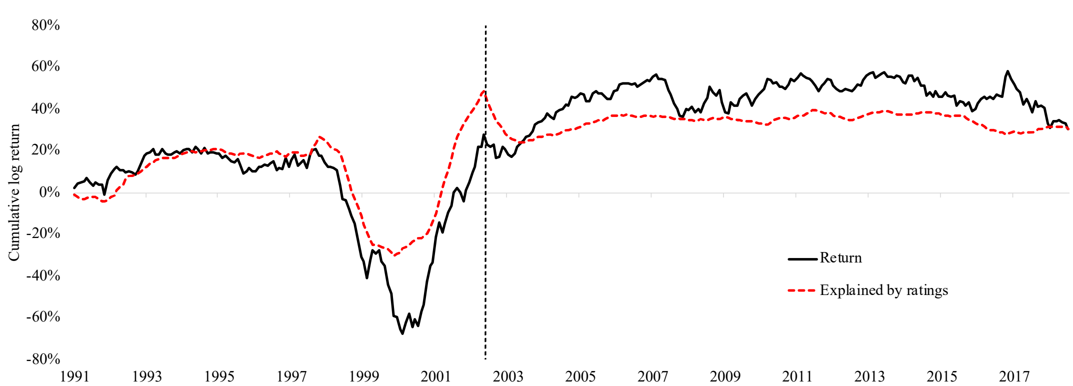
(a) Small Cap − Large Cap



(b) Value − Growth



(c) Small-Value − Large-Growth



identified λ estimate in Equation (16):

$$\text{R-squared}^f = \frac{Var(\lambda \cdot \text{ExpSum}(\Delta\text{Rating})_{f,t-1})}{Var(\text{Ret}_{f,t})},$$

$$\text{where } f \in \{\text{SMB}, \text{HML}, \text{SVMBG}\}.$$

We compute this "R-squared" measure for both before and after June 2002. Before 2002, we find that $\text{R-squared}^{\text{SMB}} = 34.7\%$, $\text{R-squared}^{\text{HML}} = 11.1\%$, and $\text{R-squared}^{\text{SVMBG}} = 27.0\%$. After June 2002, these figures drop to 9.5%, 3.3%, and 9.2%, respectively.[39] [40]

While this exercise admittedly delivers a crude estimate, the results suggest that correlated demand of styles can explain a sizeable fraction of factor return variation.

8 Conclusion

In recent years, evidence has mounted that investor demand can exert significant pressure on asset prices. However, it is difficult to identify demand that is nonfundamental, large enough to impact a broad set of securities, and that can also plausibly cause systematic price fluctuations. Our study presents evidence that advice-driven household demand for mutual funds contributes to economically significant price fluctuations at the style level.

In our empirical setting, a reform that Morningstar enacted in June 2002 serves to shift demand between two regimes. The reform equalized ratings across styles, causing capital flows to be spread more evenly across styles. Throughout the sample period, investors directed capital in accordance with Morningstar ratings, and such rating-driven flows generated price impact. Prior to the reform, style-level rating imbalances created style-level price

[39] If we only use the residual of $\text{ExpSum}(\Delta\text{Rating})_{\pi,t-1}$ after partialling out the various past return controls in Equation (16), then the R-squared measures for SMB, HML, and SVMBG become, respectively, 29.0%, 7.7%, and 20.5% before June 2002 and 9.2%, 4.0%, and 9.8% after June 2002.

[40] While the estimate of λ based on the 2002 shock is better identified, one may be worried that the price impact could vary over time. Therefore, we also repeat the exercise using λ estimated using five-year rolling-window regressions. When using this rolling-window λ as a conservative estimate, for the period before 2002, the R-squared measures for SMB, HML, and SVMBG become 12.4%, 3.5%, and 9.5%, respectively. After June 2002, they decline to 2.3%, 0.7%, and 1.9%, respectively.

pressures and increased return dispersion across styles. After the reform, these patterns became much weaker, consistent with the removal of style-level rating-induced price pressures. Using an event study around the exact reform date, we find evidence that style-level price pressure from fund flows ceased at the event date. Finally, we estimate that rating-induced price pressures can explain a sizeable fraction of the time-series variation in the size and value factors.

Our results focus on one specific source of nonfundamental correlated demand—advice given to mutual fund investors—and shows its impact on the equity market. The overall role of correlated demand in determining asset prices is likely greater than what is documented here. Correlated demand can also arise from other sources such as demand for certain styles driven by institutional frictions (Froot and Teo, 2008; Koijen and Yogo, 2019) and performance chasing in index-linked products (Broman, 2016; Dannhauser and Pontiff, 2019). Taken together, these findings should alter the way economists interpret systematic price movements: Instead of solely reflecting fundamental risks, they may also be determined by nonfundamental demand.

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Appendix A Additional Results

In this section, we provide additional results and robustness checks for the analysis presented in the main body of the paper.

A.1 Sample Statistics

Table A.1 shows detailed statistics of our mutual fund sample from 1991 to 2018. Our sample includes 433 mutual funds at the beginning of our sample period, and the number peaked in 2008 at 2,062. Since then, the number of funds decreased slightly, whereas total assets under management increased from 2009 onward, reaching about $4 trillion by the end of our sample period in 2018. Columns (4) to (8) report the distribution of funds in each rating category; Column (9) shows the fraction of sector funds; Columns (10) to (13) report the fraction of funds in different styles. Table A.2 shows the summary statistics of the nine Morningstar fund-based styles.

Table A.1. Summary Statistics of Mutual Funds, by Year

Columns (1) to (3) show the year, the number of mutual funds, and their aggregate AUM. Columns (4) to (8) indicate the fraction of funds assigned to each Morningstar star rating. Note that these fractions can differ from (10%, 22.5%, 35%, 22.5%, 10%) because Morningstar assigns those fixed fractions of ratings at the share-class level, but we follow Barber et al. (2016) in aggregating ratings at the fund level by value-weighting different share classes and rounding to the nearest integer. Column (9) indicates the fraction that are sector funds. The other U.S. domestic equity funds that are considered diversified are classified into the 3×3 style box categories, and Columns (10) to (13) indicate the fraction of funds that fall within the different styles.

Year	Number funds	AUM ($ billion)	Fraction by rating					Sector funds	Diversified fund style			
			1 star	2	3	4	5 star		Large	Small	Growth	Value
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1991	433	458.2	9%	23%	36%	23%	10%	19%	51%	16%	30%	28%
1992	466	600.8	9%	25%	32%	23%	11%	18%	52%	17%	29%	29%
1993	525	733.6	8%	22%	38%	23%	9%	17%	54%	16%	27%	30%
1994	587	748.8	7%	23%	34%	25%	10%	16%	54%	17%	27%	30%
1995	702	971.8	9%	22%	32%	27%	11%	15%	53%	17%	28%	28%
1996	826	1,177.6	8%	21%	31%	28%	13%	15%	51%	20%	30%	28%
1997	942	1,416.0	9%	22%	30%	26%	13%	14%	53%	20%	30%	29%
1998	1,069	1,524.5	10%	22%	28%	25%	14%	14%	55%	20%	33%	28%
1999	1,238	1,721.4	12%	21%	27%	26%	14%	14%	55%	22%	37%	27%
2000	1,454	1,510.0	10%	20%	30%	26%	14%	14%	57%	23%	37%	28%
2001	1,595	1,238.7	9%	20%	34%	23%	15%	15%	57%	22%	38%	27%
2002	1,731	964.3	8%	21%	36%	25%	10%	15%	57%	22%	41%	23%
2003	1,948	1,072.5	8%	22%	36%	24%	9%	16%	56%	22%	43%	22%
2004	2,020	1,224.5	8%	22%	37%	24%	8%	16%	56%	22%	43%	22%
2005	2,021	1,366.5	6%	25%	39%	23%	7%	15%	56%	22%	42%	23%
2006	1,997	1,567.6	8%	24%	38%	23%	7%	15%	56%	22%	41%	23%
2007	2,019	1,681.6	8%	25%	38%	22%	7%	15%	56%	23%	41%	23%
2008	2,062	946.6	8%	24%	37%	23%	8%	15%	55%	23%	41%	23%
2009	2,019	1,249.2	8%	23%	38%	23%	7%	14%	54%	23%	42%	23%
2010	1,912	1,472.2	7%	23%	38%	24%	8%	14%	55%	23%	41%	23%
2011	1,853	1,574.3	6%	23%	38%	26%	6%	14%	56%	23%	40%	23%
2012	1,778	1,819.9	7%	23%	37%	26%	7%	14%	56%	23%	41%	22%
2013	1,700	2,503.1	6%	24%	38%	26%	6%	15%	56%	23%	42%	23%
2014	1,651	2,924.7	7%	21%	38%	28%	7%	15%	56%	24%	41%	24%
2015	1,635	2,969.2	8%	21%	37%	27%	8%	15%	55%	24%	40%	25%
2016	1,666	3,046.6	6%	22%	37%	27%	7%	16%	55%	24%	40%	25%
2017	1,633	3,723.2	6%	22%	37%	28%	8%	16%	54%	25%	38%	25%
2018	1,563	3,820.4	7%	21%	36%	28%	9%	16%	54%	26%	38%	26%

Table A.2. Summary Statistics of Styles, by Year

A total of nine stock styles (small/mid/large cap × value/blend/growth) are used in this study. Columns (2) and (3) summarize the mean and standard deviation of Morningstar ratings for each style. Columns (4) and (5) summarize the lagged-12-month rating changes (ExpSum(ΔRating)). Columns (6) and (7) summarize monthly fund flows in the styles, and Columns (8) and (9) summarize monthly style returns.

Year	Rating		ExpSum(ΔRating)		Monthly fund flow		Monthly return	
	Average	Std Dev	Average	Std Dev	Average	Std Dev	Average	Std Dev
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1991	3.17	0.67	-0.03	0.27	0.59%	1.10%	3.20%	5.15%
1992	3.33	0.45	-0.05	0.34	1.24%	1.69%	1.10%	3.25%
1993	3.51	0.50	0.06	0.24	1.08%	1.67%	1.41%	2.74%
1994	3.68	0.44	0.04	0.17	0.98%	0.89%	0.04%	3.29%
1995	3.84	0.43	0.07	0.19	1.18%	0.82%	2.65%	2.50%
1996	3.75	0.40	-0.21	0.28	1.24%	1.06%	1.75%	3.81%
1997	3.58	0.63	-0.18	0.40	1.08%	1.04%	2.16%	4.72%
1998	3.39	0.71	-0.12	0.41	0.12%	1.08%	1.33%	7.47%
1999	3.23	0.82	-0.01	0.38	-0.49%	1.51%	2.12%	5.19%
2000	3.38	0.67	0.01	0.47	0.15%	1.37%	0.38%	7.47%
2001	3.67	0.51	-0.03	0.52	0.84%	1.23%	-0.18%	6.83%
2002	3.69	0.46	-0.16	0.35	0.46%	1.50%	-1.70%	5.86%
2003	3.58	0.23	-0.08	0.12	0.76%	0.76%	2.88%	3.91%
2004	3.57	0.19	-0.09	0.09	0.53%	0.79%	1.37%	3.17%
2005	3.58	0.20	-0.09	0.11	0.13%	0.60%	0.81%	3.23%
2006	3.65	0.20	-0.03	0.09	0.01%	0.55%	1.19%	2.85%
2007	3.64	0.23	-0.13	0.14	-0.17%	0.69%	0.51%	3.11%
2008	3.50	0.24	-0.21	0.16	-0.39%	0.73%	-3.79%	7.52%
2009	3.42	0.25	-0.14	0.12	-0.06%	0.74%	2.76%	6.95%
2010	3.41	0.19	-0.04	0.10	-0.19%	0.55%	1.92%	6.04%
2011	3.49	0.15	0.04	0.14	-0.28%	0.58%	0.08%	5.67%
2012	3.59	0.12	0.04	0.10	-0.33%	0.36%	1.41%	3.30%
2013	3.66	0.14	-0.01	0.07	0.23%	0.45%	2.76%	2.72%
2014	3.71	0.15	0.01	0.07	-0.13%	0.71%	0.84%	3.27%
2015	3.74	0.11	-0.04	0.10	-0.26%	0.48%	-0.02%	3.74%
2016	3.77	0.17	-0.01	0.16	-0.37%	0.54%	1.32%	4.01%
2017	3.83	0.15	-0.02	0.14	-0.22%	0.55%	1.57%	1.62%
2018	3.87	0.15	0.04	0.16	-0.19%	0.42%	1.43%	2.93%

A.2 Morningstar vs. Academic Style Classification

In the main text, we used Morningstar funds to define 3×3 size-value stock portfolios. These definitions are related to, but different from, the academic style definitions. For instance, Lettau et al. (2019) point out that "value funds" in the industry hold few stocks with high book/market ratios—the value stocks defined by academia. This section explores the difference between the Morningstar and the academic style definitions.

In Figure A.1, we sort stocks by market capitalization and book/market into 10×10 portfolios using NYSE breakpoints. The heat maps in Panel (a) show the academic style definitions, which are strictly based on stock characteristics. By construction, the stocks in those style portfolios are concentrated in a "rectangular region." Panel (b) presents the distribution of stocks in Morningstar-based styles, which turn out to be "smoothed" versions of the academic styles. For instance, while the academic large-cap growth style only holds stocks with large market capitalization and low book-to-market ratios, the Morningstar-based style can also hold some, albeit fewer, stocks with other characteristics.

Figure A.1. Comparison of Morningstar and Academic Stock Style Definitions

We sort stocks into 10 × 10 portfolios based on NYSE size and book/market break points. Panel (a) plots the distribution of holdings in academic style definitions. Panel (b) plots the distribution of holdings by funds in different styles. The heat map colors indicate the distribution of these style portfolios in each bin, with red indicating high weights and green indicating low weights.

(a) Academic style definitions

Academic Style: Large-Cap

Academic Style: Growth

	Growth	2	3	4	5	6	7	8	9	Value
Large	11.1%	11.1%	11.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2	11.1%	11.1%	11.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3	11.1%	11.1%	11.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
5	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
6	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
8	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
9	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Small	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Academic Style: Blend

	Growth	2	3	4	5	6	7	8	9	Value
Large	0.0%	0.0%	0.0%	8.3%	8.3%	8.3%	8.3%	0.0%	0.0%	0.0%
2	0.0%	0.0%	0.0%	8.3%	8.3%	8.3%	8.3%	0.0%	0.0%	0.0%
3	0.0%	0.0%	0.0%	8.3%	8.3%	8.3%	8.3%	0.0%	0.0%	0.0%
4	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
5	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
6	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
8	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
9	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Small	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Academic Style: Value

	Growth	2	3	4	5	6	7	8	9	Value
Large	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	11.1%	11.1%	11.1%
2	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	11.1%	11.1%	11.1%
3	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	11.1%	11.1%	11.1%
4	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
5	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
6	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
8	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
9	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Small	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Academic Style: Mid-Cap

	Growth	2	3	4	5	6	7	8	9	Value
Large	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4	8.3%	8.3%	8.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
5	8.3%	8.3%	8.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
6	8.3%	8.3%	8.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
7	8.3%	8.3%	8.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
8	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
9	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Small	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

	Growth	2	3	4	5	6	7	8	9	Value
Large	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4	0.0%	0.0%	0.0%	6.3%	6.3%	6.3%	6.3%	0.0%	0.0%	0.0%
5	0.0%	0.0%	0.0%	6.3%	6.3%	6.3%	6.3%	0.0%	0.0%	0.0%
6	0.0%	0.0%	0.0%	6.3%	6.3%	6.3%	6.3%	0.0%	0.0%	0.0%
7	0.0%	0.0%	0.0%	6.3%	6.3%	6.3%	6.3%	0.0%	0.0%	0.0%
8	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
9	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Small	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

	Growth	2	3	4	5	6	7	8	9	Value
Large	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	8.3%	8.3%	8.3%
5	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	8.3%	8.3%	8.3%
6	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	8.3%	8.3%	8.3%
7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	8.3%	8.3%	8.3%
8	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
9	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Small	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Academic Style: Small-Cap

	Growth	2	3	4	5	6	7	8	9	Value
Large	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
5	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
6	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
8	11.1%	11.1%	11.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
9	11.1%	11.1%	11.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Small	11.1%	11.1%	11.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

	Growth	2	3	4	5	6	7	8	9	Value
Large	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
5	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
6	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
8	0.0%	0.0%	0.0%	8.3%	8.3%	8.3%	8.3%	0.0%	0.0%	0.0%
9	0.0%	0.0%	0.0%	8.3%	8.3%	8.3%	8.3%	0.0%	0.0%	0.0%
Small	0.0%	0.0%	0.0%	8.3%	8.3%	8.3%	8.3%	0.0%	0.0%	0.0%

	Growth	2	3	4	5	6	7	8	9	Value
Large	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
3	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
5	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
6	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
8	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	11.1%	11.1%	11.1%
9	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	11.1%	11.1%	11.1%
Small	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	11.1%	11.1%	11.1%

(b) Morningstar fund-based style definitions

Fund Style: Large-Cap

Fund Style: Growth

	Growth	2	3	4	5	6	7	8	9	Value
Large	17.2%	10.9%	9.1%	8.3%	5.4%	4.5%	3.8%	2.6%	2.4%	2.8%
2	4.7%	3.2%	2.2%	1.6%	1.4%	1.2%	1.0%	0.7%	0.5%	0.5%
3	2.4%	1.4%	0.9%	0.8%	0.8%	0.6%	0.4%	0.3%	0.3%	0.3%
4	1.0%	0.6%	0.4%	0.3%	0.3%	0.2%	0.2%	0.2%	0.1%	0.1%
5	0.6%	0.3%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
6	0.4%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.1%
7	0.2%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
8	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
9	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Small	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Fund Style: Blend

	Growth	2	3	4	5	6	7	8	9	Value
Large	10.6%	9.0%	8.4%	8.4%	7.7%	6.8%	6.4%	5.5%	4.5%	5.1%
2	2.1%	1.7%	1.6%	1.5%	1.5%	1.4%	1.4%	1.3%	1.2%	1.3%
3	0.8%	0.7%	0.7%	0.6%	0.7%	0.6%	0.5%	0.5%	0.5%	0.5%
4	0.4%	0.3%	0.3%	0.3%	0.3%	0.3%	0.2%	0.2%	0.2%	0.3%
5	0.2%	0.2%	0.2%	0.1%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%
6	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
7	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
8	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
9	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Small	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Fund Style: Value

	Growth	2	3	4	5	6	7	8	9	Value
Large	5.0%	5.3%	6.3%	6.8%	7.8%	7.8%	8.0%	8.3%	7.3%	7.9%
2	0.9%	0.9%	1.2%	1.5%	1.8%	1.8%	1.9%	2.2%	2.4%	2.6%
3	0.5%	0.4%	0.6%	0.5%	0.6%	0.7%	0.7%	0.8%	0.8%	1.0%
4	0.2%	0.2%	0.2%	0.2%	0.3%	0.3%	0.3%	0.4%	0.3%	0.4%
5	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.2%	0.2%	0.2%	0.2%
6	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
8	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
9	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Small	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Fund Style: Mid-Cap

	Growth	2	3	4	5	6	7	8	9	Value
Large	4.2%	1.9%	1.5%	1.4%	1.3%	1.0%	0.8%	0.7%	0.7%	0.7%
2	6.4%	3.4%	2.5%	2.2%	1.5%	1.2%	1.0%	0.8%	0.5%	0.5%
3	6.2%	3.6%	2.5%	2.4%	2.1%	1.4%	1.1%	0.8%	0.8%	0.5%
4	4.7%	3.1%	2.0%	1.5%	1.4%	0.9%	0.8%	0.7%	0.5%	0.4%
5	3.3%	2.0%	1.5%	1.0%	0.9%	0.6%	0.5%	0.4%	0.4%	0.3%
6	2.2%	1.4%	0.9%	0.8%	0.6%	0.4%	0.4%	0.3%	0.3%	0.2%
7	1.8%	0.9%	0.6%	0.4%	0.3%	0.3%	0.2%	0.2%	0.2%	0.2%
8	1.1%	0.5%	0.3%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%
9	0.6%	0.3%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.1%
Small	0.2%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

	Growth	2	3	4	5	6	7	8	9	Value
Large	2.3%	1.9%	2.6%	2.7%	2.7%	2.1%	2.1%	1.8%	1.6%	1.8%
2	2.5%	1.9%	1.8%	2.0%	1.7%	1.7%	1.9%	1.4%	1.3%	1.4%
3	2.9%	2.2%	2.0%	2.0%	2.1%	1.9%	1.7%	1.4%	1.5%	1.6%
4	1.9%	1.8%	1.6%	1.4%	1.5%	1.3%	1.2%	1.2%	1.1%	1.2%
5	1.2%	1.1%	1.2%	1.0%	1.1%	0.9%	0.8%	0.8%	0.7%	0.8%
6	0.9%	0.8%	0.8%	0.8%	0.7%	0.6%	0.6%	0.5%	0.6%	0.6%
7	0.7%	0.6%	0.5%	0.5%	0.4%	0.4%	0.4%	0.4%	0.4%	0.3%
8	0.6%	0.4%	0.3%	0.3%	0.2%	0.3%	0.3%	0.3%	0.2%	0.2%
9	0.4%	0.3%	0.2%	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%
Small	0.3%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%

	Growth	2	3	4	5	6	7	8	9	Value
Large	0.6%	0.8%	1.3%	1.4%	1.6%	2.0%	2.0%	2.4%	2.2%	2.6%
2	1.6%	1.3%	2.0%	2.7%	2.7%	2.7%	3.1%	3.3%	3.1%	3.1%
3	1.3%	1.6%	1.8%	2.1%	2.3%	2.3%	2.2%	2.3%	2.4%	3.1%
4	0.7%	1.0%	1.3%	1.5%	1.6%	1.6%	1.5%	1.8%	1.7%	2.3%
5	0.6%	0.7%	0.8%	0.9%	1.0%	1.1%	1.2%	1.1%	1.0%	1.4%
6	0.3%	0.4%	0.4%	0.5%	0.5%	0.5%	0.5%	0.6%	0.6%	0.7%
7	0.2%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.4%	0.4%
8	0.1%	0.1%	0.1%	0.1%	0.1%	0.2%	0.2%	0.2%	0.2%	0.3%
9	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
Small	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Fund Style: Small-Cap

	Growth	2	3	4	5	6	7	8	9	Value
Large	0.3%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2	1.1%	0.3%	0.3%	0.3%	0.2%	0.1%	0.0%	0.0%	0.0%	0.0%
3	2.5%	1.1%	0.7%	0.7%	0.5%	0.3%	0.4%	0.2%	0.2%	0.1%
4	4.0%	2.6%	1.8%	1.3%	1.2%	0.8%	0.7%	0.6%	0.4%	0.3%
5	5.3%	3.4%	2.5%	1.7%	1.4%	1.0%	0.8%	0.7%	0.5%	0.4%
6	5.2%	3.5%	2.3%	2.0%	1.4%	1.1%	0.9%	0.7%	0.7%	0.5%
7	5.2%	3.1%	2.2%	1.6%	1.1%	0.9%	0.7%	0.7%	0.6%	0.3%
8	4.5%	2.2%	1.6%	1.2%	0.8%	0.7%	0.6%	0.5%	0.4%	0.3%
9	3.0%	1.5%	1.0%	0.7%	0.5%	0.4%	0.4%	0.3%	0.3%	0.2%
Small	1.4%	0.6%	0.4%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%

	Growth	2	3	4	5	6	7	8	9	Value
Large	0.1%	0.1%	0.0%	0.0%	0.1%	0.1%	0.1%	0.0%	0.1%	0.1%
2	0.2%	0.1%	0.2%	0.2%	0.2%	0.2%	0.1%	0.1%	0.1%	0.1%
3	0.6%	0.4%	0.5%	0.5%	0.5%	0.4%	0.5%	0.3%	0.3%	0.3%
4	1.4%	1.3%	1.3%	1.1%	1.1%	1.0%	0.9%	0.9%	0.6%	0.6%
5	2.3%	2.2%	1.9%	1.7%	1.5%	1.4%	1.3%	1.3%	1.2%	1.0%
6	2.5%	2.5%	2.2%	2.1%	1.9%	1.8%	1.5%	1.5%	1.5%	1.0%
7	2.6%	2.3%	2.2%	2.0%	1.8%	1.5%	1.5%	1.4%	1.3%	0.8%
8	2.4%	1.9%	1.7%	1.7%	1.3%	1.3%	1.2%	1.2%	0.9%	0.7%
9	2.1%	1.5%	1.4%	1.1%	1.1%	1.0%	0.9%	0.8%	0.7%	0.5%
Small	1.4%	1.0%	0.9%	0.8%	0.6%	0.5%	0.4%	0.4%	0.3%	0.2%

	Growth	2	3	4	5	6	7	8	9	Value
Large	0.1%	0.1%	0.1%	0.2%	0.2%	0.2%	0.2%	0.2%	0.1%	0.2%
2	0.1%	0.1%	0.1%	0.1%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%
3	0.3%	0.3%	0.3%	0.3%	0.3%	0.4%	0.5%	0.4%	0.4%	0.4%
4	0.4%	0.5%	0.7%	0.7%	0.8%	0.9%	1.0%	1.0%	0.8%	1.0%
5	0.6%	0.9%	1.0%	1.1%	1.3%	1.3%	1.6%	1.7%	1.7%	1.5%
6	0.8%	1.2%	1.3%	1.6%	1.6%	1.8%	2.0%	2.2%	2.4%	1.7%
7	1.0%	1.3%	1.6%	1.6%	1.8%	1.8%	1.9%	2.2%	2.4%	1.7%
8	1.1%	1.2%	1.3%	1.7%	1.6%	1.7%	1.8%	2.1%	1.7%	1.3%
9	1.2%	1.3%	1.4%	1.2%	1.5%	1.6%	1.6%	1.4%	1.2%	1.1%
Small	1.0%	1.1%	1.3%	1.2%	1.1%	1.0%	1.0%	0.9%	0.6%	0.5%

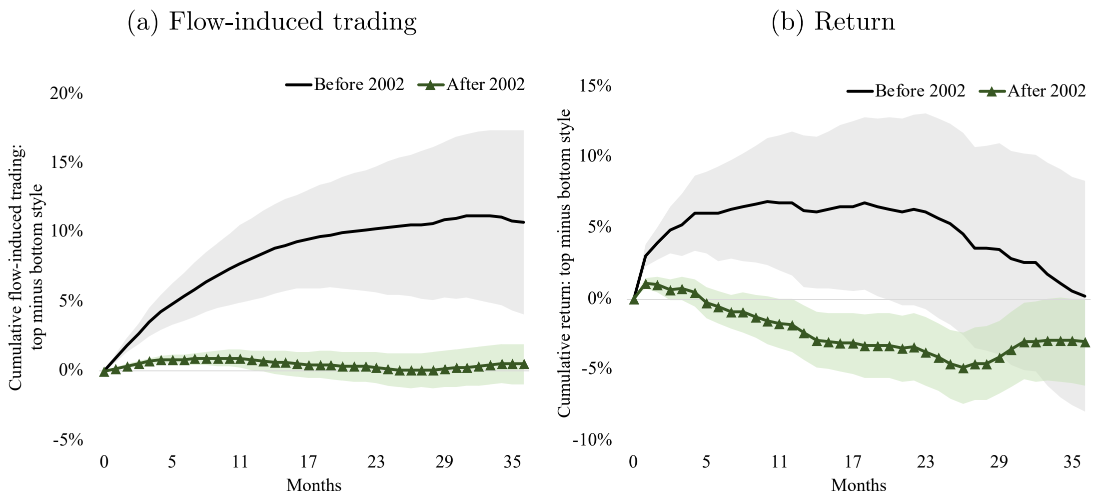
A.3 Empirical Results Using Academic Styles

This section shows that the key results based on Morningstar-defined styles also extend to the academic-defined styles using size and book/market characteristics.

Figure A.2 reproduces Panels (c) and (d) in Figure 1 with academic-defined styles. The general patterns are similar.[41]

Figure A.2. Price Pressure in Academic Style Portfolios

This figure is similar to Panels (c) and (d) in Figure 1 but is performed using style portfolios defined using stock characteristics. Stocks are sorted into 3×3 size-value styles using NYSE breakpoints of market capitalization and book-to-market ratios. In each month, we rank styles by their lagged ExpSum(ΔRating) and plot the subsequent cumulative flow-induced trading (Panel (a)) and returns (Panel (b)). We create separate estimates for the sample period before June 2002 and after June 2002. The shaded areas are 95% bootstrapped confidence intervals.



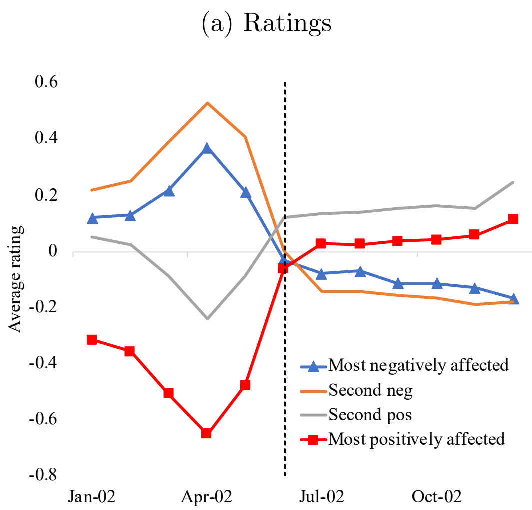
We also conduct an event study based on the academic-defined styles as in Section 6. Figure A.3 illustrates the ratings and returns of the academic styles within this one-year window when sorted on the predicted rating changes. The patterns are similar to those depicted in Figure 7, where style portfolios are instead based on Morningstar-defined styles.

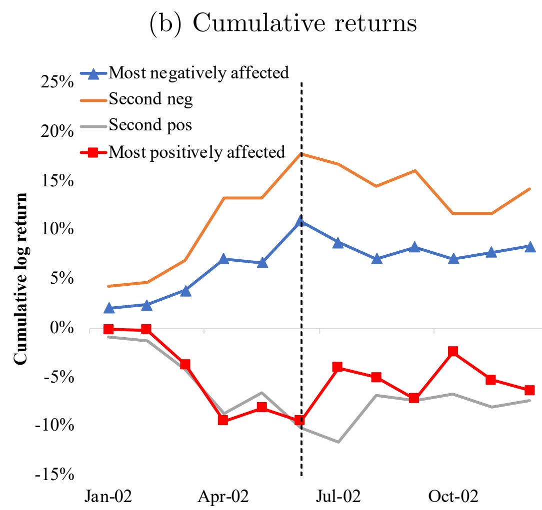
We also quantify the influence of rating-induced demand on the size and value factors that are constructed using the academic-defined styles. In Figure A.4, we plot the cumulative returns of the "academic" factors together with the price pressure driven by the rating-

[41]Results based on Morningstar-defined styles are slightly sharper, consistent with the fact that ratings—the source of change around 2002—are computed using Morningstar style definitions.

Figure A.3. Behavior of Academic Styles Around the June 2002 Event

We perform event studies on the 3 × 3 size-value academic style portfolios during the six months before and after the June 2002 methodology change. The styles are sorted by their predicted rating change at the June 2002 event using December 2001 data. These style portfolios use the standard academic definition by sorting on size and value stock characteristics (Fama and French, 1993). To focus on cross-sectional dispersion, all variables are demeaned cross-sectionally.



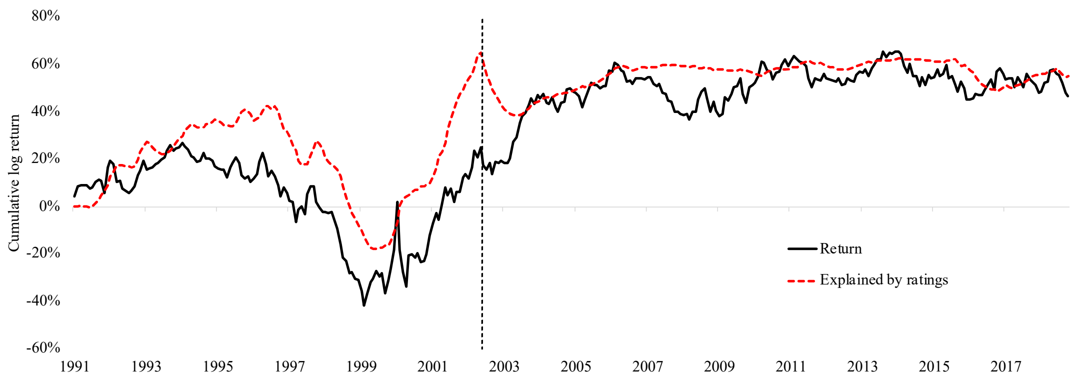


chasing demand as in Figure 10. We find that the rating-induced demand also explains a large part of the variation in academic factors before 2002. The explanatory power largely disappears after June 2002 as the demand is spread out across styles.

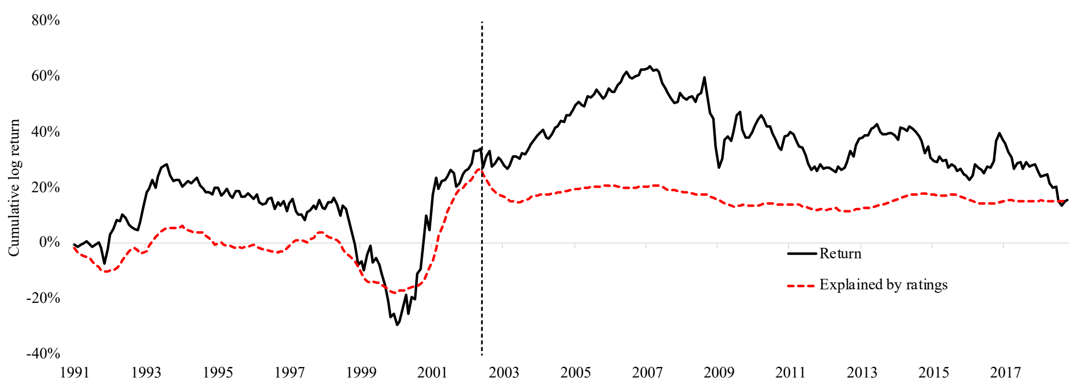
Figure A.4. Explanatory Power of Ratings on Academic Size and Value Factors

We quantify the explanatory power of rating pressure on long-short portfolios based on the 3×3 academic styles. Panel (a) plots the average returns of the three small capitalization styles minus the three large capitalization styles ("small-minus-big"). Panel (b) plots the average of the three value styles minus the average of the three growth styles ("high-minus-low"), and Panel (c) plots the small-value style minus the large-growth style. The solid black lines are the actual cumulative log returns, and the red dashed lines are the returns explained by ratings ($\lambda \cdot \mathrm{ExpSum}(\Delta\mathrm{Rating})_{\pi,t-1}$), where λ is estimated in Column (1) of Table 5.

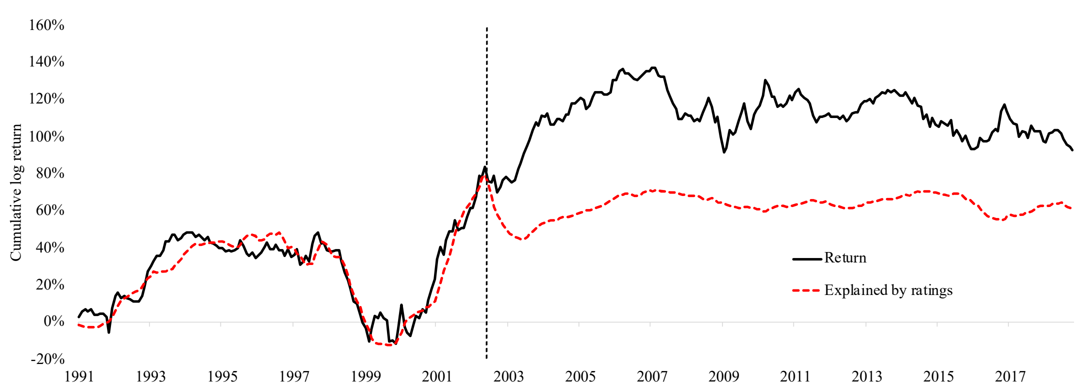
(a) Small cap − Large cap



(b) Value − Growth



(c) Small value − Big growth



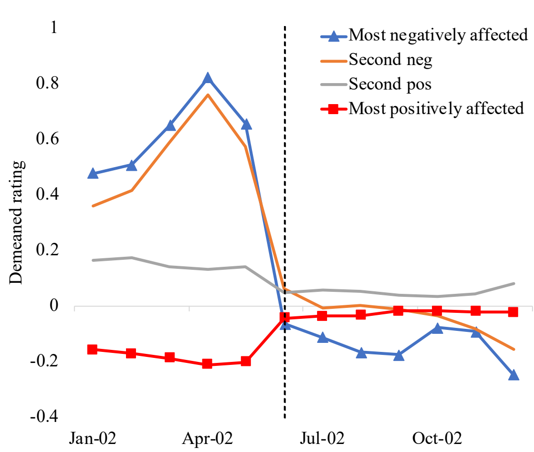
A.4 2002 Event Study At the Stock Level

As mentioned in Section 6.1, we also perform an event study in 2002 at the stock level. Specifically, we follow the same methodology as used in Section 6.1 to estimate the *predicted* stock-level methodology-induced rating change using December 2001 data. We then sort stocks into quintiles using the predicted values. Figure A.5 plots the evolution of ratings and cumulative returns of these stocks. Panel (a) shows that the prediction is useful: Those predicted to be positively (negatively) affected indeed experience large upward (downward) ratings revisions in June 2002. Panel (b) shows that the behavior of returns is consistent with ratings having a price impact. Stocks that are predicted to be positively (negatively) affected have low (high) ratings and returns before the event, and then reverse right after it.

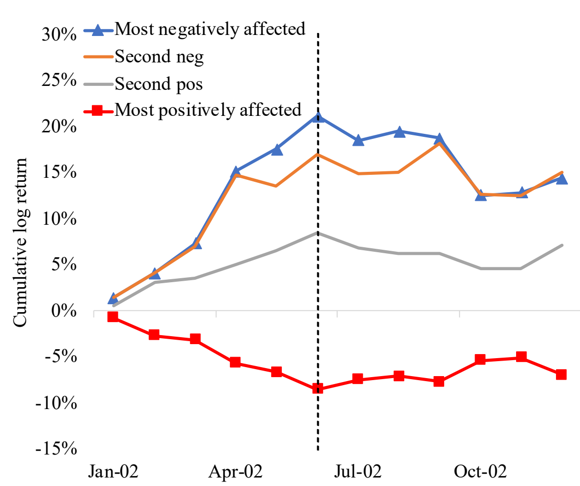
Figure A.5. Event Study Around June 2002: Stock-Level Exercise

This figure is similar to Figure 7, but here we examine individual stocks. We perform event studies on all stocks held by mutual funds during the six months before and after the June 2002 methodology change. We sort stocks into quintiles by their *predicted* rating change at the June 2002 event using December 2001 data, and then plot the evolution of their ratings in Panel (a) and cumulative returns in Panel (b). The dashed vertical line is the June 2002 event. To focus on cross-sectional dispersion, both ratings and flows are demeaned cross-sectionally.

(a) Ratings



(b) Cumulative returns



A.5 Estimating Price Impact λ

This section provides additional results for the estimation of price impact parameter λ in Section 7. Table A.3 estimates the price-pressure coefficient in Equation (16) using two alternative time windows. The results do not change materially if we decrease or increase the length of the estimation window.

Table A.3. Estimating the Price Impact of Ratings (λ) Around June 2002

This robustness check of Table 5 uses alternative sample window lengths. We estimate the rating price impact coefficient λ through a forecasting panel regression of monthly returns of the 3×3 styles on lagged rating changes ($\text{ExpSum}(\Delta\text{Rating})_{\pi,t-1}$), controlling for past style returns. Columns (1) to (3) are estimated using panel regressions with standard errors clustered by month, while Columns (4) to (6) are estimated using feasible general least squares (FGLS).

Dependent variable:	Monthly style return $\text{Ret}_{\pi,t}(\%)$					
	Panel regression			FGLS		
	6 months	12 months	18 months	6 months	12 months	18 months
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{ExpSum}(\Delta\text{Rating})_{\pi,t-1}$	3.29***	2.89**	2.77***	2.32***	2.49***	2.20***
	(1.20)	(1.16)	(0.90)	(0.86)	(0.71)	(0.60)
Past Return Controls	Yes	Yes	Yes	Yes	Yes	Yes
Style, Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	54	108	162	54	108	162
Adjusted R^2	84.5%	93.0%	91.7%	63.6%	80.6%	75.2%

$^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$

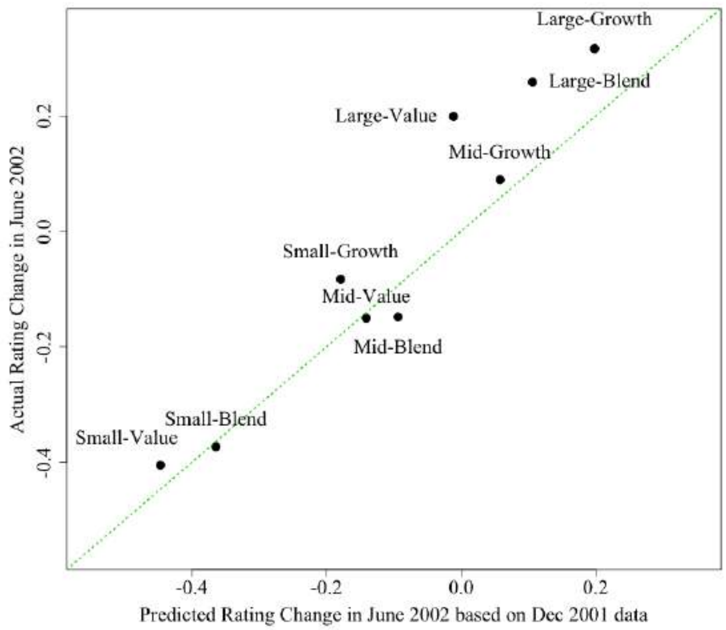
A.6 Predicting Rating Changes

We follow Morningstar's methodology in Appendix B to estimate fund ratings using fund returns and style categories data. In other words, we redo all the calculations done by Morningstar using the data we have.

Because we do not have access to the exact data set historically used by Morningstar, we cannot exactly reproduce all fund ratings. However, the computations are good enough for our purposes because when aggregated at the style-level, we can predict rating changes fairly accurately. Figure A.6 plots the actual style-level rating change in June 2002 against

Figure A.6. Predicting June 2002 Style Rating Change Using End-of-2001 Data

We follow Morningstar's rating methodology to calculate what fund ratings would have changed to in December 2001 under the new methodology. The fund ratings are aggregated at the style level. We use the difference between this counterfactual rating and the actual rating as our prediction, and then plot the actual style-level rating changes against the predicted changes. The style portfolios are labeled, and the dashed diagonal line indicates a perfect match.



our predictions (computed following the method in Section 6.1). As shown in the figure, we correctly predict that small-value is the most negatively affected style and small-blend is the second-most negatively affected, while large-growth is the most positively affected and large-blend is the second-most positively affected. The predictions are also reasonably accurate in magnitudes.

Appendix B Morningstar Methodology

In this section, we explain the construction of Morningstar ratings and the June 2002 methodology change in detail.

Morningstar ratings are updated every month. There are two steps in Morningstar's rating calculation:

1. For each fund with sufficient data, calculate performance measures using past returns, with some adjustments based on return volatility and fund loads.

2. Rank funds by the performance measure and assign ratings.

In June 2002, Morningstar changed both steps of the methodology. The steps are consecutive, though independent. Our analysis shows that the change to the second step (described in Section B.2) made the biggest difference to the issues of interest in the study.

B.1 Step One: Calculate Performance Measures

The pre-2002 methodology is described in detail in Blume (1998), and we summarize it here. First, the cumulative return is computed over three horizons (36, 60, 120 months):

$$R_i^T = \prod_{t=1}^{T}(1 + r_{i,t}) - 1, \qquad T \in \{36, 60, 120\}, \tag{19}$$

where the monthly fund returns $r_{i,t}$ are net of management fees but unadjusted for loads. Then, the cumulative return is adjusted for loads to get a load-adjusted return over the risk-free rate:

$$\text{LoadRet}_i^T = R_i^T L_i - R_f^T, \tag{20}$$

where the load adjustment L_i equals 1 minus the sum of the front- and back-end loads. R_f^T is defined as the cumulative risk-free rate return for horizon T using three-month T-bills. The measure is standardized to

$$\text{MnLoadRet}_i^T = \frac{\text{LoadRet}_i^T}{\max(R_f, \text{AvgLoadRet}^T)}, \tag{21}$$

where AvgLoadRet^T is the average of LoadRate_i^T across all funds in the same investment class (equity, corporate bonds, etc.).

Second, Morningstar derives the final performance measure by subtracting a risk-adjustment term:

$$\text{Performance}_{i,t} = \text{MnLoadRet}_{i,t}^{T} - \text{MnRisk}_{i,t}^{T}. \tag{22}$$

The risk-adjustment term is defined as a normalized average downward return deviation. Concretely, Morningstar calculates

$$\text{Risk}_i^T = \frac{\sum_{t=1}^{T} - \min(r_{i,t} - r_t^f, 0)}{T}. \tag{23}$$

Then, the measure is normalized by the relevant average risk:

$$\text{MnRisk}_t^T = \frac{\text{Risk}_i^T}{\text{AvgRisk}^T}. \tag{24}$$

After June 2002, Morningstar changed the way it adjusts for risk.[42] Morningstar summarizes a fund's past performance using the so-called Morningstar risk-adjusted return (MRAR):

$$\text{MRAR}_i^T(\gamma) = \left[\frac{1}{T}\sum_{t=1}^{T}(1 + r_{i,t} - r_t^f)^{-\gamma}\right]^{-\frac{12}{\gamma}} - 1, \tag{25}$$

where $r_{i,t} - r_t^f$ is the geometric return in excess of the risk-free rate after adjusting for loads,[43] and $\gamma = 2$ is the risk aversion coefficient.

The formula penalizes funds with higher return volatility. To see this, notice that when γ converges to 0, $\text{MRAR}^{\text{T}}(0)$ is equal to the annualized geometric mean of excess returns.[44]

[42]Morningstar explains its post-June 2002 rating methodology in a publicly available manual, available at `https://corporate.morningstar.com/US/documents/MethodologyDocuments/FactSheets/MorningstarRatingForFunds_FactSheet.pdf`. See also Blume (1998).

[43]For funds with loads, Morningstar uses the load-adjusted return r_t, defined as $r_t = a \cdot (1 + r_t^{\text{raw}}) - 1$. The adjustment factor a is defined as $a = \left(\frac{V_{\text{adj}}}{V_{\text{unadj}}}\right)^{1/T}$, where V_{adj} (and V_{unadj}) is the load-adjusted (unadjusted) cumulative fund return over the past T months. For details, see "The Morningstar Rating Methodology," June 2006.

[44]Morningstar motivates the MRAR formula using expected utility theory. Specifically, consider an investor with a power utility and relative risk aversion of $\gamma + 1$. A standard feature of the power utility is that when risk aversion decreases to 1 ($\gamma = 0$), it becomes log utility. Therefore, MRAR(0) simply calculates the geometric mean return.

When γ is set to be greater than 0, holding the geometric mean return constant, the formula yields a lower MRAR value for funds whose monthly returns deviate more from their mean. Specifically, the risk adjustment can be expressed as $\mathrm{MRAR}^{\mathrm{T}}(0) - \mathrm{MRAR}^{\mathrm{T}}(2)$.

B.2 Step Two: Rank Funds and Assign Ratings

Given rankings of funds, Morningstar calculates three-year, five-year, and 10-year ratings for funds with the necessary number of historical returns at those horizons, and then takes a weighted average of them (rounded to the nearest integer) to form an overall rating—the rating most commonly reported and used. For funds with more than three years but less than five years of data, the overall rating is just the three-year rating. For funds with more than five years but less than 10 years of data, the overall rating assigns 60% and 40% weights on the five-year and three-year ratings.[45] For those with 10 years of data, 50%, 30%, and 20% weights are assigned on the 10-year, five-year, and three-year ratings, respectively.

The ratings are based on rankings of funds. Before June 2002, Morningstar ranked the past performance of all equity funds together and assigned them ratings with fixed proportions: 10%, 22.5%, 35%, 22.5%, and 10%. Since June 2002, Morningstar has ranked funds within each style ("Morningstar category") and assigned ratings based on the within-style ranking. Styles include the standard 3×3 size-value categories in the Morningstar style box and also a number of specialized sector categories (e.g., financial, technology).

[45] Because the five-year history contains the three-year history, the three most recent years are effectively given more weight than more distant history.