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DISCONTINUED POSITIVE FEEDBACK TRADING AND THE DECLINE OF MOMENTUM PROFITABILITY

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ABSTRACT

We present evidence that equity momentum strategies are partially driven by positive-feedback trading intermediated via the mutual fund sector. We identify a U.S.-specific structural break to this channel that substantially weakened the relationship between fund flows and past style returns. As a result, trading strategies that load on flow-driven positive-feedback trading (including momentum in stocks, styles, and factors) experienced a profitability decline. Consistent with the proposed channel, the profitability decline was limited to the U.S. market. Moreover, factors that were more directly exposed to the structural break experienced a sharp return "kink" in the months after the event.

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1 Introduction

Momentum has been found to be a profitable trading strategy in markets around the world, across asset classes, and over long periods of time (Asness, Moskowitz, and Pedersen, 2013). In the equity market, momentum exists at different levels of aggregation—e.g., individual securities (Jegadeesh and Titman, 1993), industry portfolios (Moskowitz and Grinblatt, 1999), and characteristics-based factors (Ehsani and Linnainmaa, 2021). Despite the extensive empirical evidence that momentum exists, scholars disagree fiercely as to why this is the case.

Adding to the puzzle, the profitability of momentum strategies in the U.S. equity market declined precipitously starting in the early 2000s (e.g., Daniel and Moskowitz, 2016). This decline is evident in Panel (a) of Figure 1. The figure plots the returns of momentum-related factors (e.g., stock momentum and industry momentum) and of time-series factor momentum. Visibly, the profitability of these strategies declined sharply after mid-2002. For example, for the momentum factor, returns dropped from 0.92% per month during the earlier period of January 1987 to June 2002 to merely 0.16% afterward; for the factor momentum strategy, returns dropped from 0.61% to 0.14%. These sharp declines are too large to be fully explained by the "momentum crash" during the 2008–09 financial crisis (Daniel and Moskowitz, 2016) and the post-publication profitability decline of anomalies (McLean and Pontiff, 2016; Falck, Rej, and Thesmar, 2021). In addition to the long-term profitability decline, there also appears to be a "kink" around mid-2002. These findings of long-term profitability decline and short-term "kink" are robust to alternative factor construction methodologies and have also been foreshadowed by earlier studies.[1] Moreover, the sharp decline in the profitability of stock and factor momentum is specific to the U.S. market, as shown in Panels (c) and (d) of the same figure.

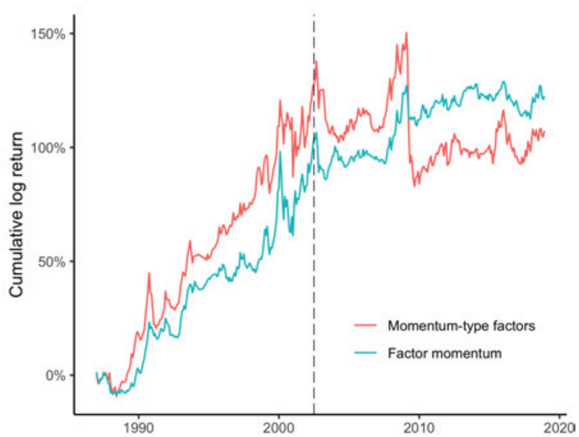
In this study, we offer new insights on the nature of equity-based momentum strategies and on why their profitability declined in the U.S. market. First, we provide evidence that

[1] See Appendix B.1 for further details.

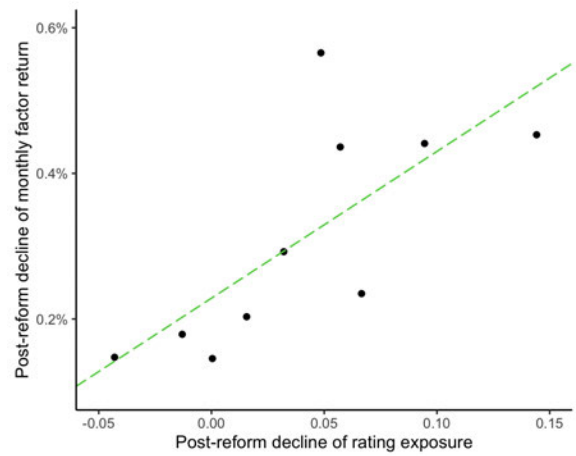
Figure 1. Mutual Fund Rating Reform and Factor Returns

Plot (a) plots cumulative returns of momentum type asset pricing factors and the time-series factor momentum strategy. The former is an average over five factors: standard $(t-1, t-12)$ momentum and the $(t-1,\ t-6)$ momentum factors (Jegadeesh and Titman, 1993), industry momentum (Moskowitz and Grinblatt, 1999), 52-week high (George and Hwang, 2004), and $(t-7,\ t-12)$ intermediate momentum (Novy-Marx, 2012). The factor momentum strategy is constructed following the methodology in Ehsani and Linnainmaa (2021) and based on our factor universe. Please see Section 2.2 and 5 for details. The vertical dashed line marks the Morningstar methodology reform in June 2002. Plot (b) examines the cross-section of post-reform profitability decline among 49 popular asset pricing factors. Factors are sorted into deciles based on their post-reform decline in exposure to Morningstar ratings, which is plotted on the horizontal axis by decile. The vertical axis plots the post-reform profitability decline. The green dashed line is the best linear fit. Rating exposure measures the degree to which each factor benefits from the positive feedback induced by Morningstar ratings and is defined in Section 2.3 (variable ExpSum(ΔRating)). Plots (c) and (d) show the post-reform change in monthly return for the stock momentum factor and the time-series factor momentum strategy, respectively. The red bars represent strategies based on U.S. stocks and the dark gray bars are based on stocks in other regions. The t-statistics are reported as data labels; $**$ denote statistical significance at 5% level; the plotted data are from Panel A of Table 2 and Panel A of Table 4, respectively.

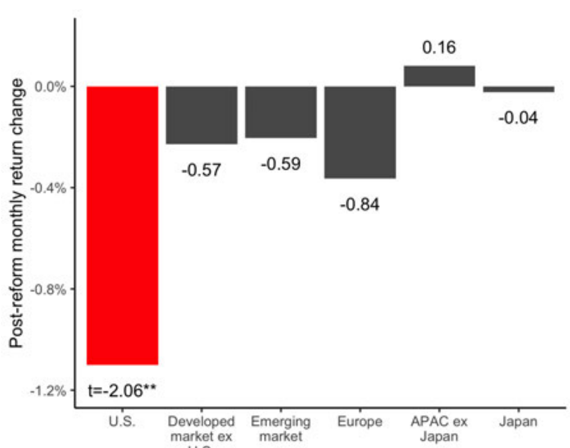
(a) Momentum-related factor returns



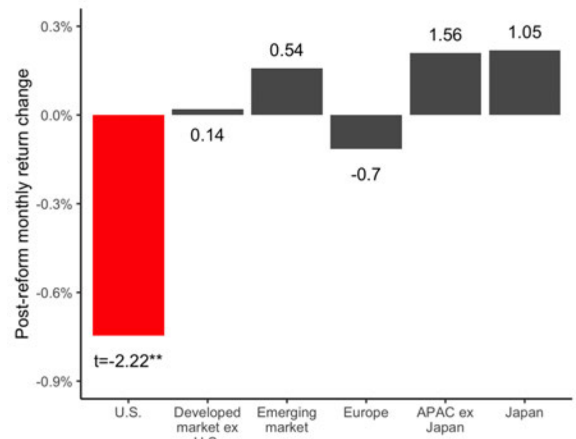
(b) The cross-section of factor return decline



(c) Post-reform return change: momentum



(d) Post-reform return change: factor momentum



momentum returns are at least partly driven by style-level positive-feedback trading via a mutual fund flow channel. Second, we show that a structural break that weakened this channel in the U.S. can account for a sizeable portion of the otherwise puzzling post-2002 drop in the profitability of stock and factor momentum.

The notion that fund flows and style investing can lead to momentum-like return dynamics has been proposed in prior studies (e.g., Barberis and Shleifer, 2003; Lou, 2012). The primary empirical innovation in our paper is the use of the influential Morningstar mutual fund rating system as an identification device. We build on Ben-David, Li, Rossi, and Song (2021b), which found that Morningstar fund ratings drive correlated fund flows that, in turn, cause sizeable price pressures.[2] In the present study, we further show that, until a reform that took place in June 2002, rating-driven flows created large positive-feedback trading at the style level.

This style-level demand led to significant price movements that bolstered the profitability of strategies that benefit from positive-feedback trading. Ceteris paribus, the reform in 2002 caused a sudden halt to this process, negatively impacting the profits of both momentum-related factors and factor momentum strategies. Consistent with the fact that the methodology reform only happened in the U.S., this profitability decline is not observed in other countries. Using multiple methods, we estimate that the Morningstar reform accounted for approximately one-third to two-thirds of the profitability decline in momentum-type factors and factor momentum.

How do Morningstar ratings relate to momentum returns, and why did the 2002 rating reform cause a structural break in this relation? Since their introduction in 1985 and until June 2002, ratings were based on each fund's past return ranking against all other equity funds. Because a significant fraction of return dispersion across funds is due to style exposures, funds in styles that recently performed well (poorly) receive high (low) ratings. And

[2]Other studies that use Morningstar ratings as part of their identification strategy include Del Guercio and Tkac (2008), Reuter and Zitzewitz (2021), Evans and Sun (2021), Ben-David, Li, Rossi, and Song (2019), and Kim (2020).

since ratings are a major driver of fund flows (e.g., Reuter and Zitzewitz, 2021; Ben-David et al., 2019), flows to mutual funds with similar styles depended strongly on recent style performance. As mutual funds scaled up or down their holdings in response to flows (e.g., Lou, 2012), their trading behavior caused substantial positive-feedback effects at the style level. In other words, funds in styles that performed well received high ratings and high flows, and had to expand their portfolios, putting further price pressure on stocks in the same style. In June 2002, Morningstar reformed its methodology and began ranking funds *within* 3×3 size-value style categories. As a result, ratings stopped depending on style returns, and the ratings-driven positive-feedback trading at the style level came to a sudden halt.

Our empirical exercises, which investigate the impact of rating-induced feedback trading on the profitability of momentum-related strategies, proceed in four parts. As a preliminary step, we verify that style-level momentum indeed dwindled after June 2002. Before the reform, mutual funds in the style with top recent performance received monthly flows that were higher by 1.7% of assets under management than funds in the bottom style. Consistent with flows creating further price impact, stocks held by funds in the top style continued to outperform those in the bottom style by 84 basis points per month. After the Morningstar rating reform, the difference between the fund flows and returns of the top and bottom styles shrank drastically.

The first part of our empirical analysis tests the prediction that the post-Morningstar-reform profitability decline should be most pronounced in momentum-type asset pricing factors, which benefit most from style-level positive-feedback trading. Prior work has identified many other mechanisms that cause factor returns to decline: changes in liquidity, arbitrage activity, and possible data-mining. Therefore, this part of the analysis also includes a broad range of other asset pricing factors as controls: Compared to momentum-related factors, the average premium on the other factors should also be affected by mechanisms such as arbitrage activity, but not by the rating-induced positive feedback trading. We construct

49 popular long/short asset pricing factors, which cover all the major categories.[3] To measure the exposure of factors to rating-induced effects, we measure the exposure of stocks to rating-induced price pressure (a summary of recent rating changes, as in Ben-David et al., 2021b) and aggregate this measure up to the factor level.

Consistent with our prediction, we find that momentum-related factors indeed suffered the largest drop in their exposure to Morningstar ratings, the largest drop in fund flow-induced trading, and also the largest profitability drop. As an illustration, Panel (b) of Figure 1 shows that factors with larger declines in rating exposure (horizontal axis) experienced larger profitability declines after the reform (vertical axis).

To further test the rating-based mechanism, we conduct a region-based placebo test using the international versions of momentum factors constructed by other researchers. Because the 2002 Morningstar reform was specific to the U.S. market,[4] we do not anticipate such a material decline in momentum profitability in markets outside the U.S. Indeed, Panel (c) of Figure 1 shows no similar declines in momentum profitability in other countries.

In the second part of our analysis, we examine the impact of the Morningstar reform on factor momentum strategies proposed by Ehsani and Linnainmaa (2021). Specifically, the authors show that strategies that go long or short in factors based on their recent 12-month return generate excess returns. Because many factors have large and persistent size and value style loadings, factor momentum is highly related to style momentum. Hence, the profitability of factor momentum should also be impacted by the decline in flow-driven positive-feedback trading after mid-2002. Consistent with our conjecture, the rating exposure of factor momentum strategies declined dramatically after the reform, and time-series factor momentum returns based on our factor universe achieves 0.61% monthly returns before the reform and only 0.14% after. Similar results are obtained when using different factors constructed by other researchers. Consistent with the conjectured mechanism, we find that

[3]Following Hou, Xue, and Zhang (2020), we use NYSE break points and market capitalization weights to reduce the impact of micro-cap stocks. Of these 49 factors, five are classified as being momentum type by Hou et al. (2020).

[4]See Morningstar (2016) for a history of the Morningstar rating system.

this decline is unique to factor momentum based on U.S. factors (Panel (d) of Figure 1).

In the third part of the analysis, we use two methods to estimate the extent to which the post-2002 profitability decrease can be attributed to the decline in flow-driven positive feedback trading. Following a standard procedure in the asset pricing literature, we first create a long-short "rating factor" based on stock-level rating exposures. Spanning tests reveal that momentum-related factors and factor momentum indeed have high exposure to the rating factor. According to this method, Morningstar can explain half and two-thirds of the post-reform profitability decline of the momentum factor and factor momentum, respectively. We view these results as an upper bound to the explanatory power of the rating-induced mechanism because spanning tests designate all returns *correlated* with the rating factor as "explained"—which is only valid in a statistical sense.

We thus also take a more direct approach. We estimate the price impact of rating exposure using the 2002 shock and multiply it by the post-2002 decline in the rating exposure of each factor, which can be measured directly. This exercise indicates that the Morningstar reform can explain approximately one-third of the decline of momentum-type factor returns and approximately two-thirds of the decline in factor momentum.[5]

While the earlier analyses focus on long-term return declines, in the last part, we zoom in on a narrow window around the June 2002 reform to examine the factor return "kink" that took place around that time. We conduct an event study of factor-level ratings, fund flows, and returns in which we use the rating reform as an instrument to predict flows and price pressure. The reason why the reform is a good instrument is that it caused exogenous rating changes in over 50% of mutual funds, with heterogeneous impacts on factor portfolios. Moreover, due to the backward-looking nature of ratings, the differential flow impact of these rating changes can be predicted using data outside of the event window.

The results of the event study show that the "kink" appears only in the factors that were

[5]The finding that ratings have higher explanatory power on factor momentum is consistent with the mechanism: ratings-driven fund flows only contribute to *style*-momentum but not to *idiosyncratic*-momentum (Blitz, Huij, and Martens, 2011; Blitz, Hanauer, and Vidojevic, 2020). Because factors are diversified portfolios, factor momentum is not affected by idiosyncratic momentum, while stock momentum is.

ex-ante more likely to be exposed to the reform. The exposed factors experienced sudden changes in flows and returns. The unaffected factors did not experience similar kinks. Using all years other than 2002 as placebo tests, we confirm that the factor-level flow and return patterns documented are unique to 2002. Moreover, proxies for other possible influences on factor returns, such as arbitrage activity and liquidity, did not vary materially around the reform event. Overall, the findings indicate that the Morningstar reform can explain why some factors experienced a profitability kink in 2002, and also further shed light on the fact that rating-induced fund flows can have a non-negligible impact on factor returns.

We emphasize that, as the quantification exercises reveal, our mechanism only explains *a portion* of the profitability decline in momentum-type strategies post-2002. Thus, the mechanism we document should be thought of as a force that *exacerbated* momentum profitability during the relevant sample period; as the rating-induced feedback trading came to a stop, so did *a component* of momentum returns. More generally, momentum is a complex phenomenon that likely defies a single explanation.[6] Other reasons for profitability decay include the post-publication decline identified by McLean and Pontiff (2016)—which includes both in-sample overfitting and post-publication arbitrage forces—and the 2008–2009 momentum crash documented by Daniel and Moskowitz (2016).[7] Combined, we estimate those two explanations can account for roughly 40% of the momentum profitability decline. Our mechanism, however, stands out in its concreteness: We tie return predictability to directly measurable quantities of ratings and flows, and base our explanation on demand-based price effects, which have been independently validated in several other studies (e.g., see Lou, 2012; Gabaix and Koijen, 2020; Ben-David et al., 2021b; Hartzmark and Solomon, 2021).

This paper contributes to the understanding of why the profitability of factor strategies

[6]Other possible explanations for the existence of momentum include delayed information diffusion (Hong and Stein, 1999) or behavioral biases (Daniel, Hirshleifer, and Subrahmanyam, 1998; Barberis, Shleifer, and Vishny, 1998; George and Hwang, 2004; Grinblatt and Han, 2005), as well as investor attention and media influences (Lee and Swaminathan, 2000; Hou, Xiong, and Peng, 2009; Hillert, Jacobs, and Müller, 2014). The literature on momentum is vast, and we cannot cover all of the explanations. Please see Jegadeesh and Titman (2011) for a survey of the literature.

[7]Our results are mostly unchanged when excluding the financial crisis period during which the momentum crash occurred.

can change over time. While prior studies emphasize the roles of liquidity (Khandani and Lo, 2011; Chordia, Subrahmanyam, and Tong, 2014; Lee and Ogden, 2015), arbitrage activity (Marquering, Nisser, and Valla, 2006; Green, Hand, and Soliman, 2011; Hanson and Sunderam, 2013; McLean and Pontiff, 2016; Calluzzo, Moneta, and Topaloglu, 2019; Cho, 2020), and potential overfitting (Harvey, Liu, and Zhu, 2016; Harvey, 2017; Hou et al., 2020; Huang, Song, and Xiang, 2020b; Falck et al., 2021), we show that profitability decline can also arise from the removal of demand pressures that contributed to the profitability in the first place. The existing explanations are not mutually exclusive to ours. However, while the previously identified mechanisms are likely important contributors to the long-term profitability decline of factors on average, they do not explain why profitability of momentum-related strategies dropped sharply after mid-2002 and only in the U.S.,—a fact that also helps the identification of the flow-driven positive-feedback trading mechanism.

This paper is also related to recent attempts to understand the impact of demand on *systematic* components of asset prices. While the work on index composition changes convincingly shows that demand can impact the prices of individual stocks (Harris and Gurel, 1986; Shleifer, 1986; Wurgler and Zhuravskaya, 2002; Chang, Hong, and Liskovich, 2015), there is relatively less consensus on whether and how demand can shape factor-level price movements. Our paper contributes to this line of inquiry by showing that ratings-induced demand can contribute to the expected return of certain asset pricing factors. Our explanation is, thus, in sharp contrast to standard explanations of factor return profitability based on compensation for risk (Cochrane, 2011). Other studies on demand-based price effects use mutual fund flows (Teo and Woo, 2004; Coval and Stafford, 2007; Lou, 2012; Huang, Song, and Xiang, 2020a; Li, 2020), exchange-traded fund flows (Ben-David, Franzoni, and Moussawi, 2018; Brown, Davies, and Ringgenberg, 2021), and other sources of institutional investor demand (Parker, Schoar, and Sun, 2020; Ben-David, Franzoni, Moussawi, and Sedunov, 2021a; Hartzmark and Solomon, 2021). More recently, Koijen and Yogo (2019) develop a structural methodology to estimate price impact, and Gabaix and Koijen (2020) show that demand-induced price impact at the aggregate market level is considerable.

Our rating-induced positive feedback mechanism is consistent with the style-investing hypothesis in Barberis and Shleifer (2003). Positive feedback trading has also been identified in Teo and Woo (2004), Lou (2012), and Wahal and Yavuz (2013). We contribute to this literature by using an exogenous event to identify the price impact of rating-induced trading and by quantifying the explanatory power of this mechanism.

This paper builds on Ben-David et al. (2021b), who show that fund flows can cause *price fluctuations in style portfolios*. While Ben-David et al. (2021b) also use Morningstar ratings as an instrument, the research objectives of the two papers are substantively different. The present paper aims to shed light on the *long-term expected return* of momentum-related factor strategies, and the explanation relies on a positive-feedback trading mechanism. Therefore, both the mechanism and scope of research in this paper are different from those of Ben-David et al. (2021b).

The rest of the paper is organized as follows. Section 2 describes the data, factor universe, and variable construction. Section 3 explains how the Morningstar reform disrupts style-level positive-feedback trading and makes testable predictions. Section 4 examines the impact of the reform on asset pricing factors, and Section 5 examines its impact on factor momentum. Section 6 describes an event study around the reform date, and Section 7 concludes. Robustness checks and additional tests are provided in the Appendix.

2 Data and Variable Construction

This section describes the data, our universe of asset pricing factors, and how we measure the impact of ratings on those factors.

2.1 Mutual Fund Data

We obtain monthly fund returns and total net assets (TNA) from the 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 fund portfolio and typically only differ in the fee structure. Therefore, we aggregate all share classes at the fund level using Russ Wermers's MFLINKS (Wermers, 2000). We also obtain quarterly fund holdings from Thomson Reuters' S12, which is based on 13F filings.

We download Morningstar ratings and fund style categories from Morningstar Direct, and we merge them with the CRSP data using the matching table from Pástor, Stambaugh, and Taylor (2020). Because Morningstar assigns ratings at the share class level, we aggregate ratings at the fund level by TNA-weighting different share classes following Barber, Huang, and Odean (2016). We restrict our analysis to mutual funds with at least $1 million TNA, and we winsorize fund flows at the 0.5% and 99.5% levels. We require the existence of 12 monthly lags of monthly flows, returns, and ratings.

Most of our exercises start in January 1987 because Morningstar ratings are available from December of 1985 and the rating exposure variable ($\text{ExpSum}(\Delta\text{Rating})_{i,t-1}$, described in Section 2.3) is constructed using 13 lagged monthly observations. When requiring fund flow data, our sample starts in 1991 due to the availability of monthly fund flow information in CRSP.

2.2 Asset Pricing Factors

The main U.S. factor universe. We compute 49 popular stock-level characteristics that have been shown to predict returns; our choice of factors mostly follows Arnott, Clements, Kalesnik, and Linnainmaa (2019), and we restrict our attention to those that can be constructed using CRSP and Compustat data. Using the classification categories proposed in Hou et al. (2020), these 49 characteristics-based factors include 14 in the profitability category (e.g., return on assets), 13 in the investments category (e.g., share issuance), eight in the value/growth category (e.g., book-to-market ratio), six in the intangibles category (e.g., industry concentration), five in the momentum category (e.g., momentum of Jegadeesh and Titman, 1993), and three in the trading frictions category (e.g., Amihud illiquidity).

We follow the prescription in Hou et al. (2020) to limit the impact of microcaps in factor construction. Specifically, we use NYSE breakpoints to sort stocks into characteristics-based quintiles and then form value-weighted long-short factors. Appendix Table A.1 lists all asset pricing factors used in this paper.

International factors. As we explain in Section 3, we expect the rating-induced post-reform profitability decline to be concentrated in U.S.-based factors, so non-U.S. factors can be used as a placebo test. For this purpose, we download the monthly global factor returns made available by Jensen, Kelly, and Pedersen (2021).[8] For constructing factor momentum strategies, we require 12 months of lagged returns and restrict attention to factors that have no data gaps since inception. The number of factors and countries covered gradually increases over the sample period, rising from 495 factors from 21 countries in 1987 to 3,615 factors from 26 countries by 2018. Appendix Figure A.1 and Table A.2 provide more details.

Partially due to differences between U.S. and non-U.S. markets, the factor construction methodology of Jensen et al. (2021) differs slightly from ours. In particular, they form long-short tercile portfolios. We use both the equal-weighted and the "capped value-weighted" returns they compute, where the latter is market value-weighted, but they also cap the market weight at the 80^{th} NYSE percentile. The capping is intended to make sure one mega-stock does not dominate a portfolio, a concern particularly relevant for less developed markets with fewer stocks. For brevity, we refer readers to the description in Jensen et al. (2021) for more details.

[8]This data source only contains factor returns; therefore, we cannot use its factors for our main U.S. factor-based exercise because we also need stock-level characteristics to compute the rating exposure measure. We downloaded these global factors data from Bryan Kelly's website on May 27, 2021.

2.3 Measuring Rating Exposure and Flow-Induced Trading

We are interested in how Morningstar ratings and rating-induced fund flows lead to price pressure on asset pricing factors. To this end, we first measure ratings and flows at the stock level, and then we aggregate them up to the factor level.

Rating exposure. Ben-David et al. (2021b) show that Morningstar ratings induce fund flows that create stock price pressures. As a consequence, they find that a simple measure of "rating exposure"—an exponential sum of recent rating changes—strongly predicts returns at the stock level. We follow their specification to measure rating exposure and briefly explain the methodology for the reader's convenience. We first define the average Morningstar rating of stock i in month t as the holding-weighted rating of all funds $\mathcal{J}$ that hold the stock:[9]

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

We then summarize the recent 12 months of stock-level rating changes with exponentially decaying weights:

$$\text{ExpSum}(\Delta\text{Rating})_{i,t-1} = \sum_{k=1}^{12} \tau_k \cdot (\text{Rating}_{i,t-k} - \text{Rating}_{i,t-k-1}), \tag{2}$$

where $\tau_k = \frac{12\cdot(1-\delta)}{1-\delta^{12}} \cdot \delta^{k-1}$ and $\sum_{k=1}^{12} \tau_k = 12$. The decay factor $\delta = 0.76$ implies a half-life of $\approx$ 2.58 months. Because the weights sum to 12 (months), in terms of units, ExpSum(ΔRating) should be interpreted as measuring a re-weighted version of rating changes over the previous year. Ben-David et al. (2021b) show that this measure strongly predicts stock returns, and the predictability is not sensitive to reasonable variations in the look-back horizon or weighting scheme.

Then, for each factor f, we measure its rating exposure by aggregating up the stock-level

[9] Note that Morningstar assigns ratings for mutual funds. The stock-level ratings are computed by us.

exposures:

$$\mathrm{ExpSum}(\Delta \mathrm{Rating})_{f,t-1} = \sum_{i \in \text{top quintile}} w^f_{i,t-1} \cdot \mathrm{ExpSum}(\Delta \mathrm{Rating})_{i,t-1} - \sum_{i \in \text{bottom quintile}} w^f_{i,t-1} \cdot \mathrm{ExpSum}(\Delta \mathrm{Rating})_{i,t-1}, \tag{3}$$

where $w^f_{i,t-1}$ is the lagged market cap weight of stock i in the corresponding quintile portfolio.

Table 1. Summary Statistics

Panels A and B present summary statistics of the monthly data at the stock and factor levels, respectively. Per Equation (4), FIT is defined as the amount of mutual fund trading induced by fund flows as a fraction of shares held. Morningstar rating is measured in stars (1 to 5), and ExpSum(Δ Rating) is an exponentially weighted sum of the past 12 months of rating changes (defined in Equation (2)). The sample period for all variables is January 1987 to December 2018 except FIT, which starts in January 1991 due to data availability. Obs is the average number of observations per month. The last five columns report 1%, 25%, 50%, 75%, and 99% percentile distributions, respectively. Panel C reports the average number of global factors in different regions in Jensen et al. (2021) after applying the data filter described in Section 2.2.

Panel A: Stock-level summary statistics								
	Obs	Mean	Std dev	1%	25%	50%	75%	99%
Market cap ($m)	4,003	3,382	15,894	7	110	397	1,586	55,308
Held by num funds	4,003	78.5	104.0	1.0	11.0	36.0	110.0	480.0
Return	4,003	1.08%	15.51%	−38.30%	−6.00%	0.44%	7.03%	51.61%
Rating	4,003	3.375	0.721	1.132	3.000	3.446	3.858	5.000
ExpSum(ΔRating)	4,003	−0.028	0.758	−2.352	−0.294	0.000	0.242	2.252

Panel B: Factor-level summary statistics								
	Obs	Mean	Std Dev	1%	25%	50%	75%	99%
Return	49	0.24%	3.57%	−9.60%	−1.57%	0.17%	1.97%	10.34%
Rating	49	0.017	0.214	−0.710	−0.069	0.014	0.106	0.570
ExpSum(ΔRating)	49	0.023	0.243	−0.699	−0.055	0.008	0.083	0.843
FIT	49	0.04%	0.43%	−1.25%	−0.14%	0.03%	0.20%	1.38%

Panel C: Number of global factors in Jensen et al. (2021)						
Period	U.S.	Developed ex U.S.	Emerging	Europe	APAC ex Japan	Japan
1987–1990	152	844	38	595	176	111
1991–1994	152	1,980	154	1,412	592	129
1995–1998	152	2,627	244	1,841	898	132
1999–2002	152	2,864	319	1,981	1,067	136
2003–2006	152	2,967	367	2,047	1,151	137
2007–2010	152	3,045	389	2,103	1,193	139
2011–2014	152	3,058	397	2,110	1,205	139
2015–2018	152	3,063	399	2,113	1,211	139

Flow-induced trading. We also want to measure the amount of fund flow-induced trading in each factor. We first follow Lou (2012) to calculate flow-induced trading (FIT) for each stock i in each month t:

$$\mathrm{FIT}_{i,t} = \frac{\sum_{\mathrm{fund}\, j \in \mathcal{J}} \mathrm{SharesHeld}_{i,j,t-1} \cdot \mathrm{Flow}_{j,t}}{\sum_{\mathrm{fund}\, j \in \mathcal{J}} \mathrm{SharesHeld}_{i,j,t-1}}. \tag{4}$$

Here, the flow of fund j in month t is defined as the net flow into the fund divided by the lagged TNA, following the literature (e.g., Coval and Stafford, 2007):

$$\mathrm{Flow}_{j,t} = \frac{\mathrm{TNA}_{j,t}}{\mathrm{TNA}_{j,t-1}} - (1 + \mathrm{Ret}_{j,t}). \tag{5}$$

In short, FIT is the total amount of nondiscretionary mutual fund trading in stock i caused by fund flows. As explained in Lou (2012), whereas discretionary trading is likely to be related to fundamentals, FIT isolates the nondiscretionary trading that is only attributable to fund flows. We then aggregate FIT at the factor level following the same method as in Equation (3). Summary statistics for the stock- and factor-level data are presented in Panels A and B of Table 1.

3 Morningstar Rating Reform and the Disruption of Style-Level Positive-Feedback Trading

In this section, we describe the Morningstar rating methodology reform in June 2002 and explain why it led to a disruption in style-level positive feedback trading. Based on this mechanism, we then make testable predictions to be examined throughout the rest of the paper.

3.1 2002 Rating Methodology Reform

We now describe the Morningstar rating methodology reform in June 2002.

Methodology before the reform. After introducing its mutual fund rating system in 1985, Morningstar quickly became the industry leader in providing independent mutual fund ratings. To assign ratings, Morningstar first summarizes the past return performance of funds and conducts minor adjustments for total return volatility and expenses. Depending on the availability of data, the look-back horizon for past performance can be up to 10 years, but more weight is applied to more recent periods.[10] Then, Morningstar ranks funds by their performance and assigns 1 to 5 star ratings with fixed proportions (10%, 22.5%, 35%, 22.5%, and 10%).[11]

The reform. While the rating methodology has been very stable over time, Morningstar implemented a major reform in June 2002.[12] After the reform, fund ratings were no longer based on how each fund ranked against *all* U.S. equity funds but only on fund rankings *within* style categories. For diverse U.S. equity funds (87% of all mutual funds in 2002), the style categories are the well-known 3×3 size-value matrix.[13] The change in methodology was announced in February 2002 and was first implemented in Morningstar's monthly ranking of funds at the end of June 2002.

This seemingly innocuous change had far-reaching consequences for the mutual fund industry. Before the change, fund ratings differed dramatically across styles based on recent style performance, as shown in Panel (a) of Figure 2, which plots the rating dispersion of

[10] For funds with over 10 years of history, Morningstar computes 3-year, 5-year, and 10-year past returns and combines them. The weights of the three horizons are set at 20%, 30%, and 50%, respectively. Because the three horizons are overlapping, however, the recent years are effectively given much more weight than more distant history.

[11] The Morningstar methodology is fully transparent. Appendix B of Ben-David et al. (2021b) provides further detail on the exact computation.

[12] The change was partially motivated by complaints from fund managers, who argued that they were receiving low ratings simply because their investment style performed poorly, but not because of how they managed the funds. Please see Section 3 of Ben-David et al. (2021b) for more details.

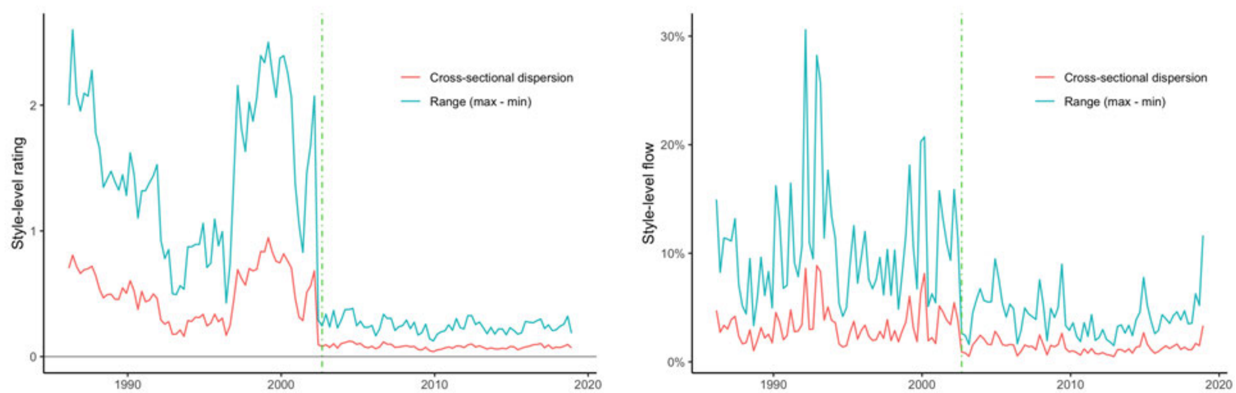
[13] Sector funds—the remaining 13%—were classified into 12 sectors (e.g., financials, utilities).

3 × 3 size-value fund styles. In the months before the methodology change, the top- and bottom-rated styles differed by up to 2 stars. After the reform, that difference dropped dramatically and ratings also became uncorrelated with past style performance.[14] Panel (b) plots the dispersion of style-level fund flows. Consistent with flows chasing ratings being a major driver of fund flows (e.g., Reuter and Zitzewitz, 2021; Ben-David et al., 2019), style-level fund flows also became less dispersed after the reform.

Figure 2. The Morningstar Methodology Reform and Style-Level Flows

Panels (a) and (b) plot the dispersion of quarterly fund ratings and TNA-weighted average fund flows by the 3 × 3 size-value Morningstar styles. Dispersion is measured either as the cross-sectional standard deviation (red lines) or the difference between maximum and minimum values (blue lines). The vertical dashed line marks the June 2002 Morningstar methodology reform event.

(a) Style-level rating dispersion (b) Style-level fund flow dispersion



Importantly for our identification purposes, investors continued to chase ratings in a similar manner before and after the reform. This has been shown by Ben-David et al. (2019); Evans and Sun (2021); Ben-David et al. (2021b) (see, for example, Figure 1(b) and Figure 4(b) in Ben-David et al. (2021b)). Therefore, the reform effectively redirected fund flows to stop chasing style-level returns.

[14] One may wonder why rating dispersion did not drop to exactly zero. A major reason is that Morningstar assigns ratings at the share-class level, so taking an average over share classes would bring the dispersion to zero. Because a fund's share classes have the same underlying portfolio, we compute average ratings at the fund-level following Barber et al. (2016).

3.2 Disruption of Style-Level Positive-Feedback Trading

We now demonstrate that the 2002 Morningstar reform disrupted style-level positive-feedback trading. Based on this disruption, we conjecture that the reform should reduce the profitability of momentum-type factors and factor momentum, and that the reduction should be specific to U.S.-based factors.

We first note that the pre-reform rating methodology generates a positive-feedback loop at the style level. This is illustrated in Panel (a) of Figure 3: Funds in styles that performed well in the recent past get high ratings and attract inflows. Funds use the new flows to increase their investments in the same style of stocks, so the prices of those stocks are pushed up even further. The mechanism also works in the other direction: Funds in underperforming styles experience correlated outflows, resulting in downward price pressure on stocks associated with these styles. The post-June 2002 rating methodology, however, should cause a sudden disruption in this rating-induced positive feedback trading at the style level.

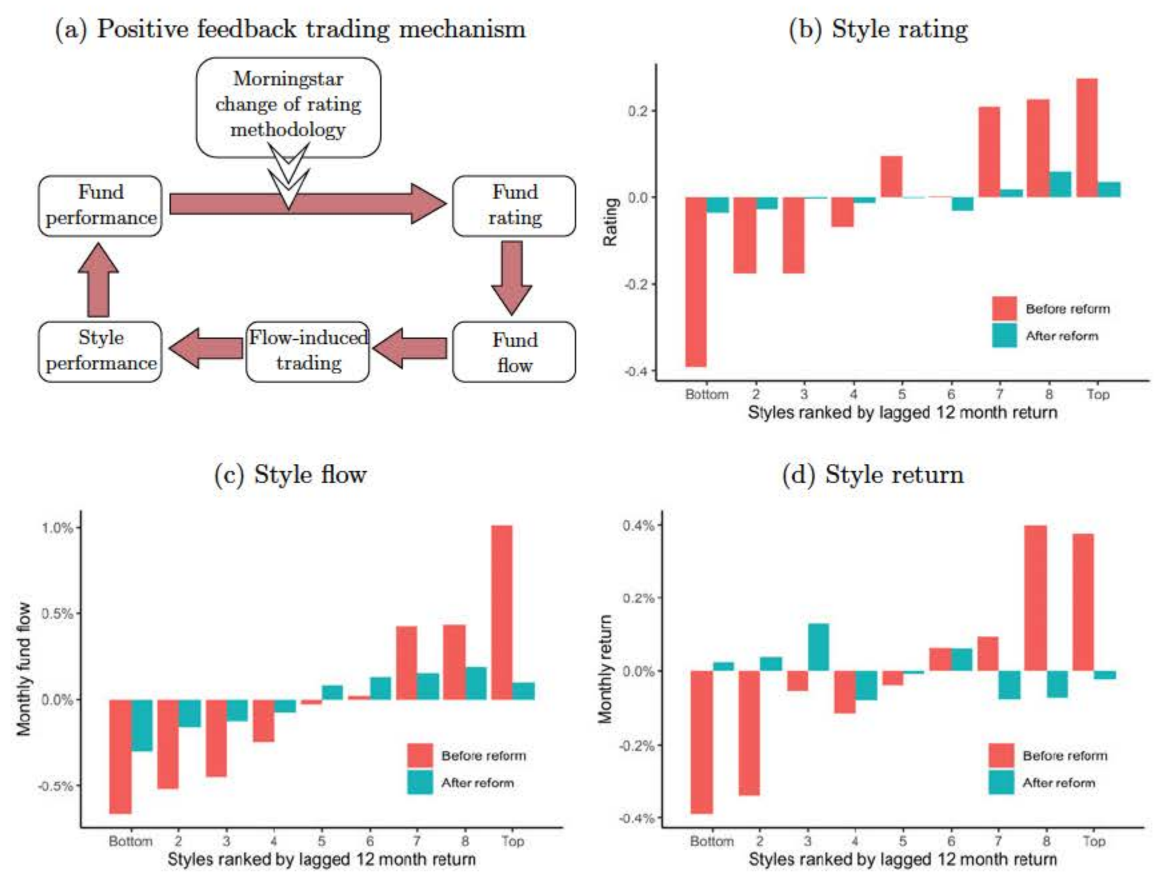
We confirm this style-level disruption in Panels (b) and (c) of Figure 3. Specifically, we sort the 3×3 Morningstar fund styles based on past-12-month returns—the typical look-back horizon used in studying momentum. Before the reform, funds in styles that recently performed well received higher average ratings and higher fund flows. The magnitudes are also large. Panel (b) shows that the average rating spread between funds in the top and bottom styles was about 0.8 stars before reform and shrank to almost zero after the reform. Because high ratings attract flows, Panel (c) shows that funds in the top style received about 1.7% higher flows per month than the bottom style before the reform, and that difference dropped to around 0.4% after the reform.[15]

This disruption also has a significant impact on style returns. In Panel (d), we plot TNA-weighted style-level fund returns. The top-ranked style exhibits approximately 0.8% higher monthly returns than the bottom-ranked style before the reform, and that difference disappears after the reform. In unreported robustness checks, we find similar patterns when

[15]The data in these graphs are demeaned within-month to focus on cross-sectional patterns across styles.

Figure 3. Style-Level Positive-Feedback Trading Before and After Reform

This figure shows that the style-level positive-feedback trading largely halted after the Morningstar methodology change in June 2002. The flow chart in Panel (a) illustrates how pre-2002 ratings generate positive style-level positive-feedback trading. In Panels (b) to (d), we sort the 3×3 Morningstar styles by their lagged 12-month returns. Panels (b) and (c) plot the TNA-weighted average rating and fund flows of the sorted styles. Panel (d) plots the return of funds in those styles. All variables are demeaned to focus on the cross-sectional difference across styles. This sample starts from 1991 due to monthly flow data availability in CRSP.



measuring returns using CAPM alpha, and the post-reform change in the alpha spread is statistically significant at the 5% level.[16]

These findings lead us to conjecture that the 2002 Morningstar reform had a negative impact on strategies that load on style momentum, which includes several momentum-type factors and the factor momentum strategies in Ehsani and Linnainmaa (2021). Of the 49 factors we study, five are classified into the momentum category by Hou et al. (2020):

[16] To alleviate the concern that fund returns may also be influenced by transaction costs and fees, we also repeated this exercise using the returns of the stocks held by the funds, rather than the fund returns. The results are unaffected.

$(t-1,\ t-12)$ and $(t-1,\ t-6)$ momentum (Jegadeesh and Titman, 1993), industry momentum (Moskowitz and Grinblatt, 1999), 52-week high (George and Hwang, 2004), and $(t-7,\ t-12)$ intermediate momentum (Novy-Marx, 2012). We predict that these factors should suffer large profitability declines after June 2002.

Testable Predictions. Based on the discussion in this section, we make three predictions.

1. **Disruption of momentum-related strategies.** Relative to other factors that do not depend on positive-feedback trading, the rating exposure and profitability of momentum-related factors and factor momentum should decline more after the reform.

2. **Disruption is specific to the U.S.** Because the Morningstar reform is specific to the U.S.,[17] the post-reform profitability decline of momentum-related strategies should be concentrated in the U.S. market.

3. **"Kink" in 2002.** Only strategies that are negatively affected by the Morningstar reform should experience a "kink" (abrupt decline) in rating, flows, and returns around the reform event of June 2002.

It is worth emphasizing that our first two predictions are *ceteris paribus* in nature. As discussed in the introduction, there are many other reasons that lead to time-varying changes in factor profitability. We are interested in the *incremental* impact of the disruption in feedback trading due to the Morningstar reform. The third prediction, by focusing narrowly on the time period around the reform event, helps identify the causal effect of ratings.

4 Effect of Reform on Factor Returns

In this section, we study the 49 asset pricing factors' rating exposure and profitability before and after the Morningstar reform. The non-momentum-related factors serve as controls,

[17] Appendix 2 of Morningstar (2016) lists all the historical major Morningstar rating methodology changes. The June 2002 change is unique to the U.S. market.

as they should be relatively unaffected by the reform. Consistent with our predictions, momentum-related factors suffered large declines in ratings and returns after 2002.[18]

4.1 Which Factors Suffered Larger Profitability Declines?

As described in Section 2.3, we measure a factor's exposure to Morningstar ratings using $\text{ExpSum}(\Delta\text{Rating})_{f,t-1}$, defined in equation (3). In Panel (a) of Figure 4, we plot each factor's average post-reform rating exposure against the pre-reform values over the sample period of 1987 to 2018. We mark factors from different categories using different colors. Clearly, before the reform, Morningstar served as an important tailwind for factors in the momentum categories (colored purple). After the reform, rating exposures of all momentum factors shrunk. This plot is consistent with our conjecture that momentum-type factors were most positively affected by rating-induced positive-feedback trading before the reform, and they suffered the largest rating drop after the reform.

To visualize the cross-sectional differences across factor returns, in Panels (b) and (c), we plot the pre- and post-reform average factor return against the pre-reform rating exposure. Consistent with our prediction, factors that benefit from pre-reform rating exposure experienced high returns before the reform but not afterward. For instance, the profit of the momentum factor was about 0.90% each month but became negligible after June 2002. Other momentum-type factors, such as the 52-week-high factor, suffered similar declines in profitability.

The results in Figure 4 may partially reflect reverse causality, so they should be seen as suggestive. However, in the subsequent quantification exercise, we focus only on the predictive rating-return relationship, thus eliminating reverse causality concerns.[19]

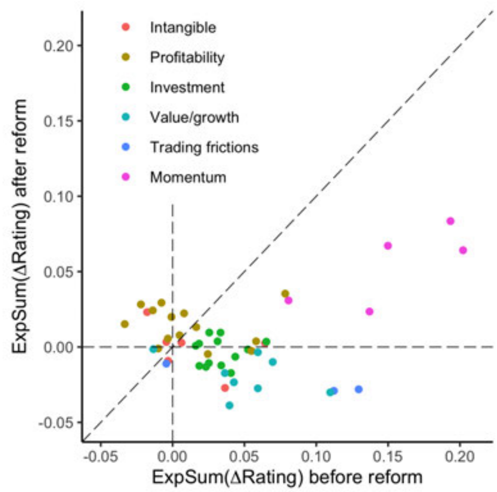
[18] Appendix B.1 shows that only a minor part of the drop can be explained by the post-publication declines documented by McLean and Pontiff (2016).

[19] Ben-David et al. (2021b) also show that past rating changes strongly predict future stock returns.

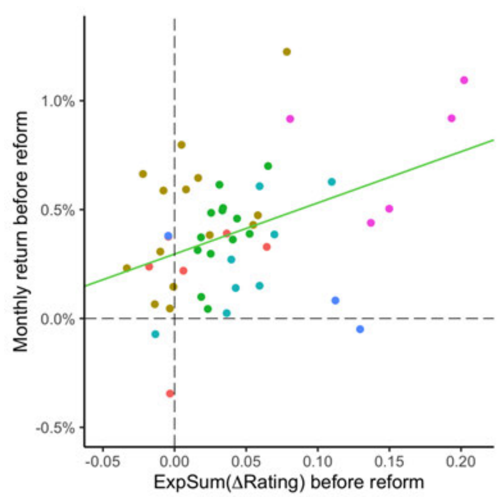
Figure 4. Factor Ratings and Returns before versus after the Reform

We compare factor statistics before and after the Morningstar methodology reform in June 2002. Panel (a) plots the post-reform ExpSum(ΔRating) (the exponentially-weighted sum of past-12-month rating changes) against the pre-reform values. Panels (b) and (c) plot average monthly factor returns before and after the reform against pre-2002 ExpSum(ΔRating). The green lines in Panels (b) and (c) are best linear fits. The different colors for the data points represent the return factor classifications in Hou et al. (2020).

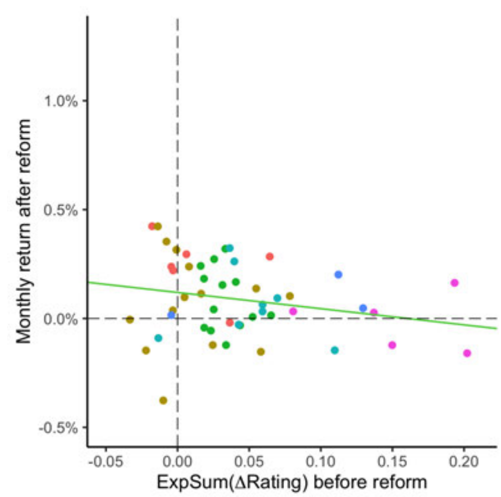
(a) Rating exposure before and after reform



(b) Factor returns before reform



(c) Factor returns after reform



Placebo Test: Momentum in Other Countries. We now test whether the post-reform momentum profitability drop is specific to the U.S. We use two sets of factor data constructed by other researchers. Because they each have distinct factor construction methodologies, to be consistent, we use their versions of U.S. momentum factors for the comparison.

Table 2. Momentum Profitability Decline: The U.S. versus Other Markets

The table reports monthly momentum factor returns across markets before and after the Morningstar reform in June 2002. Panel A uses data from Ken French's website, which start in 1991. The other two panels use data from Jensen et al. (2021), which start from 1987 like our main exercises. Panels B and C report results based on equal-weighted and capped value-weighted returns, respectively. The standard errors are reported in the parentheses, and coefficients statistically significant at the 10%, 5%, and 1% levels are denoted with ***, **, and *, respectively.

Panel A: Ken French data

	U.S.	Market type		Regions		
		Developed ex U.S.	Emerging	Europe	APAC ex Japan	Japan
	(1)	(2)	(3)	(4)	(5)	(6)
Before reform	1.13***	0.82**	0.92***	1.11***	0.75	0.13
	(0.42)	(0.33)	(0.29)	(0.33)	(0.46)	(0.46)
After reform	0.03	0.59**	0.72***	0.75***	0.83***	0.11
	(0.32)	(0.23)	(0.19)	(0.28)	(0.24)	(0.25)
After − before	−1.10**	−0.23	−0.20	−0.36	0.08	−0.02
	(0.53)	(0.40)	(0.34)	(0.43)	(0.52)	(0.52)

Panel B: Jensen et al. (2021) data, equal-weighted

	U.S.	Market type		Regions		
		Developed ex U.S.	Emerging	Europe	APAC ex Japan	Japan
	(1)	(2)	(3)	(4)	(5)	(6)
Before reform	1.27***	0.74***	0.28	1.01***	0.22	−0.07
	(0.36)	(0.09)	(0.37)	(0.10)	(0.18)	(0.34)
After reform	0.32	0.94***	0.67***	1.06***	0.73***	0.17
	(0.29)	(0.07)	(0.16)	(0.09)	(0.09)	(0.23)
After − before	−0.94**	0.20*	0.39	0.05	0.51**	0.24
	(0.46)	(0.11)	(0.40)	(0.13)	(0.20)	(0.41)

Panel C: Jensen et al. (2021) data, capped value-weighted

	U.S.	Market type		Regions		
		Developed ex U.S.	Emerging	Europe	APAC ex Japan	Japan
	(1)	(2)	(3)	(4)	(5)	(6)
Before reform	0.92**	0.61***	0.78**	0.39**	0.79***	0.25
	(0.38)	(0.09)	(0.39)	(0.19)	(0.11)	(0.39)
After reform	0.05	0.58***	0.63***	0.60***	0.63***	0.02
	(0.29)	(0.08)	(0.20)	(0.10)	(0.11)	(0.25)
After − before	−0.87*	−0.03	−0.16	0.21	−0.16	−0.23
	(0.48)	(0.12)	(0.44)	(0.21)	(0.15)	(0.47)

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

We first use the monthly momentum factors from Ken French's website, a standard data source for factor-based research.[20] In Panel A of Table 2, we compare his version of the U.S. momentum factor against momentum in other developed markets, emerging markets, and also across other regions. Consistent with our prediction, only the U.S.-based momentum strategy experienced a large decline in profitability after 2002. In contrast, momentum profits were strong both before and after the reform in all other markets except Japan.[21]

For robustness, we also produce the equivalence of Panel A using data from Jensen et al. (2021).[22] Panel B examines their equal-weighted returns, and Panel C examines capped value-weighted returns. The conclusions are qualitatively unchanged. In fact, when judged using equal-weighted returns, momentum profits actually increased across the board, and the U.S. is the only region where returns decreased. The U.S. decline is statistically significant at the 5% level. Overall, these results are consistent with the Morningstar rating-based mechanism only causing a disruption to U.S.-based momentum profitability.

4.2 Quantifying the Explanatory Power of Ratings

How much of the decline in momentum-type factor profitability can be explained by the discontinuation of rating-induced feedback trading? In this section, we estimate the explanatory power using two methodologies, each of which has benefits and drawbacks:

1. **Spanning tests**: We form a "rating factor" and examine how much of the other factor returns can be spanned by it. While commonly used in factor-based asset pricing, this approach may overstate explanatory power, as it effectively classifies all returns correlated with the rating factor as "explained," which is only valid in a statistical sense.

[20] His factor construction methodology slightly differs from ours: The monthly correlation between his and our U.S. momentum factor is 96%. Specifically, the Fama-French construction forms 2×3 size–prior return independent sorts and defines the momentum factor as 1/2 (Small High + Big High) − 1/2 (Small Low + Big Low).

[21] That momentum strategy returns are weak in Japan is a known result (Asness et al., 2013).

[22] Their methodology is also slightly different and explained in Section 2.2.

2. **Direct estimation:** We first estimate the price impact coefficient of ratings (λ) using the 2002 shock, which is well identified, and multiply it by the post-reform change in rating exposure of factors:

$$\underbrace{\lambda}_{\text{Price impact of ratings}} \times \left(\overline{\text{ExpSum}(\Delta\text{Rating})}_{f,\text{after 2002}} - \overline{\text{ExpSum}(\Delta\text{Rating})}_{f,\text{before 2002}}\right). \tag{6}$$

The key benefit of the direct approach is that rating exposure is directly measured. The drawback, which is shared with the spanning test method, is that it relies on strong functional form assumptions. Moreover, due to measurement errors introduced in matching fund ratings to stock holdings, we expect this method to underestimate the effect.

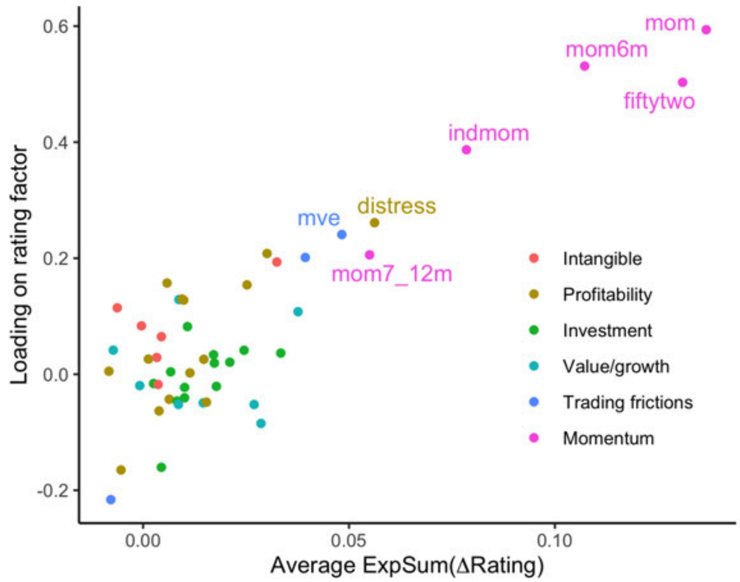
Spanning Tests. We first form a "rating factor": In each month, we sort stocks by $\text{ExpSum}(\Delta\text{Rating})_{i,t-1}$ into quintiles using NYSE breakpoints, and then form the long-short value-weighted quintile factor portfolio.[23] We then use this factor to explain the other 49 factors in spanning regressions. Figure 5 shows that each factor's loading on the rating factor, plotted on the vertical axis, is highly correlated with its bottom-up rating exposure measure ($\text{ExpSum}(\Delta\text{Rating})_{f,t-1}$), which is plotted on the horizontal axis. As expected, the factors with the highest loadings are the ones related to momentum. For instance, the standard $(t-1, t-12)$ momentum factor has a loading of 0.63 with a t-statistic of 9.94.

To what extent can the rating factor explain factor returns? We run spanning regressions for each factor separately before and after the reform. Table 3 presents results of this analysis. When focusing on the momentum factor and other momentum-type factors, we find that the spanning method estimates that ratings can explain 0.41% and 0.28% of their post-reform return decline, respectively (second row in Panel A of Table 3). This amounts to half of the overall profitability decline for momentum and around one-third of the decline for the other

[23] Over our sample period, this factor has an average monthly return of 0.41%.

Figure 5. Factor ExpSum(ΔRating) and rating factor loading

We form a rating factor using long-short NYSE quintiles based on stock-level ExpSum(ΔRating). We plot the factor loadings on the rating factor against their average ExpSum(ΔRating). Factors are colored by their categories based on the taxonomy in Hou et al. (2020).



momentum-type factors (third row in Panel A of Table 3). As discussed earlier, we consider the spanning tests to provide an *upper bound* estimate.

Direct estimation. We now use the second approach to estimate explanatory power. To obtain a well-identified estimate of the price impact λ, we run a factor-level return-predicting regression using the 12-month window around the methodology reform event:

$$\text{Ret}_{f,t} = \lambda \cdot \text{ExpSum}(\Delta\text{Rating})_{f,t-1} + X_{f,t-1} + \epsilon_{f,t}, , \tag{7}$$

where the control $X_{f,t-1}$ includes factor returns over $t-1$, $t-2$ to $t-6$, and $t-7$ to $t-12$ months as well as factor- and time-fixed effects.[24] As discussed further in Section 6, using a short window means we primarily rely on reform-induced rating variation, which

[24]These controls are motivated by the finding that factors exhibit momentum (Arnott et al., 2019; Gupta and Kelly, 2019; Ehsani and Linnainmaa, 2021).

Table 3. Explanatory Power of Post-Reform Strategy Profitability Declines

We examine how much the Morningstar reform can explain the return decline of momentum-related factor strategies after June 2002. Panel A reports results based on the full sample, and Panel B excludes the momentum crash period (January 2008 to June 2009). In both panels, the first row reports the change in average monthly returns (as a percentage) from the pre-reform period (January 1987 to June 2002) to the post-reform period (July 2002 to December 2018). The next two rows present the estimated amount explained by Morningstar ratings. "Spanning method" refers to a regression-based approach in which we use a Morningstar rating-based factor to explain factor returns. "Direct estimate" is calculated by multiplying the price impact parameter of ratings, estimated using the 2002 event, by the change in average $\text{ExpSum}(\Delta\text{Rating})_{f,t-1}$ after the reform. The last two rows present the *fraction* of the return change explained by the Morningstar reform. Column (1) examines the momentum factor; Column (2) examines other factors in the momentum category; Columns (3) and (4) examine the time-series and cross-sectional factor momentum strategies.

Panel A: Full sample (January 1987 – December 2018)

		Factors		Factor momentum	
	Methodology	Momentum factor	Other mom-type factors	Time-series	Cross-section
		(1)	(2)	(3)	(4)
Return change (%)		-0.76	-0.79	-0.46	-0.37
Explained (%)	Spanning method	-0.41	-0.28	-0.30	-0.29
	Direct estimate	-0.25	-0.22	-0.31	-0.31
Fraction explained	Spanning method	0.545	0.355	0.647	0.791
	Direct estimate	0.330	0.274	0.677	0.829

Panel B: Excluding momentum crash period

		Factors		Factor momentum	
	Methodology	Momentum factor	Other mom-type factors	Time-series	Cross-section
		(1)	(2)	(3)	(4)
Return change (%)		-0.62	-0.66	-0.50	-0.41
Explained (%)	Spanning method	-0.48	-0.33	-0.34	-0.34
	Direct estimate	-0.28	-0.24	-0.33	-0.33
Fraction explained	Spanning method	0.637	0.415	0.747	0.915
	Direct estimate	0.374	0.301	0.725	0.893

reduces endogeneity concerns. To account for the cross-sectional factor return correlation, we adjust the standard errors using a feasible generalized least squares (FGLS) approach.[25] The estimation results are shown in Appendix Table B.2. For each star rating change in $\text{Expsum}(\Delta\text{Rating})_{f,t-1}$, we find that the factor-level price impact is 2.27%, with a t-statistic of 4.28. The result is both statistically and economically significant. Appendix B.3 provides more details and robustness checks of this estimation.

We now apply the event-estimated λ coefficients to quantify the factor profitability decline that can be explained by Morningstar. The results are shown in Columns (1) and (2) of Table 3, Panel A. The first row shows that, after the reform, the monthly return of the momentum factor and other momentum-type factors dropped by 0.76% and 0.79%, respectively. Direct estimation suggests that rating-induced price pressures can explain 0.25% and 0.22% of the decline, respectively, which amounts to approximately one-third of the profitability declines. For comparison, we also report the estimates based on the spanning method, which suggests that Morningstar ratings can explain around half of the profitability decline in the momentum factor and around one-third of the other momentum factors. As discussed earlier, the spanning method is likely to overestimate, while the direct estimation methods is likely to underestimate. To be conservative, we use the latter method to inform our conclusion.

[25] We use the full sample of factor returns to estimate the covariance matrix C of factor returns and incorporate C into the estimation. Specifically, let y be the vector of factor returns stacked together so that the first 49 entries are the first month, the next 49 entries are the second month, and so forth. Then, we estimate the covariance matrix of y to be

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

where $\hat{C}$ is the estimated contemporaneous return covariance matrix of the 49 factors. Let X denote the matrix of independent variables. Then, we estimate the regression coefficients and covariance using

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

Momentum crash. Daniel and Moskowitz (2016) document that momentum strategies experienced a severe crash during the 2008–2009 financial crisis. To alleviate the concern that our results may be driven by this crash, Panel B of Table 3 reports results after excluding the recession period around the financial crisis, defined as January 2008 to June 2009 by the NBER recession dating committee.[26] The results are qualitatively unchanged, indicating that our results are not driven by the momentum crash.

Long and Short Legs. The analysis so far has focused on returns to long-short portfolios, and one may wonder whether the results are driven solely by the long or short legs. Ceteris paribus, our proposed mechanism should influence returns to the long and short legs of momentum-type portfolios in opposite directions. To better understand the impact of our mechanism, the left column of panels of Figure 6 plots the rating exposure, flow-induced trading, and returns of different quintile portfolios.[27] Panel (a) shows that before the rating reform, the long (short) legs of momentum experience significant upward (downward) rating changes. The middle column of panels shows that the same effect is barely present in the non-momentum-type factors. The second row shows broadly similar patterns for fund flow-induced trading. The third row shows that the post-2002 drop in long/short returns is more pronounced in momentum than in other factors. Overall, these findings are consistent with our predictions for how rating-induced feedback trading should influence different types of factors.

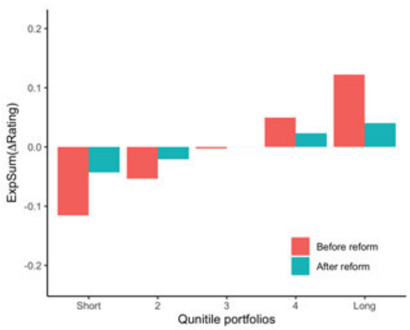
[26] After the 2002 Morningstar reform, the average monthly momentum factor return is -1.24% during the financial crisis and 0.30% otherwise.

[27] Because results for other momentum-type factors are very similar to those for momentum, we omit them for brevity.

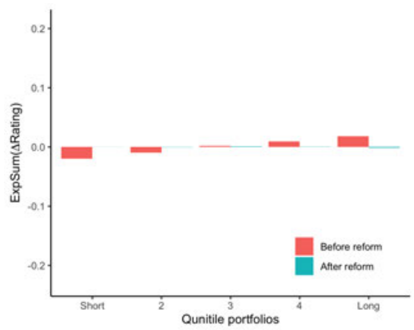
Figure 6. Morningstar Reform and the Long and Short Legs of Strategies

The three rows of this figure plot the rating exposure (ExpSum(ΔRating)$_{t-1}$), flow-induced trading (FIT), and return of different strategies by quintile, respectively. The data are separated into the periods before the reform (January 1987 to June 2002) and after reform (July 2002 to December 2018). The left column of panels show results for the stock momentum factor. The middle column of panels show results for the factors that are not in the momentum category. The right column of panels show results for the cross-sectional factor momentum strategy, where each quintile represents a portfolio of factors. All variables are demeaned to emphasize cross-sectional differences. The FIT results start in January 1991 due to the availability of monthly fund flow data.

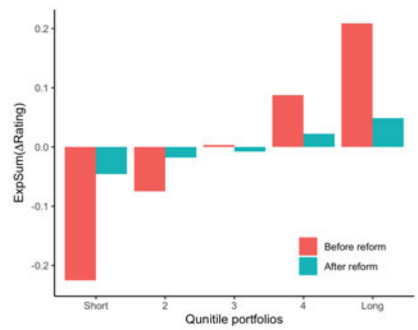
(a) ExpSum(ΔRating), momentum



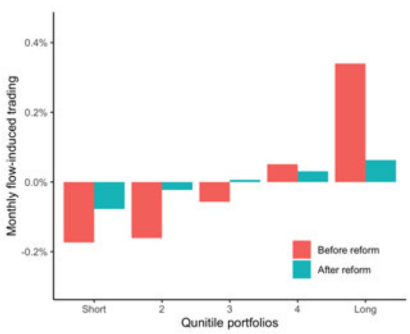
(b) ExpSum(ΔRating), non-momentum factors



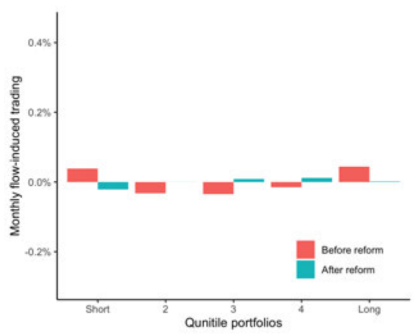
(c) ExpSum(ΔRating), factor momentum



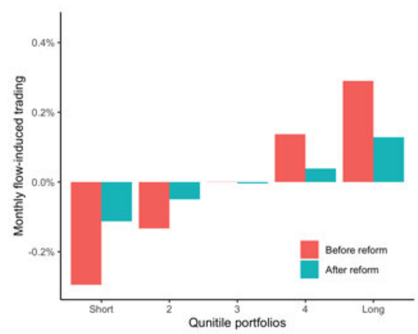
(d) FIT, momentum



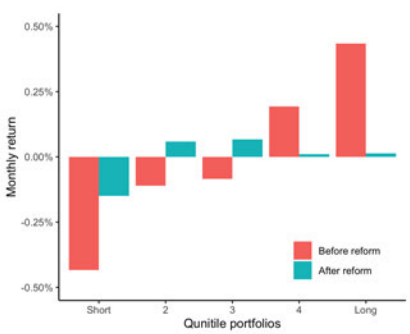
(e) FIT, non-momentum factors



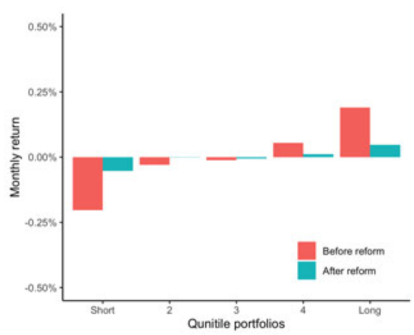
(f) FIT, factor momentum



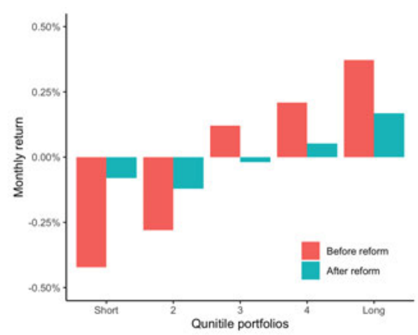
(g) Return, momentum



(h) Return, non-momentum factors



(i) Return, factor momentum



5 Effect of the Reform on Factor Momentum

Ehsani and Linnainmaa (2021) show that factors themselves exhibit momentum. Specifically, they propose two related strategies that can be implemented on any universe of factors, which they call time-series factor momentum (TSFM) and cross-sectional factor momentum (CSFM). Both are long-short strategies with equal weights across factors in each leg. In TSFM, the long (short) leg consists of all factors with positive (negative) returns over the previous 12 months. In CSFM, the long (short) leg consists of factors with above- (below-) median past-12-month returns. Therefore, while the CSFM portfolio has the same number of factors in each leg, the TSFM does not have to. We follow the factor momentum construction in Ehsani and Linnainmaa (2021) using our factor universe.

In this section, we show that factor momentum is highly exposed to style momentum, and as a consequence, is also affected by the Morningstar reform. For both TSFM and CSFM, their profitability drops after the reform, and we estimate that the Morningstar rating reform can explain approximately two-thirds of the drop.[28]

It is important to note that our findings should be seen as supplements to, rather than contradictions to, Ehsani and Linnainmaa (2021). They show that factor momentum strategies have high returns and argue that the persistence of profitability is related to difficulties of arbitrage in more systematic return components. They do not take a strong stance on the fundamental causes of factor momentum. Our exercise focuses on providing a specific (and partial) economic explanation for why factor momentum arises in the first place.

5.1 Mechanism: Factor Momentum Loads on Style Momentum

We first show that factors have large and persistent style exposure. As a consequence, factor momentum is also affected by the post-reform cessation of style-level rating-induced

[28]This higher explanatory power, relative to that of the stock momentum profitability decline, is expected: Factor momentum is more directly related to style momentum, which the Morningstar mechanism impacts. In contrast, stock momentum also depends on idiosyncratic-level momentum, which Morningstar does not impact (Appendix B.2).

positive-feedback trading.

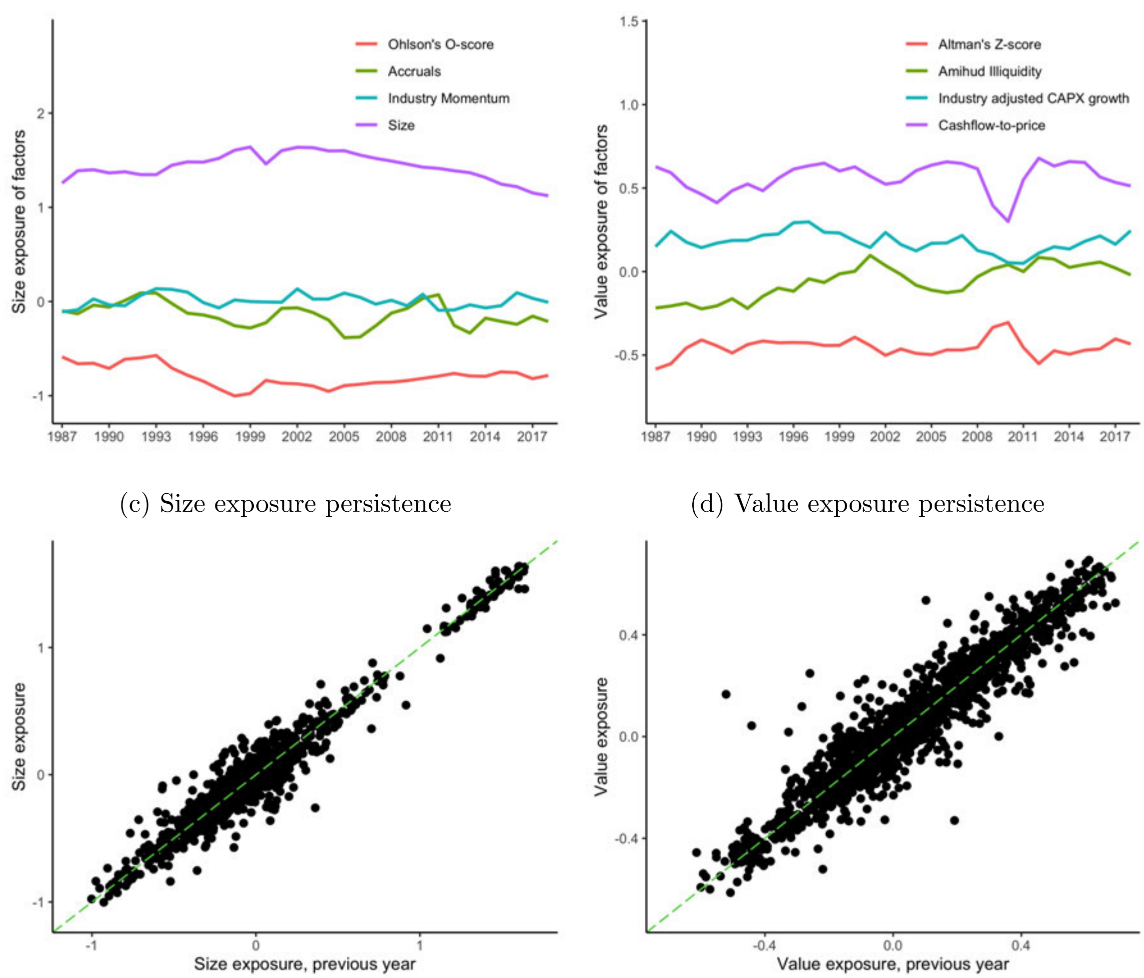
We use a simple holdings-based approach to measure the style exposure of factors. For each stock i, let $w_{i,t}^{\pi}$ denote the fraction of its mutual fund holdings in each of the 3×3 Morningstar size-value styles π in quarter t. Then, its size style exposure is given by $\sum_{\pi \in \text{three small-cap styles}} w_{i,t}^{\pi} - \sum_{\pi \in \text{three large-cap styles}} w_{i,t}^{\pi}$. Similarly, we define its value style exposure as $\sum_{\pi \in \text{three value styles}} w_{i,t}^{\pi} - \sum_{\pi \in \text{three growth styles}} w_{i,t}^{\pi}$. This holdings-based exposure measure is easy to interpret: A stock that is only held by small- (or large-) cap style funds will have a size score of $+1$ (or -1). We then aggregate these stock-level style exposures up to the factor level. Because factors are long-short portfolios, we anticipate that their exposures will be bounded between -2 and $+2$.

To visualize the style exposure of factors, Panels (a) and (b) of Figure 7 plot the annual average size and value exposure of factors. To illustrate time fluctuation in the exposures, in each panel, we rank factors by their corresponding style exposures and plot the four factors at the 0, 1/3, 2/3, and 1 quantiles. Panel (a) shows that the size exposure of factors ranges from approximately 1.5 for the size factor to -1 for Ohlson's O-score. This is a very large range, considering that the factor style exposure is designed to be bounded between -2 and 2. Panel (b) shows that value exposure ranges from approximately 0.5 for the cash flow–to-price factor to approximately -0.5 for the sales growth factor.

Not only do many factors have sizeable style exposures, more importantly, their factor exposures are very stable over time, as shown in Panels (c) and (d). Here, we plot factors' annual style exposures against their exposures in the previous year; each data point is a factor-year. The resulting points almost exactly fall on the 45% degree lines, implying that the style exposures of factors are very persistent. Therefore, we conclude that factor momentum loads onto style momentum and should be negatively impacted by the Morningstar reform.

Figure 7. Factors Have Persistent Style Exposures

We measure size and value style exposures of factors using a portfolio-based approach. For instance, holdings by funds in the small- (large-) cap Morningstar styles gets a size exposure score of +1 (-1), and we aggregate these exposure scores at the long-short factor level to measure the size exposure of the 49 factors considered in this paper. Value exposure is measured in a similar way. Panels (a) and (b) plot the annual average size and value exposures of factors over the sample period. The factors chosen are those at the 0, 1/3, 2/3, and 1 quantiles of average exposures. Panels (c) and (d) examine the persistence of style exposures by plotting factors' style exposures in the current year against exposures in the previous year. The green dashed lines represent 45% diagonal lines.



(a) Size exposure of factors

(b) Value exposure of factors

(c) Size exposure persistence

(d) Value exposure persistence

5.2 The Decline of Factor Momentum Profits

To visualize how the factor momentum strategies are impacted by the Morningstar reform, Figure 8 plots the factor-level rating exposure ($\text{ExpSum}(\Delta\text{Rating})_{t-1}$) aggregate at the factor momentum strategy level. To further shed light on the source of the effect, we decompose the ratings into the 3×3 style-level and idiosyncratic components. Specifically, we first decompose *fund* ratings into a style-level component and an idiosyncratic residual:

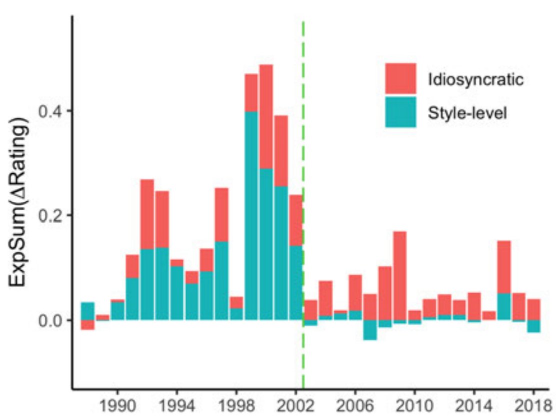
$$\text{Rating}_{j,t}^{\text{fund}} = \text{StyleRating}_{j,t}^{\text{fund}} + \text{IdiosyncraticRating}_{j,t}^{\text{fund}}, \tag{8}$$

where $\text{StyleRating}_{j,t}^{\text{fund}}$ is the value-weighted average rating for the 3×3 style that fund j belongs to, and $\text{IdiosyncraticRating}_{j,t}^{\text{fund}}$ is defined as a residual. We then use this decomposition to separately compute style-level and idiosyncratic $\text{ExpSum}(\Delta\text{Rating})_{t-1}$ for stocks and aggregate them to the factor momentum strategies. The results plotted in Figure 8 show that before the reform, factor momentum had relatively high rating exposure. Style-level rating exposure dropped to effectively zero after the reform, and as a consequence, the overall rating exposure declined.

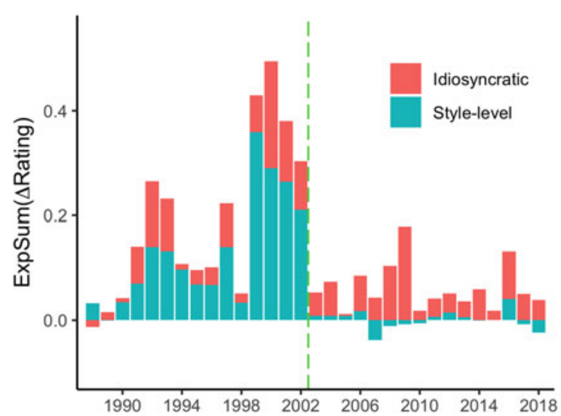
Figure 8. Rating Exposure of Factor Momentum Strategies

Panels (a) and (b) plot the annual average $\text{ExpSum}(\Delta\text{Rating}_{t-1})$ for time-series and cross-sectional factor momentum strategies, respectively. Ratings are decomposed into style-level ratings (blue bars) and idiosyncratic ratings (red bars). To make the green vertical dashed line exactly delineate the reform date, each year y is defined as July of year $y-1$ to June of year y.

(a) Time-series factor momentum



(b) Cross-sectional factor momentum



As predicted, factor momentum profits declined after the reform. This is reported in the first row of Columns (3) and (4) of Table 3, Panel A. After the reform, monthly returns of the TSFM and CSFM strategies declined by 0.46% and 0.37%, respectively, from levels of 0.61% and 0.52% before the reform. That is, the profits of both strategies declined by three-fourths after the reform.

Placebo Test: Factor Momentum in U.S. and Other Countries. We now use the global factors in Jensen et al. (2021) to examine factor momentum strategies outside of the U.S. The results are reported in Table 4. Because the results based on TSFM and CSFM are highly similar, we only report the former for brevity. Based on equal-weighted returns in Panel A, the decline of factor momentum profits is specific to the U.S.; in fact, factor momentum profits increased in most of the regions except Europe. The capped value-weighted return-based results in Panel B are broadly similar, although with lower statistical significance (the U.S. post-reform change is significant at the 10% level). Overall, these results are consistent with the prediction that the drop in factor momentum profitability is concentrated in the U.S. market.

Quantifying the Explanatory Power of Rating Reform on Factor Momentum Profitability Decline. We next follow the same methodologies in Section 4.2 to quantify the explanatory power of the Morningstar rating reform on the profitability decline of factor momentum strategy. The results are reported in Columns (3) and (4) of Table 3, Panel A. Both the spanning tests and the direct estimation method give the same conclusion: Morningstar ratings can approximately account for two-thirds of the post-2002 decline of factor momentum profits.

To visualize the effect on different parts of the factor momentum strategy, the rightmost panels of Figure 6 plots the rating exposure, flow-induced trading, and returns of the factor momentum strategy. To focus on the cross-sectional differences across different factors that compose the strategy, we examine the cross-sectional factor momentum strategy. The results are broadly consistent with our prediction that factor momentum is slightly more affected by the Morningstar-based mechanism than the stock momentum factor, which is shown in the middle panels.

Table 4. Factor Momentum Profitability Decline: U.S. versus Other Markets

The table reports monthly factor momentum returns across markets before and after the Morningstar reform in June 2002. We use the U.S. and global factors from Jensen et al. (2021). Panel A uses equal-weighted returns, and Panel B uses the capped value-weighted returns. Standard errors are reported in parentheses.

Panel A: Equal-weighted

	U.S.	Market type		Regions		
		Developed ex U.S.	Emerging	Europe	APAC ex Japan	Japan
	(1)	(2)	(3)	(4)	(5)	(6)
Before reform	1.12***	0.52***	0.41	0.58***	0.48***	0.18
	(0.30)	(0.11)	(0.28)	(0.13)	(0.12)	(0.18)
After reform	0.38**	0.54***	0.56***	0.46***	0.68***	0.40***
	(0.16)	(0.08)	(0.09)	(0.10)	(0.06)	(0.11)
After − before	−0.75**	0.02	0.16	−0.11	0.21	0.22
	(0.34)	(0.13)	(0.29)	(0.16)	(0.13)	(0.21)

Panel B: Capped value-weighted

	U.S.	Market type		Regions		
		Developed ex U.S.	Emerging	Europe	APAC ex Japan	Japan
	(1)	(2)	(3)	(4)	(5)	(6)
Before reform	0.63*	0.34***	0.53	0.41***	0.35**	0.28
	(0.32)	(0.12)	(0.36)	(0.14)	(0.14)	(0.22)
After reform	0.06	0.23**	0.30**	0.21*	0.30***	0.04
	(0.13)	(0.10)	(0.13)	(0.12)	(0.08)	(0.11)
After − before	−0.58*	−0.11	−0.23	−0.20	−0.04	−0.24
	(0.35)	(0.15)	(0.39)	(0.19)	(0.16)	(0.25)

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

In summary, this section shows that factor momentum profitability is significantly affected by Morningstar rating reform as it disrupted the style-level positive-feedback trading.

6 Which Factors Experienced "Kinks" in 2002?

So far, we have focused on explaining the long-term strategy profitability decline since mid-2002. Further, as discussed in the introduction, there is an additional puzzle that some factors appear to have experienced a sharp kink in their returns in mid-2002. In this section, we use an event-study approach to examine whether this is explained by the Morningstar reform. In addition to explaining the kink, this exercise sheds light on how rating-induced fund flows impact factor-level returns.

We zoom in on a one-year window (January to December 2002) around the rating reform. There are two benefits to using a short window. First, rating changes in this period are predominantly caused by the rating methodology change. Second, using a short window also reduces the chance that factor returns are impacted by other events such as the NYSE decimalization in early 2001 or the introduction of NYSE auto-quoting in 2003 (Hendershott, Jones, and Menkveld, 2011).

6.1 Predicting How the Reform Would Impact Factors

We sort the 49 factors into quintiles based on how their rating is affected by the reform event. To alleviate endogeneity concerns, we sort the factors using the *predicted* reform-induced rating change computed using data in December 2001, which is *prior to* the event study window. Specifically, using data available up to December 2001, we estimate mutual fund ratings by following the pre-2002 and post-2002 Morningstar rating methodologies, and then aggregate these ratings up at the factor level. We then predict that each factor f will experience a rating change of

$$\text{PredictedChange}_f = \widehat{\text{Rating}}_{f,\text{Dec 2001}}^{\text{post-2002 methodology}} - \widehat{\text{Rating}}_{f,\text{Dec 2001}}^{\text{pre-2002 methodology}}, \tag{9}$$

where the two terms on the right-hand side represent estimated the factor-level rating under the two different rating methodologies, respectively.[29] Appendix B.4 explains the prediction process in more detail and verifies that the predictions can accurately forecast actual factor-rating changes at the reform event.

[29] We estimate the pre-2002 ratings using the old methodology, instead of using the actual pre-2002 ratings, to reduce estimation errors. Because we do not have exactly the same data set that Morningstar uses internally, our rating estimation contains errors. However, the same data-induced error is present in both terms in Equation (9), so we are able to difference it out.

6.2 Event Study

Figure 9 plots what happened to the factors in 2002. Panel (a) plots average ratings of factors and shows a sharp methodology-induced change exactly at the event. Factors in quintile 1 suffer a drop of 0.43 stars, while those in quintile 5 experience a small increase of 0.19 stars. Panels (c) and (e) plot cumulatively monthly factor FIT and returns around the event, respectively. Quintile 1—the factors that benefited from ratings pre-event but suffered post-event—experienced a decline of 1% in monthly FIT and a sharp decline of -3.7% in monthly returns. At the same time, quintile 5 experienced an increase of 0.14% in monthly FIT and a slight increase of 0.75% in monthly returns.[30]

To alleviate the concern that the return and FIT changes could have other causes, we also conduct the same exercise in all years other than 2002. The results on rating, FIT, and return changes in other years are shown as the white bars in Panels (b), (d), and (f) with 95% confidence intervals. These panels show that the large change around June is unique to 2002.

6.2.1 Alternative Hypotheses to Explain the Event Study Results

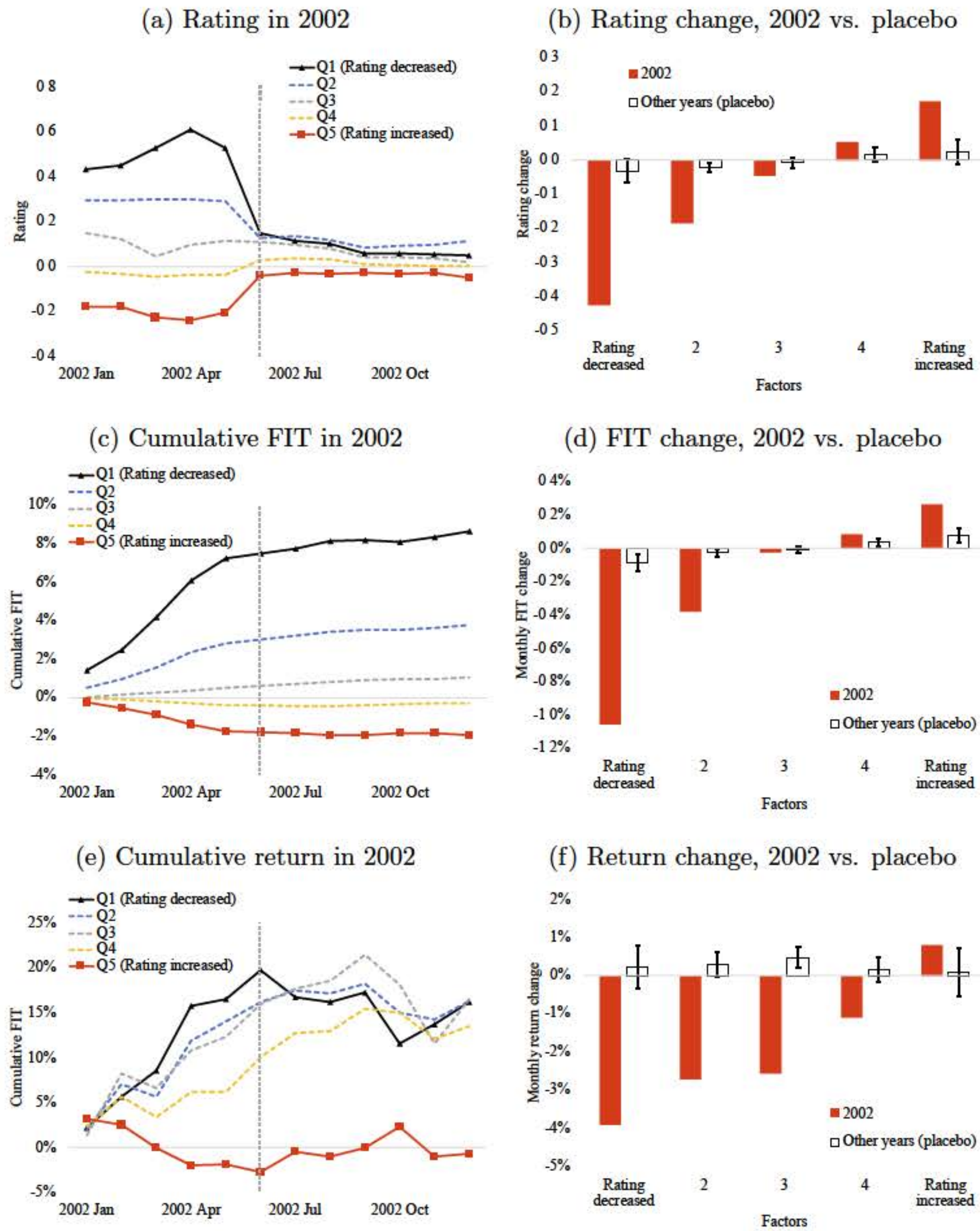
We now discuss the concern that the factor price fluctuations around June 2002 may have been triggered by changes other than the Morningstar reform.

Arbitrage activity. One natural worry is whether arbitrage forces in these factors suddenly became stronger in mid-2002. A number of papers present evidence that factor profitability is related to arbitrage activity. For instance, Hanson and Sunderam (2013) argue that value and momentum strategy profits decrease when more capital is devoted to them. McLean and Pontiff (2016) show that factor profitability declined after the strategies were published in academic papers and link it to arbitrage actions. Relatedly, Lou and Polk

[30] In a companion paper, we show that the implied style-level price impact coefficient (the reciprocal of demand elasticity) is approximately 5 (Ben-David et al., 2021b). That is, buying 1% of the market cap outstanding creates a price impact of approximately 5%. This magnitude is consistent with the existing literature that estimates the price impact of undiversifiable demand shocks (e.g., Gabaix and Koijen, 2020).

Figure 9. Stock Factors around the June 2002 Event

We perform event studies on the 49 factors using a 12-month window around the reform event (January to December 2002). In the left panels, we sort factors by their *predicted* reform-induced rating change into quintiles and then plot the evolution of their ratings in Panel (a), cumulative fund flow-induced trading (FIT) in Panel (c), and cumulative returns in Panel (e). To alleviate endogeneity concerns, the rating change prediction only uses data up to December 2001 (prior to the event window). The dashed vertical line is the June 2002 reform event. The right panels conduct the same exercises in years other than 2002 as a placebo test. The red bars plot the average rating, FIT, and return changes after June (the average of July to December 2002 minus the average of January to June 2002), and the white bars plot the corresponding results for years other than 2002. The whiskers represent 95% confidence intervals. To focus on cross-sectional dispersion, all variables—ratings, returns, and flows—are demeaned by period.



(2018) show that a return-based measure of arbitrageur activity negatively predicts momentum profits.

Did arbitrage activity change in June 2002? We use two measures proposed in the literature to proxy for arbitrage activity in factors. First, we follow Chen, Da, and Huang (2019) to construct a net arbitrage activity (NAT) measure. For each stock, the authors measure the long position of arbitrageurs using aggregate 13F holdings of hedge funds and the short position using aggregate short interest from Compustat.[31] The authors combine the long and short positions into a net position and subtract the past four-quarter average to arrive at a measure of arbitrageur position changes, which they call NAT. We follow them in computing stock-level NAT and aggregate it at the factor level.

Second, we follow Lou and Polk (2018) to construct a correlation-based measure of arbitrage activity. These authors measure arbitrage activity in the momentum strategy by estimating excess return correlation within the long and short portfolios, which can be generated by arbitrageurs trading in the factor.[32] We also compute this measure for all factors.[33]

We plot the evolution of these measures in the 12-month event window in Figure 10. As in Section 6, we sort factors into quintiles by their predicted rating change using data up to December 2001. Panel (a) plots the NAT measure, and Panel (b) plots the correlation-based measure. There is no noticeable change in either measure during the event window.

[31] We use the list of 13F institutions identified as hedge funds in Aragon, Li, and Lindsey (2018). We thank the authors for kindly sharing the data. Note that, while the short side of NAT is updated monthly, the long side relies on 13F holdings and is only updated quarterly.

[32] Specifically, in any given month, they use the previous 52 weeks of data to compute a "comomentum" measure:

$$\begin{aligned}\text{CoMomentum}_t = \frac{1}{2} \cdot \Bigg[&\frac{1}{N^L(N^L-1)} \sum_i \sum_{j \neq i} \text{PartialCorr}(\text{Ret}_i, \text{Ret}_j) \\ &+ \frac{1}{N^S(N^S-1)} \sum_i \sum_{j \neq i} \text{PartialCorr}(\text{Ret}_i, \text{Ret}_j)\Bigg],\end{aligned}$$

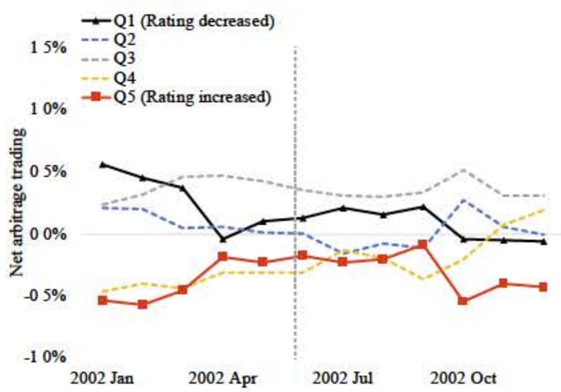
where N^L and N^S are the number of stocks in the long and short leg portfolios, respectively. To compute the partial return correlations, they first subtract Fama-French 30 industry returns from weekly stock returns and then regress the residuals on the Fama-French three factors to obtain alphas. Finally, they compute equal-weighted averages of the pairwise correlations of the alphas within the portfolios and take an average.

[33] As a sanity check on our replication of their methodology, consistent with Lou and Polk (2018), we find that this measure indeed negatively predicts returns of factors in the momentum category.

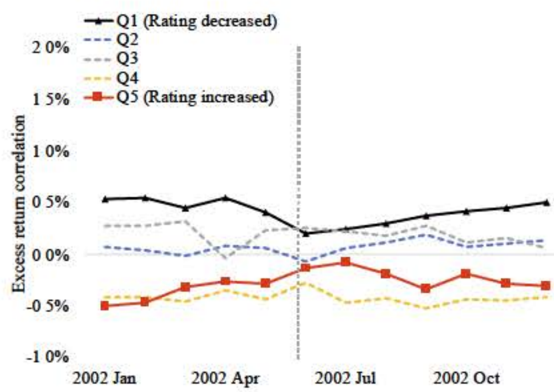
Figure 10. Alternative Explanations: Other Influences around 2002

As in Figure 9, factors are sorted into quintiles by the predicted rating change using data in December 2001. Thus, quintile 1 (or 5) factors are those predicted to experience the largest rating decrease (increase) at the reform event. Panel (a) plots the net arbitrage trading measure in Chen et al. (2019). Panel (b) plots excess return correlation in extreme factor quintiles, a measure of arbitrage activity developed in Lou and Polk (2018). Panel (c) plots the average bid-ask spread, measured following Corwin and Schultz (2012), of the long and short factor legs. Panel (d) plots the average monthly trading turnover of the long and short factor legs. To focus on cross-sectional dispersion, all variables are demeaned by month. In all panels, the vertical dashed line marks the Morningstar methodology change event.

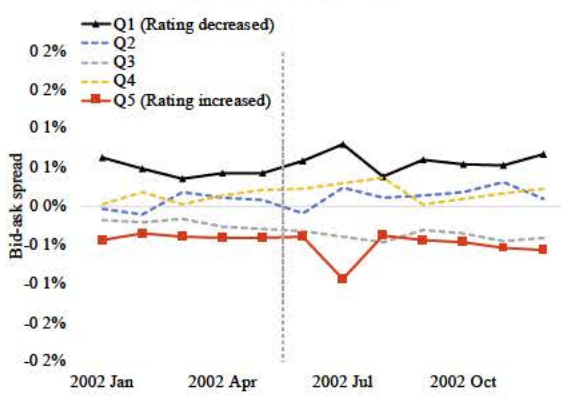
(a) Net arbitrage trading



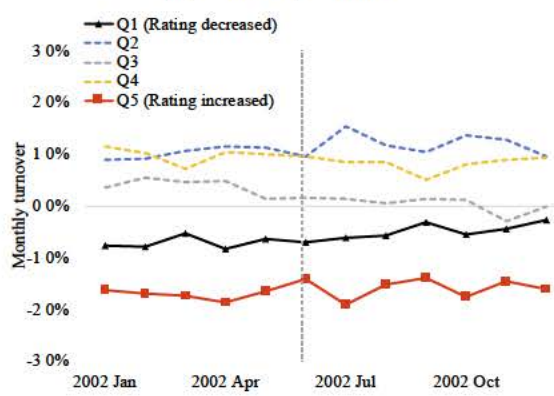
(b) Excess correlation in extreme deciles



(c) Bid-ask spread



(d) Monthly turnover



Changes in liquidity. One may also hypothesize that stock market liquidity increased dramatically in June 2002.[34] To examine this possibility, we aggregate the stock-level Corwin

[34]Increasing liquidity may explain factor profitability declines through two possible mechanisms. First, if a factor's profitability comes from demand price pressures, then increasing liquidity will reduce the price impact of such demand shocks. Second, if factor profitability is the result of arbitrageurs not being able to arbitrage away profits, then increasing liquidity may facilitate arbitrage effectiveness and thus reduce residual factor profitability. Of course, the asset pricing literature has also found evidence that illiquidity is a priced risk, so the changes may also come from changes in equilibrium-required rates of return (Amihud, 2002; Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005).

and Schultz (2012) bid-ask spread measure for the factors (averaging over the long and short legs) during this period. The results, plotted in Panel (c), show no evidence that liquidity changes account for our findings. Panel (d) shows that monthly trading turnover also had no clear change around the event.

In summary, we do not find around June 2002 any noticeable change in arbitrage trading activity or liquidity, two major forces that could impact factor returns. Thus, the event study supports the idea that Morningstar rating changes can exert a tangible price impact on factor returns.

7 Conclusion

Since mid-2002, returns of stock-based and factor-based momentum strategies have dwindled substantially. This paper proposes that a significant part of the post-2002 profitability decline can be attributed to a seemingly innocuous change in Morningstar's rating methodology. Before June 2002, Morningstar rated funds using their past performance ranking relative to all other U.S. equity funds. As a consequence, funds pursuing investment strategies associated with recently outperforming styles were rated higher than funds in recently underperforming styles. Ratings-driven fund flows led to significant style-level positive-feedback trading. After the reform, Morningstar started rating funds using their past performance ranking against their 3×3 size-value style peers, causing an immediate halt to this positive-feedback trading. Because momentum-related factors and factor momentum benefited from the earlier positive-feedback trading, this halt caused a decline in their profitability. We estimate that the Morningstar rating reform accounts for approximately one-third and two-thirds of the post-2002 profitability decline of the momentum factor and factor momentum, respectively. Further validating the mechanism, factors that were more directly impacted experienced a sharp return "kink" in the months following the reform, while less exposed factors did not.

More broadly, our findings are in line with a number of recent studies indicating that demand effects can drive systematic price movements (Gabaix and Koijen, 2020; Li, 2020). For identification, our paper focuses closely on the role of Morningstar ratings. However, it is possible that the role of correlated demand, arising from other institutional features or frictions, may be even more consequential for asset pricing than is documented here. Therefore, unlike the assumption embedded in classical "frictionless" asset pricing, demand effects may be a first-order driver of asset prices (Koijen and Yogo, 2019).

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Appendix A Data and Measures

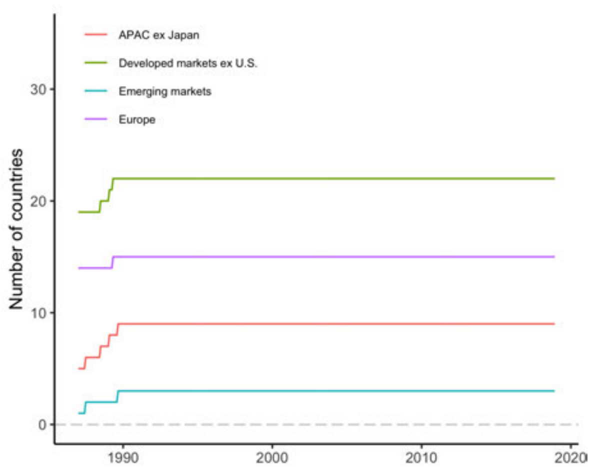
A.1 Asset pricing factors

Table A.1 shows the list of 49 U.S. asset pricing factors used in this paper. Following Hou et al. (2020), we classify them into six categories: intangibles, investment, momentum, profitability, trading frictions, and value/growth. Figure A.1 and Table A.2 provide more details on the global factors we use from Jensen et al. (2021).

Figure A.1. Global Factors Data in Jensen et al. (2021)

This figure tallies the global factors covered by Jensen et al. (2021). We divide data into different geographic areas and plot the number of countries and factors covered in Panels (a) and (b), respectively. As described in Section 2.2, we focus on factors that have full data since inception.

(a) Number of countries covered



(b) Number of factors covered

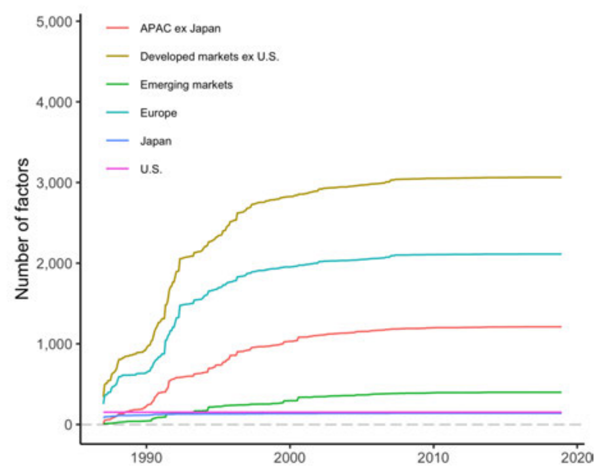


Table A.1. U.S. Asset Pricing Factors

The table lists the factors used in this study. The categorization is based on Hou et al. (2020).

Category	Factor	Publication
Intangibles (6)	Industry concentration	Hou and Robinson (JF 2006)
	Operating leverage	Novy-Marx (RF 2010)
	Firm age	Barry and Brown (JFE 1984)
	Advertising expense	Chan, Lakonishok, and Sougiannis (JF 2001)
	R&D expense	Chan, Lakonishok, and Sougiannis (JF 2001)
	Earnings persistence	Francis, LaFond, Olsson, and Schipper (AR 2004)
Investment (13)	Abnormal capital investment	Titman, Wei, and Xie (JFQA 2004)
	Accruals	Sloan (AR 1996)
	Asset growth	Cooper, Guylen, and Schill (JF 2008)
	Five-year share issuance	Daniel and Titman (JF 2006)
	Growth in inventory	Thomas and Zhang (RAS 2002)
	Industry-adjusted CAPEX growth	Abarbanell and Bushee (AR 1998)
	Investment growth	Xing (RFS 2008)
	Investment-to-assets	Hou, Xue, and Zhang (RFS 2015)
	Investment-to-capital	Xing (RFS 2008)
	Net operating assets	Hirshleifer, Hou, Teoh, and Zhang (JAE 2004)
	Net working capital changes	Soliman (AR 2008)
	One-year share issuance	Pontiff and Woodgate (JF 2008)
	Total external financing	Bradshaw, Richardson, and Sloan (JAE 2006)
Momentum (5)	52-week high	George and Hwang (JF 2004)
	Intermediate momentum ($t-7,\ t-12$)	Novy-Marx (JFE 2012)
	Industry momentum	Grinblatt and Moskwotiz (1999)
	Momentum ($t-2,\ t-6$)	Jegadeesh and Titman (JF 1993)
	Momentum ($t-1,\ t-12$)	Jegadeesh and Titman (JF 1993)
Profitability (14)	Cash-based profitability	Ball, Gerakos, Linnainmaa, and Nikolaev (JFE 2016)
	Change in asset turnover	Soliman (AR 2008)
	Distress risk	Campbell, Hilscher, and Szilagyi (JF 2008)
	Gross profitability	Novy-Marx (JFE 2013)
	Ohlson's O-score	Griffin and Lemmon (JF 2002)
	Operating profitability	Ball, Gerakos, Linnainmaa, and Nikolaev (JFE 2016)
	Piotroski's F-score	Piotroski (AR 2000)
	Profit margin	Soliman (AR 2008)
	QMJ profitability	Asness, Frazzini, Israel, Moskowitz, and Pederson (JFE 2018)
	Return on assets	Haugen and Baker (JFE 1996)
	Return on equity	Haugen and Baker (JFE 1996)
	Sales-minus-inventory growth	Abarbanell and Bushee (AR 1998)
	Sustainable growth	Lockwood and Prombutr (JFR 2010)
	Altman's Z-score	Dichev (JFE 1998)
Trading frictions (3)	Size	Banz (JFE 1981)
	Amihud illiquidity	Amihud (JFM 2002)
	Maximum daily return	Bali, Cakici, and Whitelaw (JFE 2011)
Value/Growth (8)	Book-to-market	Fama and French (JF 1992)
	Cash flow-to-price	Lakonishok, Shleifer, and Vishny (JF 1994)
	Earnings-to-price	Basu (JF 1977)
	Enterprise multiple	Loughran and Wellman (JFQA 2011)
	Sales growth	Lakonishok, Shleifer, and Vishny (JF 1994)
	Sales-to-price	Barbee, Mukherji, and Raines (FAJ 1996)
	Long-term reversals	Debondt and Thaler (JF 1985)
	Net payout yield	Boudoukh, Michaely, Richardson, and Roberts (JF 2007)

Journals: AR: Accounting Review, FAJ: Financial Analysts Journal, JAE: Journal of Accounting and Economics, JF: Journal of Finance, JFE: Journal of Financial Economics, JFQA: Journal of Financial and Quantitative Analysis, JFR: Journal of Financial Research, RAS: Review of Accounting Studies, RFS: Review of Financial Studies, RF: Review of Finance.

Table A.2. Countries Covered in Global Factors Data

This table tallies the countries covered by the Jensen et al. (2021) global factors data. Panel A classifies countries or regions by market type, and Panel B classifies by region.

Panel A: By market type					
Market type	Country or region	Inception month	Number of factors		
			On average	At inception	By 2018
U.S.	United States	1987-01	152	152	152
Developed markets ex U.S.	UK	1987-01	143	90	150
	Netherlands	1987-01	133	77	143
	Japan	1987-01	133	80	139
	Germany	1987-01	125	2	152
	France	1987-01	125	2	150
	Sweden	1987-01	125	64	136
	Spain	1987-01	122	2	145
	Australia	1987-01	121	2	139
	Hong Kong	1987-01	120	2	144
	Switzerland	1987-01	119	2	146
	Denmark	1987-01	119	2	145
	Finland	1987-01	117	2	142
	Italy	1987-01	116	2	140
	Belgium	1987-01	116	2	143
	Singapore	1987-01	115	2	139
	Norway	1987-01	112	2	135
	Austria	1987-01	110	2	139
	New Zealand	1987-01	104	2	125
	Ireland	1987-01	102	2	126
	South Korea	1988-07	98	17	132
	Taiwan	1989-02	101	2	133
	Portugal	1989-05	97	2	121
Emerging markets	Malaysia	1987-01	110	2	133
	Thailand	1987-07	98	1	133
	India	1989-09	89	2	133

Panel B: By region					
Region	Country or region	Inception month	Number of factors On average	At inception	By 2018
Europe	UK	1987-01	143	90	150
	Netherlands	1987-01	133	77	143
	Germany	1987-01	125	2	152
	France	1987-01	125	2	150
	Sweden	1987-01	125	64	136
	Spain	1987-01	122	2	145
	Switzerland	1987-01	119	2	146
	Denmark	1987-01	119	2	145
	Finland	1987-01	117	2	142
	Italy	1987-01	116	2	140
	Belgium	1987-01	116	2	143
	Norway	1987-01	112	2	135
	Austria	1987-01	110	2	139
	Ireland	1987-01	102	2	126
	Portugal	1989-05	97	2	121
APAC ex Japan	Australia	1987-01	121	2	139
	Hong Kong	1987-01	120	2	144
	Singapore	1987-01	115	2	139
	Malaysia	1987-01	110	2	133
	New Zealand	1987-01	104	2	125
	Taiwan	1989-02	101	2	133
	South Korea	1988-07	98	17	132
	Thailand	1987-07	98	1	133
	India	1989-09	89	2	133
Japan	Japan	1987-01	133	80	139

Appendix B Additional Empirical Results

B.1 The Momentum Profitability Drop since Mid-2002

This section examines the robustness of the finding that momentum-type factors became less profitable after mid-2002. It also shows that the post-publication profitability decline documented by McLean and Pontiff (2016) and Falck et al. (2021) can only explain a minor part of the drop off.

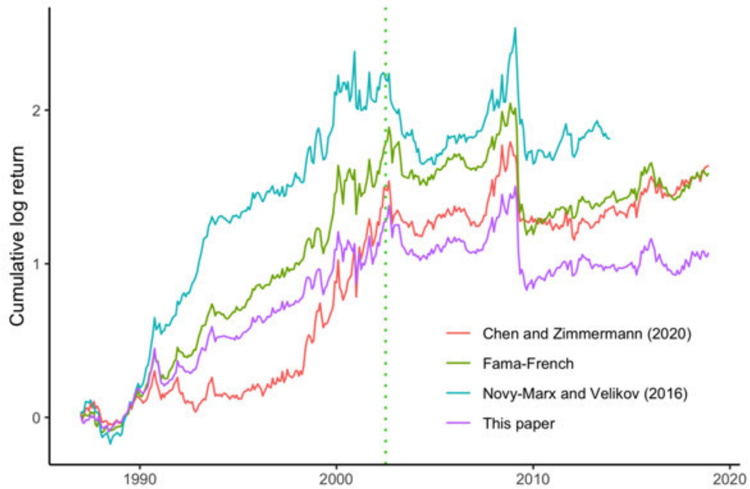
Robustness to alternative data sources. This finding is not specific to our factor universe or our factor construction methodology. Figure B.2 plots the cumulative return to momentum-related factors constructed from various sources. The purple line averages over the five momentum-type factors discussed in this paper. The olive line uses the momentum factor downloaded from Ken French's website. The blue line, which ends in 2013 due to data availability, plots the average return of the two momentum-type factors in Novy-Marx and Velikov (2016). Finally, the red line plots the average return of the five momentum-type factors in Chen and Zimmermann (2021).[35] Despite differences in factor universe and factor construction, all four data sources show that momentum-related factors have suffered profitability declines since mid-2002.

Existing studies. We note that earlier studies have also shown evidence that suggests post-2002 return declines, even though detecting structural breaks is not their objective. For the reader's convenience, we present screenshots from those papers in Figure B.3. Panel (a) shows a chart from Green, Hand, and Zhang (2017) summarizing the average performance

[35] We obtain data in Novy-Marx and Velikov (2016) from Novy-Marx's website (`http://rnm.simon.rochester.edu/data_lib/ToAatTC/index.html`). We use their gross long-short factor returns in "returns to simple strategies." The two momentum-related factors are momentum and industry momentum. For data in Chen and Zimmermann (2021), we accessed the 0.1.2 version at `https://sites.google.com/site/chenandrewy/open-source-ap`, and used their "test asset portfolios" for NYSE-based value-weighted decile portfolios. We then constructed factors as longing the top decile and shorting the bottom decile. The five momentum-type factors include junk stock momentum, 11-month residual momentum, 6-month residual momentum, 52-week high, and industry momentum.

Figure B.2. Momentum Profitability Decline after 2002: Other Data Sources

This figure plots the cumulative returns of momentum-related factors from various data sources. Please see the text for details about the data sources and factor construction process. The vertical dashed line marks the June 2002 Morningstar rating reform event.



(equally-weighted as well as value-weighted) of 94 characteristics. Panel (b) shows a chart from Daniel and Moskowitz (2016) summarizing the performance to the momentum strategy. In both charts, we added a dashed line for June 2002.[36]

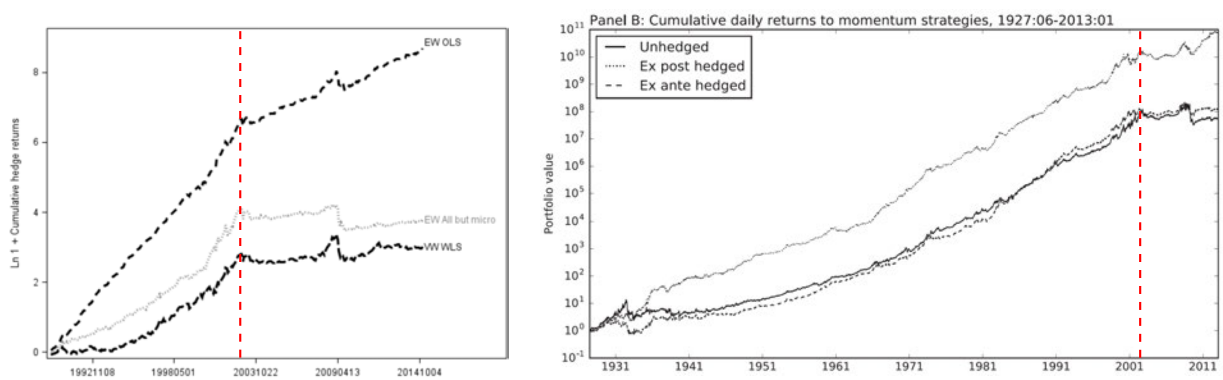
How much can be explained by post-publication decline? McLean and Pontiff (2016) show that profitability of strategies declines by 26% out-of-sample and 58% post-publication. They also provide evidence consistent with arbitrage forces reducing the profitability of these strategies. This explanation does not apply to factor momentum, which was published after our sample period (Gupta and Kelly, 2019; Ehsani and Linnainmaa, 2021). However, it is applicable to the momentum-related asset pricing factors, which were published in 1993 ($(t-1, t-6)$ and $(t-1, t-12)$ momentum), 1999 (industry-momentum), 2004 (52-week high), and 2012 ($(t-7, t-12)$ momentum).

[36] Methodologically speaking, the finding of Green et al. (2017) is closer to our finding of factor momentum profitability decline. Specifically, they investigate the profits to predicting stock returns based on rolling multivariate Fama-MacBeth regressions with many stock characteristics. Therefore, their strategy ends up going long on characteristics that recently performed well and short on those that performed poorly—which is more similar to the factor momentum strategy in spirit. Even though they investigate characteristics and do not form factors, Cochrane (2011) notes that "portfolio sorts are really the same thing as nonparametric cross-sectional regressions," so the Green et al. (2017) findings also shed light on factor-based results.

Figure B.3. Previous Evidence of Momentum-Type Strategy Profitability Decline

The figure presents charts in previous studies showing a kink in cumulative factor returns. In both panels, we added a red dashed line to mark the approximate location of June 2002 on the timeline. Panel (a) reproduces Figure 3 of Green et al. (2017). They study a strategy that uses 94 stock characteristics, and the different lines in the Figure represent different portfolio weighting methodologies. "EW OLS" refers to equal-weighting; "EW All but micro" refers to equal-weighting but excluding microcap stocks; "VW WLS" refers to value-weighted strategy. Panel (b) reproduces Figure 4b of Daniel and Moskowitz (2016) which plots the cumulative return to the momentum strategy. The Figures are taken from the latest SSRN versions of each paper: October 2016 version for Green et al. (2017), and July 2015 version of Daniel and Moskowitz (2016), with the authors' permissions.

(a) Green, Hand, and Zhang (2017, Fig 3) (b) Daniel and Moskowitz (2016, Fig 4b)



Can this fully explain the post-2002 profitability decline in momentum strategies? To examine this possibility,for each momentum-related factor f, we first use the in-sample period starting from July 1963 to compute the average in-sample return $\overline{\text{Ret}}_{f,IS}$. Following McLean and Pontiff (2016), we then estimate the in-sample, out-of-sample (and before publication), and post-publication period returns explained by this mechanism as

$$\widehat{\text{Ret}}_{f,\text{in-sample}} = \overline{\text{Ret}}_{f,IS} \tag{10}$$

$$\widehat{\text{Ret}}_{f,\text{out-of-sample}} = (1 - 26\%) \times \overline{\text{Ret}}_{f,IS} \tag{11}$$

$$\widehat{\text{Ret}}_{f,\text{post-publication}} = (1 - 58\%) \times \overline{\text{Ret}}_{f,IS}. \tag{12}$$

We obtain the sample end and publication years from the internet appendix of McLean and Pontiff (2016). We then use these predicted returns to quantify how much of the post-2002 return declines identified in our paper can be explained by the post-publication decline channel. We find that it can explain 27% for the momentum factor and 34% for the other four momentum-type factors: ($(t-1, t-6)$ momentum, $(t-7, t-12)$ momentum, industry momentum, and 52-week high). Therefore, we conclude that only a small portion of the profitability decline is due to this channel.

The post-publication profitability decline estimated in McLean and Pontiff (2016) is based on *all factors*. Falck et al. (2021) further argue that we may expect strategies that are based on more liquid stocks or that have more complexity in their construction to suffer larger declines. However, relative to the other factors, momentum-related factors focus on stocks with lower liquidity and thus that are harder to arbitrage. Further, momentum is a relatively simple strategy that is low on complexity. Therefore, according to the findings in Falck et al. (2021), we would expect the post-publication declines in McLean and Pontiff (2016) to be overestimations for momentum strategies.

B.2 Further Discussion about the Mechanism

Section 3.2 explains that the Morningstar reform impacts style-level positive-feedback trading. In this section, we show that the reform does not impact idiosyncratic-level positive-feedback trading. Standard stock momentum strategies contain both a style component and an idiosyncratic component. The former refers to the fact that styles achieving higher past returns continue to do so in the future. The latter refers to the fact that, even after controlling for style-level effects, stocks with higher idiosyncratic past returns also have higher returns in the future (Blitz et al., 2011).

While the Morningstar reform disrupted style-level momentum, it did not disrupt idiosyncratic momentum. This is because the positive-feedback mechanism we study works through the fund flows induced by ratings. The average stock is held by 78.5 funds (see Table 1), so for any given stock, there has to be a *correlated* change in the ratings of funds holding that stock in order to generate sufficiently large rating-induced flow pressure. Therefore, while past style-level returns—which can induce correlated fund return changes—can have a large impact on a stock's rating, past idiosyncratic stock returns do not.

For a concrete example, consider a small-cap growth stock that is held by many small-cap growth funds. Suppose the stock's idiosyncratic return was high in the recent past. Because that stock is only a small part of each fund's portfolio, this shock is unlikely to have a sufficiently large effect on fund ratings. In contrast, suppose the style-level (small-cap growth) return was high in the recent past. Under the pre-reform methodology, this means that all small-cap funds would have performed well and thus receive higher ratings, leading to more positive feedback fund flows across small-cap growth stocks. After the methodology reform, this style-level positive-feedback trading became muted by design.

Figure B.4. Morningstar Reform Only Impacted Style-Level Positive Feedback

This figure plots the panel regression coefficients of stock-level ratings (Equation (1)) on the past 36 lags of monthly stock returns, which have been decomposed into style-level returns (3 $\times$ 3 Fama-French size-book/market styles) and idiosyncratic-level returns (the residual). Panels (a) and (b) plot the regression coefficients, and the shaded areas represent 95% confidence intervals. The regressions control for month fixed effects and cluster standard errors by month.

(a) Before the 2002 Morningstar reform　　(b) After the 2002 Morningstar reform

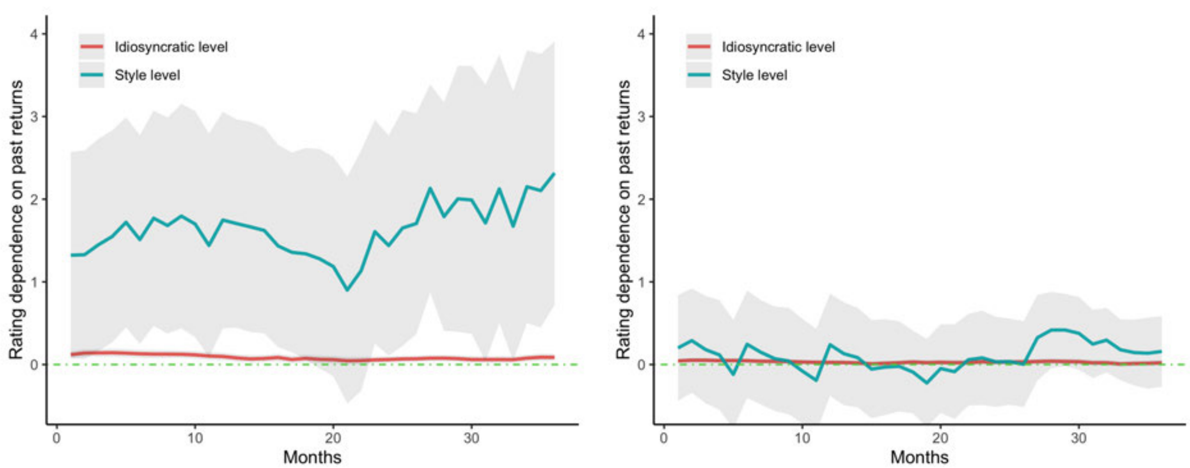


Figure B.4 illustrates these points using panel regressions of stock-level ratings on the past 36 monthly lags of stock returns. To separately estimate the impact of different return components, we decompose each stock's return into

$$\text{Ret}_{i,t} = \text{StyleRet}_{i,t} + \text{IdiosyncraticRet}_{i,t}, \tag{13}$$

where $\text{StyleRet}_{i,t}$ is defined as the market cap–weighted average return of the corresponding 3×3 Fama-French size-book/market style portfolio, and $\text{IdiosyncraticRet}_{i,t}$ is the residual. We regress stock ratings on 36 lags of each of these two components, controlling for month fixed effects, and plot the coefficients in Figure B.4. Panel (a) shows that before the reform, stock ratings heavily depended on past style-level returns but not idiosyncratic returns. This confirms that the Morningstar-induced positive-feedback trading happens exclusively at the style level. Panel (b) shows that after the reform, the rating dependence on past style returns becomes muted.

These patterns have important implications for the impact of this reform. The degree to which a trading strategy is impacted should *only* depend on its relationship with style momentum. As explained by Blitz et al. (2011), stock momentum includes both style-level momentum and idiosyncratic momentum. That is, in addition to style-level returns exhibiting positive autocorrelation, idiosyncratic components of returns also do. In contrast, because factors tend to be diversified portfolios in which idiosyncratic stock returns cancel out, factor momentum strategies load much less on stock-level idiosyncratic momentum.

B.3 Estimating the Price Impact Parameter for Explanatory Power Quantification

As described in Section 4.2, we use a 12-month window around the June 2002 methodology change to estimate the price impact of ratings. The regression results are shown in Table B.2.

Table B.2. Estimating Price Impact Coefficient (λ) around the June 2002 Event
We use a panel regression to estimate the predictive relationship between monthly factor returns and the exponentially summed lagged ratings (ExpSum(ΔRating)$_{f,t-1}$). The sample period is the 12 months around the reform (January to December 2002). We control for lagged factor returns in months $t-1$, $t-6$ to $t-2$, and $t-12$ to $t-7$. The four specifications differ in whether factor and month fixed effects are included. The standard errors in parentheses are adjusted for the cross-sectional correlation between factor returns using feasible generalized least squares.

Dependent variable:	Monthly factor return Ret$_{f,t}$(%)			
	(1)	(2)	(3)	(4)
ExpSum(ΔRating)$_{f,t-1}$	2.270***	2.057***	2.388***	2.033***
	(0.534)	(0.493)	(0.516)	(0.478)
Lagged returns	Yes	Yes	Yes	Yes
Factor FE	Yes	No	Yes	No
Month FE	Yes	Yes	No	No
Observations	588	588	588	588
Adjusted R^2	14.36%	7.21%	12.73%	5.86%

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

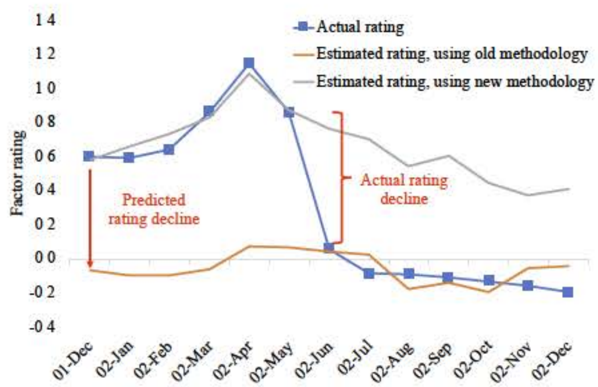
B.4 Event Study: Predicting Factor Rating Changes at the Reform Event

In this section, we examine the accuracy of the factor-level rating change prediction in Equation (9). We first illustrate the prediction method in Panels (a) and (b) of Figure B.5. The two panels plot the two factors predicted to experience the largest rating decline (size) and increase (O-score). Our estimation matches actual ratings quite well. Before June 2002, the actual ratings closely match the estimated ratings under the old methodology (grey lines), and, after June 2002, the actual ratings closely match the estimated ratings under the new methodology (orange lines). Further, because the changes in factor-level ratings of factors over a few months are small, the predicted rating change using December 2001 data ends up being a reasonable predictor of the actual rating change that occurred in June 2002. This is further shown in Panel (c), where we plot the actual June 2002 rating changes of factors against the predicted changes. The latter explains the former with an R^2 of 84%.

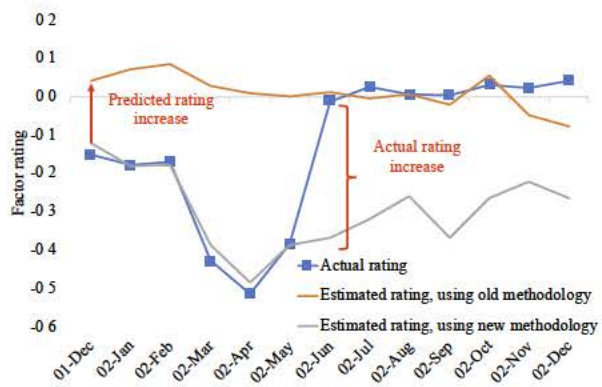
Figure B.5. Predicting Factor-Level Rating Changes at the 2002 Reform Event

Panels (a) and (b) illustrate how we predict rating changes of factors at the June 2002 event using data in December 2001. Following Morningstar's rating construction process, we estimate ratings from the ground up using fund returns. The grey lines plot the estimated rating under the old (pre-change) methodology, and the orange lines plot the estimated rating under the new (post-change) methodology. We use the difference between the two estimates in December 2001 (marked using red arrows) as the predicted rating change. The blue lines are the actual ratings. Panels (a) and (b) plot the factor with the largest predicted rating decline and increase, respectively (size and O-Score factors). Panel (c) compares the actual rating change in June 2002 against the predicted change using data in December 2001. The factors are sorted into quintiles based on the predicted rating change and colored differently.

(a) Most negatively affected factor



(b) Most positively affected factor



(c) Accuracy of rating change prediction