Mutual Fund Risk Shifting and Risk Anomalies*

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Abstract

Risk-shifting by underperforming funds increases their demand for risky stocks. We show that well-known risk anomalies such as the apparent overvaluation of stocks with high beta, idiosyncratic volatility, and skewness are concentrated among stocks held by laggard funds. Exploiting the Morningstar rating methodology change in 2002 we show that the beta anomaly is significant only when beta is measured against the S&P 500 index for the pre-2002 period and against the relevant category index for the post-2002 period. Counterfactual estimates from an asset demand system imply that removing demand by the laggard funds essentially eliminates the beta anomaly.

Key words: Beta Anomaly, Morningstar Ratings, Mutual Funds, Risk Shifting, Idiosyncratic Volatility, Skewness, Demand System

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1 Introduction

A trade-off between (systematic) risk and average return is one of the central tenets of financial economics, yet its empirical relevance has been controversial, at least insofar as it relates to the role of "market beta" in reflecting cross-sectional variation in average stock returns.[1] Similarly debated is the role of incentives (explicit or implicit) in driving risk-taking by mutual funds, while there is ample evidence showing that fund managers whose performance lags behind the benchmark (or their peer funds) in the first half of the year tend to increase the riskiness of their portfolio in order to catch up by the year-end.[2] Can the observed risk-return trade-off be distorted by the demand pressure emerging from this risk-shifting behavior?

The economic intuition is straightforward: underperforming funds struggling to "catch up" will find high-beta stocks attractive since, by definition, their prices move *more* than one-for-one with the benchmark returns, on average. This is especially true for mutual funds, which are limited in their ability to use leverage (either explicitly or implicitly, with derivatives). The demand from underperforming funds would then contribute to overpricing of high-beta stocks, provided that the demand for stocks by other market participants is sufficiently inelastic (e.g., Shleifer (1986), Gabaix and Koijen (2021)). The overpricing of high-beta stocks leads to a "beta anomaly," i.e., a negative alpha for stocks with high exposure to systematic risk.[3]

Consistent with this explanation, we find that the beta anomaly can only be detected among stocks that are largely held by underperforming mutual funds, i.e., those in the bottom quintiles of funds ranked on past performance. The alphas range from −0.76% to −0.61% per month, with t-statistics of −2.76 to −2.38. Furthermore, the beta anomaly becomes insignificant in the top two performance quintiles with spreads of −0.38% and −0.19% (t-statistics are −1.59 and −0.74, respectively). These findings suggest that risk-shifting by

[1] See Black et al. (1972), Fama and French (1992), and Frazzini and Pedersen (2014).

[2] See, e.g., Brown et al. (1996), Chevalier and Ellison (1997), Huang et al. (2011), Lee et al. (2019).

[3] While tournament-type intuition suggests that risk-shifting involves increase in idiosyncratic risk, within the mutual fund setting, and in particular in the presence of benchmarks, it can take the form of higher systematic risk, i.e. beta, as shown theoretically by Basak et al. (2007) and confirmed empirically by Huang et al. (2011). Baker et al. (2011) point to the role of benchmarks in asset management as a source of limited arbitrage, especially in the context of the beta anomaly. Cuoco and Kaniel (2011) demonstrate the impact of fund demand on the pricing of stocks included in the benchmark index within an equilibrium model. Frazzini and Pedersen (2014) emphasize the importance of leverage constraints for the beta anomaly.

underperforming funds might induce overpricing of high-beta stocks, thus helping to produce the beta anomaly. We provide evidence in support of this mechanism by investigating the role of equity investing "styles" as determinants of funds' demand for stocks (Barberis and Shleifer (2003)).

If relative performance drives the risk-shifting behavior that is behind the beta anomaly, we should expect the relevant style benchmark to matter (e.g., Pavlova and Sikorskaya (2022)). For example, if a small-cap value fund is attempting to "catch up" to its Small Value benchmark, or to its category peers, it should prefer stocks that have a high beta with respect to this Small Value benchmark to stocks with a high beta with respect to a Large Growth benchmark, all else equal. Typically, a fund belongs to a specific style-based category, and other funds in the same category would be regarded as its peers. One of the prominent explanations of mutual fund risk-shifting behavior has to do with competition for investor flows. It is a well-known fact that recent performance is important for driving flows, but there is also substantial evidence that ratings assigned by intermediaries, such as Morningstar, play a key role (Del Guercio and Tkac (2008)). We exploit an exogenous change in these "star" ratings in order to help us establish the causal effect of risk-shifting.

In June 2002, Morningstar reformed its rating methodology: instead of simply pooling and ranking all funds together, Morningstar began assigning ratings based on how funds rank within their "style" category.[4] Due to this change in methodology, the relevant peer group changed for most funds that now found themselves competing mostly with other funds pursuing a similar "style", defined as a combination of value/growth metrics and market capitalization, and generally sharing a style-specific benchmark. By splitting our sample period, we only find a beta anomaly among stocks held by underperforming funds if we use a commonly-used market-wide benchmark such as the S&P 500 index *before* the 2002 ratings reform. In addition, using benchmark returns of any one of the four main Morningstar categories (Large Value, Large Growth, Small Value, and Small Growth) to estimate stocks' betas does not produce evidence of a significant beta anomaly among stocks held by underperforming funds in this earlier period. Importantly, we find the reverse following the ratings

[4] Blume (1998) documented several drawbacks of the original Morningstar ratings methodology, while Evans and Sun (2021) and Ben-David et al. (2022) show the impact of the change in the Morningstar methodology on the subsequent fund flows and performance of popular fund styles, respectively.

reform: the S&P 500 beta anomaly disappears and a category-beta anomaly emerges. For example, the Large Value category beta anomaly returns for stocks held by underperforming funds reach -1.16% per month with a $t-$statistics of -3.14, which is actually larger in magnitude than our full-sample beta anomaly. These patterns are consistent with the idea that relative performance vis-a-vis the relevant category peers is what matters for fund risk taking and the resulting (lack of) risk-return trade-off.[5]

In order to further corroborate our story, we examine portfolio holdings of mutual funds and we find that the Morningstar's rating reform alters their risk taking behaviors: after the reform, funds that underperformed their peers invest more in stocks with higher exposures to the relevant Russell index, which is a common benchmark for funds in the same category. However, before the reform, underperforming funds shifted their portfolios towards stocks with higher exposures to the S&P 500 index but not necessarily to the category index. This evidence helps explain our findings that beta anomaly is significant for the S&P 500 index for the pre-2002 period and with the relevant Russell index for the post-2002 period.

In order to quantify the impact of underperforming funds on the beta anomaly, we employ the demand system approach developed in Koijen and Yogo (2019). First, by exploiting the plausibly exogenous flow-induced price pressure generated by Morningstar rating methodology change in 2002, we estimate all institutional investors' (including mutual funds') characteristics-based demand function for stocks, which depends on firm characteristics (e.g., market capitalization, book equity, profitability, investment growth, and most importantly, stock beta) and latent demand (i.e., characteristics unobserved to the econometrician). Consistently with our previous results, we find that after the Morningstar rating change in June 2002, funds that underperform their category peers in the first half of the year prefer stocks with a high beta with respect to the category benchmark index, whereas outperforming funds (as well as other types of investors) prefer stocks with low betas, as finance theory predicts.

Based on the estimated demand system, we conduct a counterfactual experiment in 2002 by eliminating funds in the bottom quintile of performance and proportionally reallocating their assets under management to all other investors and re-computing the resulting equilibrium asset prices. We find that eliminating the demand from the most severely under-

[5]While the S&P 500 is still the most popular index, its relative importance has declined over time as style-based benchmarks have grown - e.g., see Pavlova and Sikorskaya (2022).

performing funds causes a larger price decline for high-beta stocks than for low-beta stocks: the downward repricing is around 1% greater for high-beta stocks (since all investors' demand curves for stocks are downward-sloping, eliminating some of them causes all stock prices to go down).[6]

Further, we conduct a similar counterfactual experiment over the post-2002 sample. This allows us to compute the style-level beta anomaly returns in the counterfactual equilibrium. We find that for categories of Small Value and Small Growth, the realized monthly alphas of the style beta anomaly are -0.64% and -0.71%, respectively, which are statistically significant. However, the alphas drop by around 50% when using counterfactual returns, and become statistically insignificant. While the realized alphas for categories of Large Value and Large Growth are not statistically significant (-0.36% and -0.49%, respectively), both become much smaller with counterfactual returns (-0.18% and -0.35%, respectively). These findings indicate that, following the Morningstar rating reform, funds underperforming their category have exerted an upward pressure on prices of stocks with a high beta relative to category benchmarks. This effect is both economically and statistically significant, and may be sufficient to account for the extent of the beta anomaly in this latter part of the sample.

While most of our analysis focuses on betas, what about other measures of risk? After all, risk-shifting can take many forms. We find that other risk-related anomalies, including the apparent overpricing (as manifested by subsequent underperformance) of stocks with high idiosyncratic volatility, high skewness, or "lottery-like" return distributions are also concentrated among stocks that are mostly held by funds who underperform their (relevant) peer groups. Again, this evidence is consistent with the idea that risk-shifting by underperforming mutual funds might be behind these anomalies.

1.1 Related literature

The beta anomaly as one of the important challenges to the Capital Asset Pricing Model (CAPM) has attracted a lot of attention. An incomplete list of prior explanations include institutional investor mandates to beat a fixed benchmark (Baker et al. (2011) and Christoffersen and Simutin (2017)); leverage constraints of mutual funds (Frazzini and Pedersen

[6]We provide a detailed explanation for the downward-sloping demand curve in Section 5.

(2014) and Boguth and Simutin (2018)); speculative overpricing of high-beta stocks (Antoniou et al. (2015) and Hong and Sraer (2016)); investors' lottery preference (Bali et al. (2017)); and the confounding role of positive correlations between beta and idiosyncratic volatility or skewness (Liu et al. (2018); Schneider et al. (2020)). We contribute to this strand of literature in the following two ways. First, we not only examine the beta anomaly with respect to the CAPM but, more importantly, provide novel evidence of the anomaly at the style-index level. Our results show that it is important to measure beta with respect to the *relevant* benchmark index that matters for mutual funds' incentives. Second, we also consider other risk anomalies, including idiosyncratic-volatility and lottery-like payoffs and we find evidence that they are more significant for stocks mainly held by underperforming funds, suggesting a unified explanation for these anomalies.[7]

Our paper is also related to the mutual fund risk-taking literature. Brown et al. (1996) show that underperforming funds tend to increase their risk levels to catch up. Chevalier and Ellison (1997) find that mutual funds alter the riskiness of their portfolios at the end of the year based on their year-to-date performance. Goetzmann et al. (2007) show that fund managers have an incentive to change risk levels to "game" their performance measures. Huang et al. (2011) study the impact of risk-shifting on funds' subsequent performance. Christoffersen and Simutin (2017) find that fund managers who control large pension assets have more incentives to hold high-beta stocks to beat relative benchmarks. Using lab-in-the-field experiments, Kirchler et al. (2018) find that underpeforming professionals take more risk in their investment decisions when relative ranking is displayed. We contribute to this literature by showing the impacts of the Morningstar rating methodology change on the risk-taking behaviours of underperforming mutual funds. It sheds further lights on the risk-shifting incentives of fund managers.

Finally, our paper is related to a recent literature on the demand system approach to asset pricing. Koijen and Yogo (2019) develop an asset pricing model where an investor's demand depends on observed and unobserved characteristics of the assets.

[7]An interesting paper by Barberis et al. (2021) proposed a unified behavioral explanation for the risk anomalies (such as IVOL and skewness) based on prospect theory.

2 Data and Methodology

2.1 Stock and fund data

Our sample covers the period from January, 1982 to December, 2018. The sample of stocks consists of all common stocks (share code 10 and 11) listed on NYSE, AMEX, and NASDAQ. Monthly stock returns are obtained from the Center for Research in Security Price (CRSP). We drop stocks whose price in the last month is lower than \$5 since these stocks have low liquidity and therefore are unlikely to be tradable.

We obtain fund level data such as returns, expense ratios, and turnover from the Center for Research in Security Prices (CRSP) Survivor-Bias-Free Mutual Fund Database. We follow Kacperczyk et al. (2008) and Evans (2010) to screen for domestic equity mutual funds in the CRSP mutual fund data set. We exclude funds that hold on average less than 80% or more than 105% of assets in equity. Next, we obtain style categories from Morningstar Direct and merge them with the CRSP mutual fund data. We choose to focus on the nine popular Morningstar investment styles (e.g., value/blend/growth × small/mid/large) for two reasons: First, these nine categories are commonly studied in the literature. Second and more importantly, these categories have well-defined and consistent benchmark returns as provided by FTSE Russell.

Having selected CRSP fund sample, we then merge this sample with the Thomson Reuters (TR) Mutual Fund Stock Holdings data set by using the MFLINKS file provided by Wharton Research Data Services. We exclude funds with assets under management of less than \$5 million. We are able to merge approximately 93% of CRSP funds to the TR database. Until 2003, mutual funds are required to disclose their holdings semiannually, and most funds in our sample disclose holdings quarterly. We therefore populate the holding data that is reported as of fiscal quarter end into subsequent months until the next holding report date. However, a very small number of funds have gaps between holdings disclosure dates of more than 6 months. For these funds, we use 6-months as a cut-off for holding periods.

2.2 Estimating stock beta

Following Fama and French (1992) and Liu et al. (2018), we estimate a stock's CAPM beta by regressing the stock's monthly excess return on the contemporaneous market excess return plus lagged market excess return. We include lagged market excess returns to accommodate non-synchronous trading effects. For stock n in month t, we run the regression using the most recent five-year data.[8] The regression is as follows:

$$r_{n,t} = a_n + \beta_{n,1} r_{m,t} + \beta_{n,2} r_{m,t-1} + \epsilon_{n,t}. \tag{1}$$

The stock's time-series beta estimate is computed as:

$$\hat{\beta}_n^{ts} = \hat{\beta}_{n,1} + \hat{\beta}_{n,2}. \tag{2}$$

As in Vasicek (1973), Frazzini and Pedersen (2014) and Liu et al. (2018), we apply shrinkage method to shrink the time-series beta estimate toward one,

$$\hat{\beta}_n = \kappa_n \hat{\beta}_n^{ts} + (1 - \kappa_n) \times 1, \tag{3}$$

where $\kappa_n = \frac{\sigma_{cs}^2(\hat{\beta}^{ts})}{\sigma_{cs}^2(\hat{\beta}^{ts}) + \hat{\sigma}^2(\hat{\beta}_n^{ts})}$. $\hat{\sigma}(\hat{\beta}_n^{ts})$ is the standard error of $\hat{\beta}_n^{ts}$ for stock n, and $\sigma_{cs}^2(\hat{\beta}^{ts})$ is the cross-sectional variance of $\hat{\beta}^{ts}$.

In addition to CAPM beta, we also measure stocks' index betas since there is strong comovement within each investing style (Barberis and Shleifer (2003)). To measure stocks' index betas, we repeat the above procedures and replace the market excess returns with index excess returns. We focus on the S&P 500 index, a common benchmark to all mutual funds, and categories' benchmarks[9] associated with the four main investment categories provided by Morningstar: Large-Value, Large-Growth, Small-Value, and Small-Growth.

[8] We require a minimum window of 24 months for the regression.

[9] They are Russell 1000 Value Index for the Large-Value category, Russell 1000 Growth Index for the Large-Growth category, Russell 2000 Value Index for the Small-Value category, and Russell 2000 Growth Index for the Small-Growth category.

2.3 Stock-level fund performance

Following Brown et al. (1996) and Chevalier and Ellison (1997), we measure the performance of a mutual fund in month t as the cumulative year-to-date excess returns to two benchmarks: a) index returns of S&P 500; b) the returns on the corresponding Russell index for the category of which the fund belongs to.[10] In the first case, the S&P 500 index is a common benchmark to all funds. In the second case, the fund benchmark is specific to the index at the category level. For example, if a fund's investing style is large value stocks, then the benchmark will be the Russesll 1000 Value index.

Having measured the fund-level performance, we calculate the stock-level fund performance in month t as the holding-weighted average year-to-date excess returns (in month $t-1$) of funds that hold the stock. The formula is:

$$Performance_{n,t}^{stock} = \frac{\sum_{i=1}^{I}[FundHoldings_{i,n,t-1} \times Performance_{i,t-1}^{fund}]}{\sum_{i=1}^{I} FundHoldings_{i,n,t-1}}, \tag{4}$$

where i and n index for funds and stocks, respectively.

Our measure resembles Cohen et al. (2005)'s quality measure of stocks. They define the the quality of stock n as "the average skill of all managers who hold stock n in their portfolios, weighted by how much of the stock they hold." There are two distinctions between our stock-level average performance and their quality measure: 1) they use Jensen's alpha as the skill measure of fund managers whereas we use the benchmark adjusted return (either adjusted by S&P 500 or Russell index); 2) They weight the fund performance by the portfolio weight of a given stock (for details, see Cohen et al. (2005) Equation 1), whereas we weight the performance by the number of shares held by each fund. Our goal is to check if a stock is mainly held by underperforming funds, how does that affect their returns. But the goal of Cohen et al. (2005) is to see whether two managers' portfolios are similar or not. So using the number of shares as the weight is more appropriate in our setting. However, despite those minor differences, the spirit of our measure is very similar to theirs. We both want to tell

[10]We focus on the measure of year-to-date fund performance, as prior studies find that due to compensation incentives fund managers with poor mid-year performance tend to catch up towards to the end of the year (Kempf and Ruenzi (2008) and Kempf et al. (2009)). Nevertheless, we also consider the rank method of Morningstar to estimate the fund performance as in Ben-David et al. (2022) and Evans and Sun (2021). Overall, we find consistent results: risk anomalies are more significant across stocks held by funds who are assigned lower Morningstar rankings (poor past performance).

whether a stock is mostly held by underperforming or outperforming funds.

[Insert Table 1 about here]

Table 1 reports the summary statistics of the fund-level variables (monthly frequency) for the merged CRSP and Thomson Reuters fund sample. The average of monthly gross returns, defined as monthly net return plus the annual expense ratio divided by 12, is around 0.8%. The average of total net assets of funds is around $1,433.4 million. The averages of annual expense ratio and turnover ratio are 1.2% and 0.81, respectively. The average of fund age, defined as months since funds appear in the data set, is 168 months. The last two rows of Table 1 report the cumulative year-to-date returns relative to the two benchmarks. On average, the cumulative year-to-date excess returns to the S&P 500 index return is 1.8% and to the Russell index return is 0.4%.

3 Fund Performance and Beta Anomaly

Our main hypothesis is that the stocks mainly held by underperforming funds should generate significant beta anomalies. Section 3.1 tests the hypothesis regarding the beta measured against Capital Asset Pricing Model (CAPM). Section 3.2 test the hypothesis regarding the beta measured against category benchmark index.

3.1 CAPM beta anomaly

Numerous studies find that stocks with high CAPM beta tend to earn lower alpha than stocks with low CAPM beta (see Frazzini and Pedersen (2014)). In this Section, we show that the beta anomaly returns are significant only among stocks mainly held by underperforming funds.

In each month, we first sort stocks into five quintiles by the stock-level fund performance measured as in Equation 4. The bottom (top) quintile consists of stocks that are mainly held by underperforming (outperforming) funds. Due to the changes of the Morningstar rating methodology in June 2002, funds' performance benchmarks also changed. Before 2002, all funds are ranked together, so a common benchmark such as the S&P 500 index is suitable.

After 2002, funds are ranked within each "style", so, a style specific benchmark is more appropriate. Thus, we use the S&P 500 index as the performance benchmark during the pre-June 2002 periods and the corresponding Russell category index as the performance benchmark during the post-July 2002 periods. Then, within each stock-level fund performance quintile, we sort stocks into deciles based on their CAPM betas. This sequential sorting forms 50 portfolios. All of the portfolios are value-weighted. For each portfolio, we compute its alphas with respect to the three-factor model of Fama and French (1993).[11]

Table 2 presents our main results. To demonstrate that our stock universe (i.e., the stocks held by mutual funds) is similar to the commonly used stock universe in the literature, we reproduce the "beta anomaly" in the bottom row in Panel A, labeled as "All Stocks". We find the alphas in each portfolio decline nearly monotonically as beta increases. And the difference in monthly alphas between the highest and lowest beta deciles equals -52 bps, with a t-statistic of -2.40, both values are in line with the previous literature (see Liu et al. (2018) Table 2).

The top 5 rows in Table 2 contain the alphas of portfolios double sorted by the stock-level fund performance and CAPM betas. Quintile 1 contains the stocks mostly held by underperforming funds, while quintile 5 contains the stocks mostly held by outperforming funds. For the ease of illustration, we plot those portfolio alphas in Figure 1. For the stock-level fund performance quintile 1 to 3, there is a clear pattern of alphas declining as beta increases. And for the quintile 1 and 2, the highest beta deciles' alphas are significantly negative which is consistent with our explanation that the demand from underperforming funds for high-beta stocks causes overpricing on high-beta stocks. In addition, this is not just for the highest decile of beta stocks. The negative alpha pattern exists for almost the top half of all the beta deciles. The beta anomaly, i.e., the alpha difference between the highest and lowest beta deciles, is -76 bps for the underperforming quintile with a t-statistics of -2.76. However, for the quintile 4 and 5, there does not exist a clear decreasing pattern between alphas and betas. In particular, the beta anomaly within quintile 5 is -19 bps with a t-statistics around -0.74, which is statistically insignificant.

One might concern that the stocks mainly held by underperforming funds might have

[11] We use the Fama French three-factor model to compute alphas since it is widely used in the beta anomaly literature. See, for example, Liu et al. (2018).

different beta characteristic than the stocks mainly held by outperforming funds. Panel B of Table 2 reports the value-weighted CAPM beta for each double sorted portfolio. Focusing on each beta decile, there is virtually no difference between the underperforming quintile vs. the outperforming quintile. This suggests that all the funds would invest in both high-beta and low-beta stocks. But only the underperforming funds push the prices of high-beta stocks too high.

[**Insert Figure 1 and Table 2 about here**]

One might also concern that the above findings could be driven by funds who are just dumb and always invest in high-beta stocks that generate lower alphas. To rule out this possibility, we conduct two tests. In the first test, we check whether mutual funds who underperform previously will continue to hold overpricing stocks and therefore, underperform subsequently. To measure stock overpricing, we use the mispricing score developed in Stambaugh and Yuan (2017): the mispricing score ranges from 1 to 100, and a higher score indicates more overpricing. Based on each fund's holdings data, we calculate the mispricing score of a fund's portfolio in each month. Having measured the mispricing score at fund portfolio level, the change of mispricing score is measured as the difference between the mispricing score of holdings in the current period and the mispricing score of the holdings 12 months ago. We then sort funds into 3×3 portfolios based on their current and past performance. Fund's current (past) performance is defined as the year-to-date excess returns relative to benchmarks in the current (last) year. We use a 12 months gap between the current and the past performance. Finally, we compute the average change of mispricing score for each portfolio and the results are provided in Internet Appendix Table A2. We find that funds who underperform last year are not always holding overpricing stocks this year. For example, funds who perform the worst in the last year tend to hold less overpricing stocks in the current year, as shown in the column "Underperform" of Internet Appendix Table A2. In addition, underperforming funds tend to perform better when they reduce their investment in overpricing holdings. Overall, these findings suggest that underperforming funds are not always dumb and investing in overpricing stocks.

In the second test, we check whether the stocks held by mutual funds who underperform previously but outperform currently could generate a significant beta anomaly. We first sort stocks into three portfolios based on the stock-level fund-current-performance, defined as the weighted-average of the year-to-date excess returns (relative the benchmark index) of funds that hold the stock. Within each of the three portfolios, we further sort stocks into three portfolios based on stock-level fund-past-performance, defined as the weighted-average of the last-year year-to-date excess returns (relative the benchmark index) of funds that hold the stock. Finally, we sort stocks into decile portfolios based on their betas and measure the alpha of the beta anomaly for each of the 3×3 portfolios formed on stock-level fund-current-performance and stock-level fund-past-performance.[12] The results are provided in Internet Appendix Table A3. If our main results are driven by funds who are dumb and always investing in high-beta stocks, then we should expect a more prominent beta anomaly among the stocks held by funds who underperform in both current and past periods. However, we find that this is not the case: there is little variation in the beta-anomaly alphas across portfolios with different past performance, i.e., the beta anomaly depends on whether a fund underperform this year.

Further, we show that the main results in Table 2 are robust when using other methods to estimate beta including using one year daily returns with the Dimson correction (Hong and Sraer (2016) and Cederburg and O'doherty (2016)) and estimating the correlations between stocks and market portfolio and the volatility of market portfolio separately as in Frazzini and Pedersen (2014) (see Internet Appendix Table A4 and A5). Consistent with the finding that funds who underperform in the first-half year increase their portfolio risk to catch up toward the year end (Chevalier and Ellison (1997)), we also find that the beta anomaly across the stocks held by underperforming funds is more significant in the second-half year. The result is reported in Internet Appendix Table A6.

Finally, prior studies find that flow-induced trading has significant impacts on stock prices (Coval and Stafford (2007) and Lou (2012)). In particular, fund outflows may force funds to liquidate their equity positions (Edmans et al. (2012), Wardlaw (2020)). In this case, the low alpha of high-beta stocks could also arise from the selling pressure of underperforming funds resultant from investor redemption. To investigate the flow-based explanation for the

[12] We sort stocks into 3×3×10 portfolios rather than 5×5×10 portfolios in order to have more stock observations in each portfolio so that the portfolio returns are not dominated by few stocks.

beta anomaly, we sort stocks into 3×3 portfolios based on the stock-level fund performance and the stock-level fund flow (sequentially); we further examine the beta anomaly of each portfolio. Funds' monthly flows are calculated as $\frac{TNA_t}{TNA_{t-1}} - (1+ret_t)$. The stock-level fund flow is defined as the weighted-average of flows of funds that hold the stock, and a smaller value of this measure indicates the stock is mainly held by funds who have smaller or potentially negative flows. Internet Appendix Table A7 reports the monthly alpha of the beta anomaly. If flow-induced selling pressure drives the low alpha of high-beta stocks, then for stocks that are mainly held by underperforming funds, the beta anomaly should be more prominent for stocks that are mainly held by funds with smaller flows. However, we find that this is not the case: there is little variation in the beta-anomaly alphas across portfolios with different flows and the beta anomaly is only dependent on the fund performance.

3.2 Beta anomaly with different benchmarks

The results in the previous section suggest that risk-shifting by underperforming funds might induce overpricing of high-beta stocks, thus helping to generate the beta anomaly. If it is indeed the relative performance concerns driving the beta anomaly, we should expect the "relevant" benchmark to matter. The rationale is as follows: for instance, if a large-cap value fund is attempting to "catch up" to its Large Value benchmark, or to its category peers, it should prefer stocks that have a high beta with respect to this Large Value benchmark to one with a high beta with respect to a large-cap growth index, all else equal.

To identify the "relevant" benchmark for each fund, we rely on Morningstar. There is ample evidence that Morningstar star ratings are crucial for the success of a mutual fund (Del Guercio and Tkac (2008)). The star ratings are assigned based on a *relative* ranking system, i.e., mutual funds are ranked against funds in their peer group. In other words, the peer group's average performance could be viewed as the "relevant" benchmark for a given fund. More interestingly, before June 2002, all the domestic equity funds were ranked against each other without regard for their own investment style (e.g., large value). Then the "relevant" benchmark should be a common benchmark such as the S&P 500 index. However, in June 2002, Morningstar reformed its rating methodology: instead of simply pooling and ranking all funds together, Morningstar began assigning ratings based on how funds rank within their "style" category (e.g., Large Value). So that, post June 2002, the "relevant" benchmark should be the category specific benchmarks, such as Russell 1000 Value Index for the Large-Value category funds. Based on the exogenous change of the "relevant" benchmarks around 2002, we hypothesize that the commonly-used market-wide benchmark beta anomaly is significant before 2002, and a category-beta anomaly emerges after 2002.

To test this hypothesis, we first sort stocks into five quintiles by the stock-level fund performance defined in Equation 4. According to the Morningstar rating methodologies implemented in different time periods as described above, we use the S&P 500 index returns as the benchmark for the periods before June 2002 and the category specific Russell index returns as the benchmark for the periods post June 2002. Next, within each stock-level fund performance quintile, we further sort stocks into ten deciles based on its category-beta. The category beta is estimated in the same way as the CAPM beta as described in Section 2.2. We replace the monthly market excess returns with the following 5 index returns, respectively: S&P 500 index, Russell 1000 Value Index, Russell 1000 Growth Index, Russell 2000 Value Index, and Russell 2000 Growth Index.

Table 3 Panel A reports the alphas of beta anomaly for each of the five quintile portfolios sorted on the stock-level fund performance during the pre-June 2002 period. Consistent with the rating method used by Morningstar before June 2002, we find that the beta anomaly is only significant within stocks mainly held by underperforming funds when using the S&P 500 index to estimate the beta. Specifically, in the first row, the alphas for the beta anomaly in the bottom quintile sorted on the stock-level fund performance are -0.72% with a t-statistics of -1.82. And as the stock-level fund performance increases, the beta anomaly gradually disappears which is also consistent with what we found in Table 2. However, when using the Russell index to estimate the beta during this period, neither a significant beta anomaly for any performance quintile nor the variation in beta anomaly across the stock-level fund performance quintiles exist. These findings suggest that before June 2002, underperforming funds tend to overweight stocks with higher exposures to the common benchmark, i.e., S&P 500 index, without regard for their own investment style.

[Insert Table 3 about here]

Table 3 Panel B reports the results for the post-June 2002 period. In sharp contrast to the pre-June 2002 period results, the beta anomaly of the S&P 500 index becomes insignificantly negative within stocks largely held by underperforming funds. The alpha of the beta anomaly in the bottom performance quintile is -0.16 with a t-statistic of -0.43. When using the Russell category index as the benchmark to measure beta, we find that the alpha of the beta anomaly becomes significantly negative within stocks largely held by underperforming funds for various categories. Specifically, we find that for styles of large-cap value, small-cap value, and small-cap growth, the alphas of beta anomaly in the bottom stock-level fund performance quintiles are -1.16% (t-statistic of -3.14), -0.82% (t-statistic of -2.18), and -0.91% (t-statistic of -2.20), respectively.[13]

These patterns in Table 3 strongly support the idea that relative performance vis-a-vis the relevant category peers is what matters for fund risk-shifting and the resulting (lack of) risk-return trade-off.

4 Style Investing and Mutual Fund Risk Shifting

The results from the previous section show that the beta anomaly is driven by stocks that are largely held by underperforming funds. In this section, motivated by the mutual fund tournament literature, we provide evidence that underperforming funds would like to catch up with their peers and therefore, overweight on high-beta stocks, causing overpricing on these stocks.

4.1 Exogenous ranking change and risk shifting

In June 2002, Morningstar changes its rating methodology. Instead of ranking all funds together, Morningstar began assigning ratings based on how funds performed within their style category. We exploit this exogenous shock to provide (possible) causal evidence that funds' ranking changes affect their risk shifting behaviors. We conjecture that funds who experienced more downward ranking change caused by the Morningstar rating change would invest more into the stocks with higher beta exposures to the benchmarks. To test this hypothesis,

[13]However, our hypothesis does not work in the large-cap growth style in which the beta anomaly is insignificant for all fund-performance quintiles.

we construct two fund-level measures: ranking changes and beta changes. Fund's ranking change in 2002 is measured as the difference between its ranking within a fund category using its first-half year performance and its ranking within the fund universe. We compute a fund's first-half-year performance as the cumulative excess monthly returns (relative to the benchmark index) in the first half year. Then, we rank funds in two ways: decile and vigintile (i.e., 20 quantiles).[14] We define changes in a fund's holding beta as the difference between the beta (with respect to Russell category index) of change of stock holdings in the fourth quarter (relative to the second quarter) and the beta (with respect to the S&P 500 index) of stock holdings in the second quarter.

Table 4 reports the results of the cross-sectional regression of beta changes on ranking changes in 2002. We include the total net assets, the expense ratio, the turnover ratio, and the fund age as control variables:

$$Beta\_Change_i = \alpha + \beta Rank\_Change_i + \gamma_k \sum_{k=1}^{4} Control_{k,i} + \epsilon_i. \tag{5}$$

In the univariate regression presented in column (1), we find a significant negative relation between beta changes and ranking changes: a one unit decrease in the decile ranking after the Morningstar rating change results in a 0.058 increase in the fund's holding beta. Further, the results remain robust when controlling for other variables or when using the vigintile ranking. Overall, our findings provide evidence that funds' ranking changes affect their risk shifting behaviors.

[**Insert Table 4 about here**]

When estimating the β coefficient in front of *Rank_Change* in Equation 5, we assume there is a simple linear relationship between *Beta_Change* and *Rank_Change*, i.e., a fund's beta increases when they experienced a ranking decrease, and a fund's beta decreases when they experienced a ranking increase. However, according to our main hypothesis, it should be mainly the funds that experienced ranking decreases engaging in risk shifting, while the

[14] Because of the small number of fund-quarter level observations for each category, we pool the four different categories (LG, LV, SG, and SV) together when performing regression analysis.

reaction of upgrading funds is ambiguous. To investigate whether it is indeed the downgrading funds engaging in risk shifting, we consider the regression excluding the funds who experienced ranking increase after the Morningstar rating method change. We find that if we remove these funds, there is still a negative relation between rank change and beta change in the sense that funds experience more downward changes in their ranks do more risk shifting. We report the results in Internet Appendix Table A8.

4.2 Fund performance and risk shifting

Though the Morningstar rating methodology change provides us with a clean setting to identify the relationship between funds' ranking changes and their risk shifting behaviors, this type of reform only happened once. To explore this relationship for the full sample, we replace ranking changes with a fund's first-half-year performance. We conjecture that funds invest more into high-beta stocks when they underperform.

To test the hypothesis that funds invest more into high-beta stocks when they underperform the benchmarks, we run the pooled cross-sectional time-series regressions of changes in funds' holding beta and their first-half-year performance. Similar to the last section, we define the changes in funds' holding betas as the difference between the beta of changed stock holdings in the fourth quarter relative to the second quarter and the beta of stock holdings in the second quarter. The empirical specification is as follows:

$$Beta\_Change_{i,t} = \alpha + \beta Fund\_Performance_{i,t} + \gamma_n \sum_{k=1}^{4} Control_{k,i,t} + \epsilon_{i,t}. \tag{6}$$

The control variables include: total net assets, the expense ratio, the turnover, and fund age. Table 5 presents the results. In column (1), we run an univariate regression without control variables. When using the S&P 500 index as the benchmark, we find that the relation between beta change and fund performance is significantly negative, indicating that underperforming funds shift their holdings to stocks with a high beta relative to the the S&P 500 index. In terms of economic magnitude, a one unit decrease in the fund's first-half-year performance leads to an increase of 0.075 for the holding beta in the second half year. In column (2), we include additional control variables and the results remain quantitatively similar.

[**Insert Table 5 about here**]

Further, the above findings remain qualitatively similar when we use Russell indices as benchmarks. Specifically, funds who underperform their category benchmarks invest more into stocks with higher betas relative to the corresponding benchmark index including the Russell 1000 Value index (large-cap value funds), the Russell 1000 Growth index (large-cap growth funds), the Russell 2000 Value index (small-cap value funds), and the Russell 2000 Growth index (small-cap growth funds). The results are reported in Table 5. Taking the large-cap growth funds as an example, a one unit decrease of the fund performance relative to the Russell 1000 Growth index leads to an increase of around 0.31 for the holding beta with respect to the Russell 1000 Growth index.

4.3 Relevant benchmarks and risk shifting

Based on a similar rationale as is discussed in Section 3.2, if it is indeed the relative performance concerns driving the risk shifting behaviors, we should expect the "relevant" benchmark to matter. For instance, if a small-cap growth fund is attempting to "catch up" to its Small Growth benchmark, or to its category peers post June 2002, it should prefer stocks that have high betas with respect to this Small Growth benchmark to the ones with high betas with respect to say, S&P 500 index, all else equal.

To test this conjecture, we split the sample into two periods—pre-2002 and post-2002—and run the regressions of changes in funds' holding betas on their first-half-year performance. The control variables include: fund net assets, expense ratio, turnover, and fund age. The empirical specification is as follows:

$$Beta\_Change_{i,t} = \alpha + \beta Fund\_Performance_{i,t} + \gamma_k \sum_{k=1}^{4} Control_{k,i,t} + \epsilon_{i,t}. \tag{7}$$

Table 6 Panel A reports the regression results for the pre-2002 periods. We find that the beta change and the fund performance are significantly negatively correlated when using the S&P 500 index as the benchmark. However, when using the Russell index as the benchmark to measure stock beta and fund performance, this relationship is not statistically significant for most categories except the small-cap growth category. This finding indicates that during pre-2002 periods, funds care about their performance relative to the S&P 500 index instead of their performance relative to the category benchmark index. And underperformance relative to the S&P 500 index induces funds to engage in risk shifting. Table 6 Panel B reports the regression results for the post-2002 periods. In sharp contrast to the results for the pre-2002 periods, the relationship between beta change and fund performance is significantly negative for most category benchmarks (3 out of 4). The combined results from Panel A and Panel B of Table 6 strongly suggest that it is the relative performance concerns that drives the risk shifting behavior, which subsequently causes the overpricing of high-beta stocks.

[Insert Table 6 about here]

In order to examine the diverging risk-shifting behavior of outperforming and underperforming funds, we group funds based on their performance in the first half of a year and report the changes in the betas of funds' portfolios with their respective benchmarks in the second half of the year (we consider the subsample following the change in Morningstar rating methodology in 2002). In doing so, we can examine to what extent that underperforming funds deviate from the benchmarks and whether outperformings funds will lower the risk. Internet Appendix Table A9 Panel A reports the demeaned beta changes for fund quintile portfolios sorted on their first half-year year-to-date excess returns (relative the benchmark index) within a category. The beta change is computed the same way as in Table 6. We demean the beta changes within each year for funds in each category, since funds' betas can shift in a common direction, e.g., Boguth and Simutin (2018). Consistently with our regression-based result, we find that funds that underperform in the first half of the year tend to increase their portfolio betas in the second half of the year; the difference in the beta changes between underperforming and outperforming funds is 0.015.

In Internet Appendix Table A9 Panel B, we group funds using cutoffs based on the cross-sectional standard deviation of the performance. Each year we sort funds into groups based on their year-to-date excess returns (relative to the appropriate benchmark). We then group them into five portfolios with breakpoints equal to -1, $-\frac{1}{2}$, $\frac{1}{2}$, and one standard deviation around zero, since zero indicates that a fund has the same year-to-date return as the benchmark. We find that funds in the second group, i.e. funds that just underperform the benchmark by small amount (with average returns of -2.1% in the first half of a year) have the strongest incentive to risk shift, with demeaned beta changes of 0.005.

5 Quantifying the Impact of Underperforming Funds

In this section, we quantify the impacts of underperforming funds on beta anomaly by employing the demand system approach to asset pricing developed in Koijen and Yogo (2019) (KY hereafter). We provide evidence that the holdings from underperforming funds significantly contribute to the overpricing of high-beta stocks and removing their holdings substantially reduces the beta anomaly returns.

5.1 Model

5.1.1 Notation

There are N financial assets, indexed by $n = 1, ..., N$. Following KY, we use lowercase letters to denote the logarithm of the corresponding uppercase variables. We denote characteristic k of asset n at date t as $x_{k,t}(n)$. The financial assets are held by I investors, indexed by $i = 1, ..., I$. One of the investors is a household sector, which holds all remaining shares that are not held by institutional investors.

5.1.2 Asset demand

Each investor allocates wealth $A_{i,t}$ at date t across assets in its investment universe $N_{i,t} \subseteq \{1, ..., N\}$ and an outside asset. Here, following KY, we assume an investor's choice set is a subset of assets that the investor considers or is allowed to hold. Restrictions on the choice set may be driven by investment mandates or benchmarking. We model the weight in asset n for investor i's portfolio at date t as $\omega_{i,t}(n)$:

$$\omega_{i,t}(n) = \frac{\delta_{i,t}(n)}{1 + \sum_{m \in N_{i,t}} \delta_{i,t}(m)}, \tag{8}$$

where

$$\delta_{i,t}(n) = \frac{\omega_{i,t}(n)}{\omega_{i,t}(0)} = \exp\left\{\lambda_{i,t}\mathrm{me}_t(n) + \sum_{k=1}^{K-2}\theta_{k,i,t}x_{k,t}(n) + \eta_{i,t}Beta_t(n) + \theta_{K,i,t}\right\}\epsilon_{i,t}(n). \tag{9}$$

$\mathrm{me}_t(n)$ denotes the log market equity, $x_{k,t}(n)$ denotes firm characteristics (i.e. the log book equity, profitability, and investment), and $Beta_t(n)$ denotes the stock beta.

Accordingly, the portfolio weight of the outside asset is

$$\omega_{i,t}(0) = \frac{1}{1 + \sum_{m \in N_{i,t}} \delta_{i,t}(m)}.$$

An investor's demand depends on the log market equity, firm characteristics, and the latent demand, $\epsilon_{i,t}(n)$. Latent demand captures the unobserved characteristics of the asset.

5.1.3 Market clearing

We complete the model with the market clearing condition for each asset n,

$$ME_t(n) = \sum_{i=1}^{I} A_{i,t}\omega_{i,t}(n). \tag{10}$$

The above equation implies that the market value of shares outstanding equals the asset-weighted sum of portfolio weights across all investors. Following KY, we assume that shares outstanding and the firm characteristics are exogenous.

5.2 Demand system estimation in 2002

In this section, we structurally estimate all investors' demand system using data from 2002. And we test whether the revealed preference of the underperforming funds for high-beta stocks is significantly stronger than that of the outperforming funds. In what follows, we introduce the data, discuss the instrumental variable and the estimation procedures, and then present the estimation results.

5.2.1 Data

In the characteristic-based demand system, an investor's demand is determined by market equity, firm characteristics, and latent demand. Following KY, we use log of book equity, profitability, investment, and beta as the stock characteristics. Book equity is as measured in Fama and French (1993). Profitability is measured as the ratio of operating profit to book equity. Investment is measured as the annual log growth rate of assets.[15] Stock beta is estimated in the same way as in Section 2.2.[16] As in KY, inside assets are defined as stocks who have non-missing values of the aforementioned firm characteristics and returns. We also require the closing price of an inside asset to be higher than \$5, consistent with our screening criteria in Table 2.

Based on the results from Section 3.2 which suggests that category beta is more "relevant" post-June 2002, we use the category beta during the periods after June 2002 for mutual funds. As above, we are focusing on the four extreme categories—Large Value, Small Value, Large Growth and Small Growth —in this section. And due to the small number of observations from each category, we pool observations from all four categories together to conduct the estimation. But for all other types of investors, such as pension funds, banks, we use CAPM beta throughout the whole periods.

We classify investors into four types: active equity mutual funds (which are the focus of our study), index mutual funds, other institutional investors (e.g., banks, pension funds, hedge funds), and households. We use S&P 500 funds as our proxy for index mutual funds for two reasons. First, they can be accurately identified through checking fund names and holdings data. Second, the S&P 500 index is a capitalization-weighted index which enables us to test the validity of our estimator for characteristics-based demand. As shown by KY, the point estimate of the sensitivity of holdings to price $\lambda_{i,t}$ for a capitalization-weighted index fund should be one since their portfolio weights only depend on stocks' market capitalization (implying a demand elasticity of zero). We show in Section 5.2.4 that the estimated $\lambda_{i,t}$ is close to one for S&P 500 index funds. If we were able to identify other capitalization-weighted

[15] We winsorize profitability and investment at one percentile to remove outliers.

[16] Differently from KY, we exclude dividend payout as one of the characteristics in our estimation for two reasons: *i*) we find more than 60% of the annual dividends (Compustat item *DVC*) in our sample are zeros; *ii*) dividend yield is not a widely used variable in the leading empirical asset pricing models, such as Fama and French (2015) and Hou et al. (2015).

indexes accurately, we can also categorize those funds as the index fund in our demand system estimation. Meanwhile, other index funds that are not constructed based solely on market capitalization would have exposure to other characteristics such as book-to-market ratios.[17] Data on institutional holdings are obtained from Thomson Reuters s34 files. Data on mutual fund holdings are obtained from Thomson Reuters s12 files, the same source as in Section 3. Mutual fund family-level holdings data in the s34 files aggregates all the holdings across mutual funds within the same fund family. To avoid double counting, we use the s12 type5 file to merge mutual fund holdings with the institutional holdings. We then remove the mutual fund holdings from institutional holdings. Finally, following KY we define household holdings for any stock as the difference between the stock's total shares outstanding and the sum of the holdings from mutual funds and institutional investors (note that this definition might include institutional investors with less than \$100 million in AUM since they are not required to report their holdings to the SEC).

5.2.2 Instrumental variable

In KY, $\epsilon_{i,t}(n)$ denotes the latent demand, which captures investor i's demand for unobserved (by the econometrician) characteristics of asset n. For example, we can think of $\epsilon_{i,t}(n)$ as the management quality of the firm, or the innovation prospect of this firm. It is possible that the asset prices are correlated with the latent demands. Consequentially, we cannot estimate an investor's demand curve using simple linear least squares estimator due to this endogeneity issue. We need an instrument that could affect the price of the asset n, but not the unobserved characteristics of asset n. Our instrumental variable is based on the idea that the change of Morningstar rating method in June 2002 could generate exogenous downgrades for certain funds (e.g., in June 2002, a fund might be ranked 5 stars according to its performance relative to the whole mutual fund universe, however, this fund might be ranked 3 stars according to its performance within the relevant category). As a result, the downgrades could lead to outflows from those funds due to investors' "star"-chasing behaviors.[18] And a stock that is held by more of those downgraded funds could experience

[17]We detail the selection of S&P 500 index funds in Internet Appendix Section A10.

[18]Indeed, for this type of funds, we find that they have lower flows than funds that experience upgrades, as reported in Internet Appendix Table A10.

an outflow-induced downward price pressure. The exclusion restriction is satisfied because the downgrades are caused by the rating methodology change conducted by Morningstar and therefore is not driven by an unobserved characteristic shift in a given portfolio's stocks. In addition, given the diversification requirements imposed on mutual fund holdings, such reverse causality is even less likely. This type of instrument is widely used in the corporate finance literature when examining the impact of stock mispricing on various firm policies (Edmans et al. (2012), Wardlaw (2020)).

We define our instrument for stock n held by investor i at time t as:

$$\widehat{\mathrm{me}}_{i,t}(n) = \frac{1}{Q}\sum_{j\neq i}\left(\text{rank decline}_j \times \frac{Shares_{j,n,t-1}}{Volume_{n,t-1}}\right), \tag{11}$$

where Q is the number of investors that hold stock n. rank decline$_j$ equals the difference between fund j's decile ranking within the fund universe and its decile ranking within a fund category in June 2002 if the difference is positive, and 0 otherwise. $Shares_{j,n,t-1}$ denotes the number of shares that investor j holds in asset n at time $t-1$. $Volume_{n,t-1}$ denotes the trading volume for asset n at time $t-1$.

Besides the relevance and exclusion conditions, a valid instrument should be free of weak identification problems. Internet Appendix Table A11 reports the minimum eigenvalue statistics (i.e., Cragg Donald statistics) for the first-stage regression of log market equity onto the instrument and other firm characteristics. We find that the first-stage minimum eigenvalue statistics are all above the critical value proposed by Stock and Yogo (2005).

5.2.3 Estimation procedure

We use linear GMM to estimate the model. For any $w_{i,t}(n) > 0$, we take logarithms of both sides of Equation 9, so that we have

$$\ln\left(\frac{w_{i,t}(n)}{w_{i,t}(0)}\right) = \lambda_{i,t}\mathrm{me}_t(n) + \sum_{k=1}^{K-2}\theta_{k,i,t}x_{k,t}(n) + \eta_{i,t}Beta_t(n) + \theta_{K,i,t} + \ln\epsilon_{i,t}(n). \tag{12}$$

The moment condition is $\mathbb{E}\left[\ln\epsilon_{i,t}(n) \mid \widehat{me}_{i,t}(n), \mathbf{x}_t(n)\right] = 0$, with $\widehat{me}_{i,t}(n)$ as the instrument defined in Equation 11 for each investor.

Specifically, to investigate whether funds that underperform their category benchmarks have stronger preferences for stocks with a high beta relative to the benchmark index, we group mutual funds into five quintile portfolios based on their performance relative to their peers in the same category over the first half of 2002. For all other investor types (institutional investors, index mutual funds, and households) we pool holdings of all entities within each group together. Then we estimate the demand coefficients for each group of mutual funds indexed by performance, and for all other investors by type of entity.

5.2.4 Estimation results

Among all the demand system parameters, the η coefficients associated with a stock's beta are of particular interest. A positive (negative) η indicates that investors prefer (dislike) high-beta stocks, holding all other characteristics fixed. Table 7 Panel A reports the point estimates of the η coefficient associated with a stock's beta loading on the benchmark in the second half of 2002, i.e. immediately following the Morningstar methodology change. We find that for both the third and fourth quarters in 2002, the η coefficients for the most under-performing (bottom quintile) funds are significantly positive. In contrast, the coefficients for outperforming funds are significantly negative, consistent with the standard finance logic that investors prefer less exposure to systematic risk, *ceteris paribus*. They are also significantly negative for other categories of investors—index funds, other institutions, and households (although the latter category might include institutions that are too small to be required to report their holdings to the SEC). The substantially higher t-statistics for institutional investors reflect the effect of aggregation at the type of investor as well as greater persistence in holdings of these investors at this level of aggregation. Overall, these findings indicate that funds that underperform in their category do indeed have a uniquely strong preference for high-beta stocks.

[Insert Table 7 about here]

What about the demand elasticities of underperforming funds and other investors? As we have shown above, underperforming funds tend to hold high-beta stocks even when these stocks appear overpriced. As such, the demand of underperforming funds might be particularly inelastic, compared to the demand by other funds. Following KY, we rewrite the market clearing condition in Equation (10) as $\boldsymbol{q}_{i,t} = \log(A_{i,t}\boldsymbol{\omega}_{i,t}) - \boldsymbol{p}_t$, where bold letters denote the N-dimensional vectors. The elasticity of individual demand is

$$\frac{\partial \boldsymbol{q}_{i,t}}{\partial \boldsymbol{p}_t'} = \lambda_{i,t}\mathrm{diag}(\boldsymbol{\omega}_{i,t})^{-1}\left(\mathrm{diag}(\boldsymbol{\omega}_{i,t}) - \boldsymbol{\omega}_{i,t}\boldsymbol{\omega}_{i,t}'\right) - \boldsymbol{I}, \tag{13}$$

where demand elasticity is decreasing in $\lambda_{i,t}$, the sensitivity of fund's holdings to price. An index fund whose portfolio weights are proportional to market equity has $\lambda_{i,t}$ of one and thus inelastic demand (i.e. the elasticity above is equal to zero). The restriction that $\lambda_{i,t} < 1$ implies a downward demand slope function in the sense that for a given investor to hold more shares in a stock n, the stock n's price needs to fall.

In order to verify the validity of our estimates of $\lambda_{i,t}$, we focus on the implied demand elasticity of S&P 500 index funds, whose portfolio weights are proportional to market equity by definition. Figure 2 plots the distribution of the estimated sensitivities of holdings to price $\lambda_{i,t}$ for each of the S&P 500 index funds in the third and fourth quarters of 2002. We find that $\lambda_{i,t}$ ranges from 0.90 to 1.11 and on average is 0.97, a number close to one, implying an average demand elasticity of zero, as expected.

[**Insert Figure 2 about here**]

Having validated our demand elasticity estimator, we then study $\lambda_{i,t}$ and the implied demand elasticity for each group of investors. Table 7 Panel B reports $\lambda_{i,t}$ and Panel C reports the corresponding demand elasticity for each group of investors. A larger (absolute) value of the demand elasticity suggests a larger change in demand given the same change in asset prices. Consistent with our conjecture, we find that underperforming funds are substantially more inelastic than other active mutual funds (with elasticity of -0.175 and -0.37 in Q3 and Q4 of 2002, respecitively, where other funds' elasticities range between -0.75 and -0.62 in Q3 and between -1.13 and -0.62 in Q4 of 2002). The lack of sensitivity of holdings to asset price indicates that they are more likely to hold overpriced (high-beta) stocks than other funds. Only that index funds have substantially lower demand elasticity (which is essentially zero), while other institutional investors have comparably low elasticities to the underperforming funds, perhaps due to large allocations to passive strategies. In contrast, households (broadly defined) have demand elasticities that are comparable to those of active funds in the top four quintiles of performance.

5.3 Counterfactual Analysis

We conduct counterfactual analysis to quantify the impact of underperforming funds on the prices of high-beta stocks and on the beta anomaly. More specifically, we sort mutual funds into five quintiles according to their year-to-date performance (i.e., returns relative to category peers, as above). For bottom quintile funds, which are the most underperforming, we simulate an outflow equals to their full AUMs. In other words, we "close" those underperforming funds and reallocate their AUMs to all other investors proportionally to those investors' AUM (Koijen et al. (2020)). We assume that these latter investors allocate the additional capital towards the existing positions. We then solve for the counterfactual equilibrium prices so that the market clearing condition (Equartion 10) is satisfied. The counterfactual AUM for all other investors at time t is given by:

$$A_{i,t}^{CF} = A_{i,t} + F_{i,t}, \tag{14}$$

where CF denotes counterfactual values and $F_{i,t} = A_{i,t}A_{k,t}(\Sigma_{j,j\neq k}A_{j,t})^{-1}$. $A_{k,t}$ represents the total AUM of all underperforming funds.

After we obtain the counterfactual equilibrium prices of N inside assets at time t, we compute the repricing measure ζ^{B_t}:

$$\zeta^{B_t} = \frac{\Sigma_{n\subseteq B_t}[ME_t^{CF}(n) - ME_t(n)]}{\Sigma_{n\subseteq B_t}ME_t(n)}, \tag{15}$$

where B_t is a given portfolio of stocks (e.g. high-beta stock portfolio) and $ME_t(n)$ ($ME_t^{CF}(n)$) is the actual (counterfactual) market value for stock n at time t. The repricing measure ζ captures the change of market value caused by the disappearance of underperforming funds for the portfolio B_t.

Since underperforming funds aim to catch up with their peers in the same category by investing more stocks with a high beta relative to their category benchmark (see Tables 4 and 5), we conduct the counterfactual exercise for each fund category. For example, to study underperforming funds' impact in the Small Growth category, we reallocate the AUM of underperforming funds in the Small Growth category to all other investors (including other active funds, index funds, and institutional and retail investors). After obtaining counterfactual equilibrium prices, we sort stocks into 10 decile portfolios based on the beta with respect to the Small Growth benchmark (Russell 2000 Growth) and calculate the repricing measure ζ for ten deciles of stock portfolios. As such, we can estimate to what extent the demand of underperforming funds in the Small Growth category contributes to the overpricing of stocks that have high betas with respect to the Small Growth benchmark.

Table 8 reports the results. We find that the repricing measure is negative for high-beta decile portfolios and the outflows of underperforming funds result in larger price declines in high-beta stocks than in low-beta stocks, consistent with our argument that demand from underperforming funds contributes to potential overpricing of high-beta stocks. For example, in the Large Growth category the repricing is 2.44% and 1.13% more negative for high-beta stocks in the third and fourth quarter of 2002, respectively. The reason is as follows: in both the counterfactual and the actual equilibrium, the total number of shares outstanding for each stock is fixed and in the counterfactual experiment, the underperforming funds are closed and the stocks that were held by the underperforming funds need to be held by some other investors. As Table 7 Panel C shows, the demand elasticity is negative in the sense that for a given investor to hold more shares in a stock n, the stock n's price needs to fall. Since underperforming funds have a positive preference for high-beta stocks while other funds dislike high-beta stocks (as documented in Table 7 Panel A and discussed above), the prices of high-beta stocks need to drop more so as to make the other investors willing to hold them.

[Insert Table 8 about here]

Alternatively, we can explain the above repricing results through the lens of the demand elasticity. One direct implication from this explanation is that the average elasticity of stock portfolios formed on beta should be decreasing with beta due to the fact that the high-beta stocks are more likely to be held by inelastic underperforming funds. A second implication is that the demand elasticity should be lower for overpriced high-beta stocks than for other normal high-beta stocks. This is because the overpriced high-beta stocks are the ones that are more likely to be held by underperforming funds, while outperforming funds could hold some underpriced high-beta stocks. We define a high-beta stock as overpriced (underpriced) if its realized price is higher (lower) than its counterfactual price. Results from Internet Appendix Table A12 supports our first prediction, and results from Internet Appendix Table A13 support our second prediction.

In all, the above findings indicate that underperforming mutual funds have a disproportionately large impact on high-beta stocks, which contributes to high-beta stocks' overpricing.

5.3.1 Counterfactual: style-level beta anomaly

In this section we quantify the impact of underperforming funds' demand for high-beta stocks on the style-level beta anomaly following the Morningstar rating method change. Specifically, we use the estimates of the demand system parameters obtained using the 2002 Morningstar ratings change, as described above, to conduct counterfactual experiments where we reallocate underperforming funds' AUM to all other investors and re-compute the equilibrium asset prices over the subsequent years, i.e. 2002-2018. We use the demand coefficients estimated in September of 2002 and assume that these coefficients apply to all the funds in the corresponding performance bin over the entire period following the 2002 ratings reform until the end of our sample period (using the average of demand coefficients estimated in September and December of 2002 instead does not materially alter the results). This assumes that the investors' demand elasticities and, in particular, their "preference" for beta (as well as other characteristics) are stable over time. The Morningstar rating methodology change provides us with a clean exogenous shock to stock prices, which allows us to sharply identify the most relevant features of investors' demand for stocks. Since we cannot construct a similar measure for other quarters in our sample that would allow us to identify the parameters of the demand system as cleanly, we opt for the parsimonious assumption that preferences are stable over time.

In order to compute counterfactual stock prices at the monthly frequency we interpolate quarterly holdings for the intra-quarter months. As such, we are able to estimate the monthly alpha, consistent with our previous exercise. The counterfactual return in month t for stock

n is computed as $\frac{P_{n,t}+D_{n,t}-P_{n,t-1}}{P_{n,t-1}}$, in which P denotes the monthly counterfactual share price and D denotes actual monthly dividend per share (we calculate the monthly dividend using the CRSP total returns and returns without dividends following Cochrane (2008)).

[Insert Table 9 about here]

Having obtained the counterfactual returns, we then sort stocks into ten decile portfolios based on their beta with the appropriate benchmark. Table 9 reports realized and counterfactual monthly alphas for decile portfolios sorted on stocks' beta with the relevant Russell index, including Large Value (Russell 1000 Value), Large Growth (Russell 1000 Growth), Small Value (Russell 2000 Value), and Small Growth (Russell 2000 Growth). For each style-level beta anomaly, we look at the stocks held by funds in that category. Alphas are computed with respect to the Fama-French three-factor model. We find that for categories labelled Small Value and Small Growth, the realized monthly alphas of the style beta anomaly are -0.64% and -0.71%, respectively, which are statistically significant. In contrast, when using counterfactual returns instead, the alphas drop by around 50%, and become insignificant. In particular, we find that the reductions in the alphas of these two style beta anomalies arise largely stems from the less negative alphas earned by high-beta stocks when using counterfactual returns. This implies that removing the holdings of underperformings funds only has a prominent impact on the (over-)pricing of high-beta stocks, and thus attenuates the beta anomaly payoff. While the realized alphas for categories labelled Large Value and Large Growth are not statistically significant (-0.36% and -0.49%, respectively), both become much smaller when counterfactual returns are used to construct them (-0.18% and -0.35%, respectively). Internet Appendix Table A14 reports the repricing statisitics of underperforming funds in each category by allocating underperforming funds' AUM proportionally to all other investors' in the post-2002 period. We find consistent result that underperforming mutual funds in each investing category have larger impacts on stocks that have a high beta with respect to the category benchmarks.

How does this decline in the beta anomaly profits relate to the repricing (in particular, of high-beta stocks) that occurs in the counterfactual equilibrium? To answer this question we start with the familiar Campbell and Shiller (1988) approximation applied to an individual stock return (for ease of exposition, we omit the n subscript for stock n):

$$r_{t+1} \approx \kappa_0 + \kappa_1 z_{t+1} - z_t + g_{t+1}, \tag{16}$$

where the log of price-dividend ratio is $z_t = \log\left(\frac{P_t}{D_t}\right)$ and g_{t+1} is the log dividend growth rate. Solving forward for z_t, we have

$$z_t = \frac{\kappa_0}{1-\kappa_1} + \left[\sum_{j=0}^{\infty} \kappa_1^j \left(g_{t+1+j} - r_{t+1+j}\right)\right]. \tag{17}$$

We assume the returns follow: $r_{t+1} = \alpha_{t+1} + \beta_t' f_{t+1} + \epsilon_{t+1}$, where $\beta_t' f_{t+1}$ represents the compensation for exposure to systematic risk factor(s) f and the decay in mispricing α_{t+1} is captured by an autoregressive process: $\alpha_{t+1} = \phi\alpha_t + \varepsilon_{t+1}$. If the current dividend D_t is the same in both the counterfactual and the real world, the repricing ζ at time period t for a given stock can be expressed as (see Internet Appendix Section A12 for the derivation),

$$\zeta_t(n) = \exp\left(\frac{\alpha_{t+1}^{dif}}{1-\phi\kappa_1}\right) - 1, \tag{18}$$

where α_{t+1}^{dif} is the difference between the empirically realized alpha on the beta anomaly and its counterfactual alpha, using the returns at $t+1$ following the formation period t. The above expression explicitly links the (stock-level) repricing with (stock-level) alpha. While stock-level conditional alpha is not observed, it is common to proxy for it with the alphas of corresponding value-weighted decile portfolios, which attributes the variation in alpha to the stocks' relative rank when sorting on beta.

Let's take the high-beta stock portfolio in Small Growth fund category (beta is measured with the Small Growth category benchmark) as an example. By looking at the alpha of the high-beta stock for different horizons, we find out a decay parameter of 0.50 using a AR(1) model (see the graph in Internet Appendix Section A12). If we plug in the value of $\kappa_1 = 0.96$ (4% dividend price ratio), $\phi = 0.50$ and $\alpha_{t+1}^{dif} = -0.28\%$ (shown in Table 9) we have

$$\zeta = exp(-0.0058) - 1 = -0.58\%.$$

Therefore, the repricing of high-beta stocks needs to be at least -0.58%, so as to generate a alpha decline of 0.28%. As shown in Table 8, the average repricing is -0.99% in 2002 Q3 for high-beta stocks in the Small Growth category. Similarly, we show that the repricing of -0.91% is enough to explain the alpha decline of 0.38% for the high-beta portfolio in the Small Value category. We do not apply this analysis to the two large-cap categories, as the high-beta portfolio does not earn a significant negative alpha in either one.

Overall, our findings indicate that the demand by underpeforming funds has a prominent impact on the prices of high-beta stocks and, therefore, their subsequent returns. Reallocating underperformings' AUM to all other investors attenuates the style-level beta anomaly significantly by reducing the overpricing of stocks with high betas to the respective style benchmarks.

6 Fund Performance and Other Risk Anomalies

Besides beta anomaly, there are other well known risk anomalies: the apparent overvaluation of stocks with high-idiosyncratic-volatility (IVOL) and lottery-like payoffs, which are related to large positive skewness. In this section, we examine whether the two anomalies—IVOL and lottery-like payoffs—are primarily driven by stocks that are largely held by underperforming funds.

6.1 Idiosyncratic volatility

In a well-cited paper, Ang et al. (2006) find that stocks with high-IVOL earns lower returns than low-IVOL stocks. In fact, Liu et al. (2018) argue that the beta anomaly tends to be driven by the positive IVOL/beta correlation.

Since IVOL also represents risk, funds that underperform their benchmarks are likely to overweight high-IVOL stocks and therefore cause those stocks' overpricing. To test this, we sort stocks into 5×10 portfolios on the stock-level fund performance and IVOL, sequentially.[19] As in Ang et al. (2006), the monthly IVOL for individual stocks is calculated as the standard

[19]We use the S&P500 index return to measure the stock-level fund performance during pre-June-2002 periods and Russell category index returns to measure the stock-level fund performance during post-June-2002 periods

deviation of the residuals from the regression of the most recent month's daily returns on the Fama-French three factors.

Figure 3 and Table 10 Panel A present the monthly alpha (relative to the Fama-French three-factor model) of the 5×10 portfolios. Consistent with the beta anomaly results in Section 3.1, the IVOL anomaly is primarily driven by stocks that are largely held by underperforming funds. Specifically, focusing on IVOL decile 10 portfolios, we find that as the stock-level fund performance increases, the portfolio alpha decreases monotonously ranging from -1.39% to -0.38% per month. Therefore, the high-IVOL stocks held by underperforming funds are more likely to be overpriced. Accordingly, the long-short strategy that long the highest-IVOL- and short the lowest-IVOL-stocks in the bottom fund-performance quintile portfolio earns the most significantly negative alpha, which is -1.55% per month. Moreover, the difference in alphas of this long-short strategy between outperforming- and underperforming- fund quintiles is 0.78% with a t-statistic of 2.24.

[**Insert Figure 3 and Table 10 about here**]

Table 10 Panel B reports the value-weighted IVOL of each double-sorted portfolios. We find the IVOL dispersion is very similar across different quintile portfolios sorted on the stock-level fund performance. Therefore, both outperforming and underperforming funds invest in stocks with high IVOL, but only underperforming funds cause overpricing on high-IVOL stocks.

6.2 Lottery stocks

Bali et al. (2011) finds negative relation between expected returns and stocks' lottery payoff, which is measured as return skewness. Like beta and IVOL, skewness is also a proxy for risk. Since funds who underperform their benchmarks can overweight high-skewness stocks to increase their portfolio risks, it is likely that this risk-shifting behavior could cause overpricing on high-skewness stocks.[20] To examine this, we sort stocks into 5×10 portfolios on the stock-level fund performance and return skewness, sequentially. Following Bali et al. (2011),

[20] Agarwal et al. (2019) find that fund who underperform tend to invest in lottery stocks to increase risks towards the end of the year.

we measure stocks' return skewness as the average of its five highest daily returns in each month.[21]

Figure 4 and Table 11 Panel A present the monthly alpha (relative to the Fama-French three-factor model) of the 5×10 portfolios. Consistent with the beta and IVOL anomalies, the skewness anomaly is primarily driven by stocks that are largely held by underperforming funds. Specifically, we find that the alpha on stocks with the highest skewness in each fund-performance quintile portfolios decreases monotonously with fund performance, ranging from −1.19% to −0.43% per month. Therefore, the high-skewness stocks held by underperforming funds are more likely to be overpriced. Accordingly, the long-short strategy that long the highest-skewness- and short the lowest-skewness-stocks earns the most significantly negative alpha, −1.55% per month. Moreover, the difference in alphas of this long-short strategy between outperforming- and underperforming- fund quintiles is 0.83% with a t-statistic of 2.30.

[**Insert Figure 4 and Table 11 about here**]

Table 11 Panel B reports the value-weighted return skewness of each double-sorted portfolios. We find the dispersion in skewness is very similar across different quintile portfolios sorted on the stock-level fund performance. Therefore, both outperforming and underperforming funds invest in stocks with high return skewness, but only underperforming funds cause overpricing on high-skewness stocks.

7 Conclusion

In this paper we explore the relationship between risk-shifting by underperforming mutual funds and several well-known risk anomalies. We show that these anomalies are concentrated among stocks mainly held by underperforming funds. In addition, exploiting the rating methodology change by Morningstar in 2002 we provide causal evidence of risk-shifting by

[21]The skewness measure in Bali et al. (2011) has widely cited, e.g., Barberis et al. (2016) and Kumar et al. (2019). We do not use other skew measures such as skewness of monthly returns over the previous five years, expected idiosyncratic skewness (Boyer and Vorkink (2014)), and coskewness (Harvey and Siddique (2000)), because none of them predict cross-sectional stock returns significantly (see Table 5 in Barberis et al. (2016)).

underperforming funds and its impact on anomaly returns. We discover that a significant beta anomaly for the S&P 500 index for the pre-2002 period is largely replaced by category-index beta anomaly over the post-2002 period. We further quantify the impact of underperforming funds' risk shifting on the beta anomaly by employing the demand system approach. We find that the beta anomaly gets attenuated significantly in the counterfactual equilibrium that eliminates the demand for high-beta stocks by underperforming funds.

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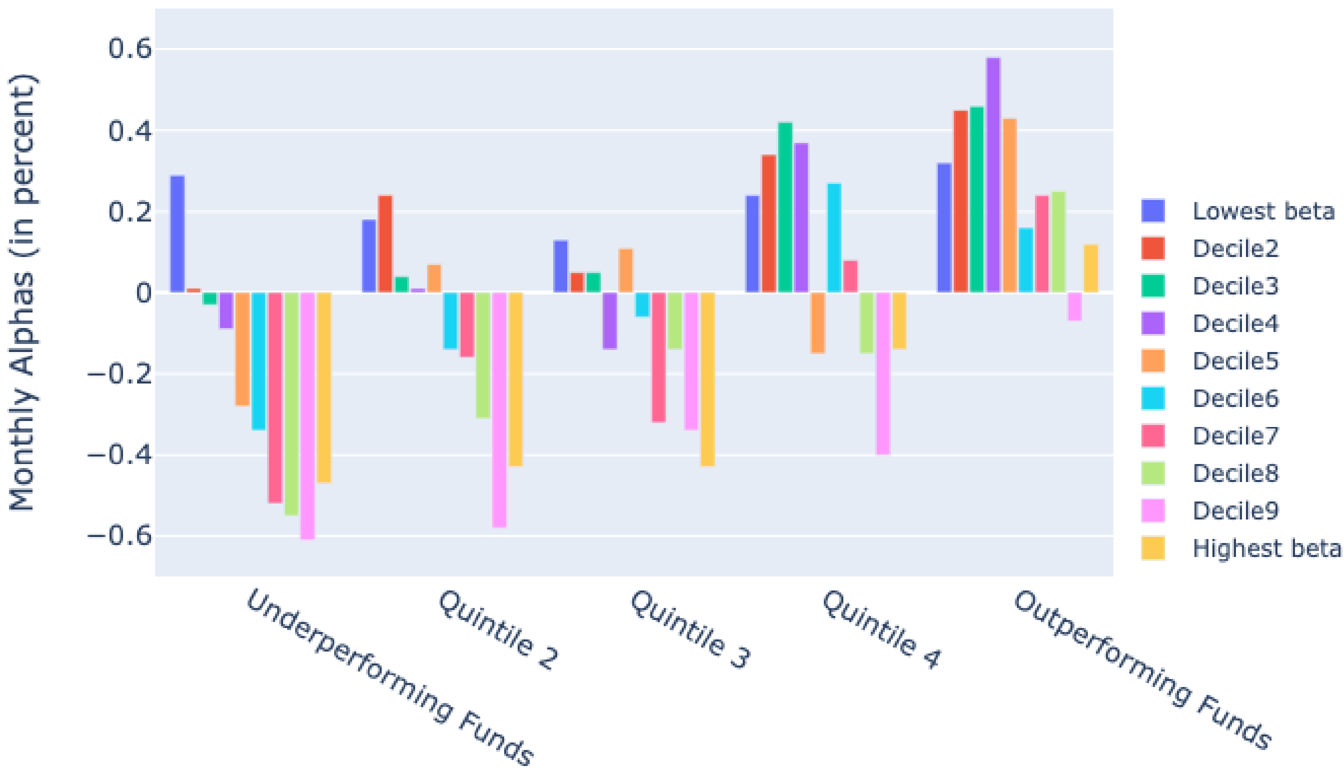
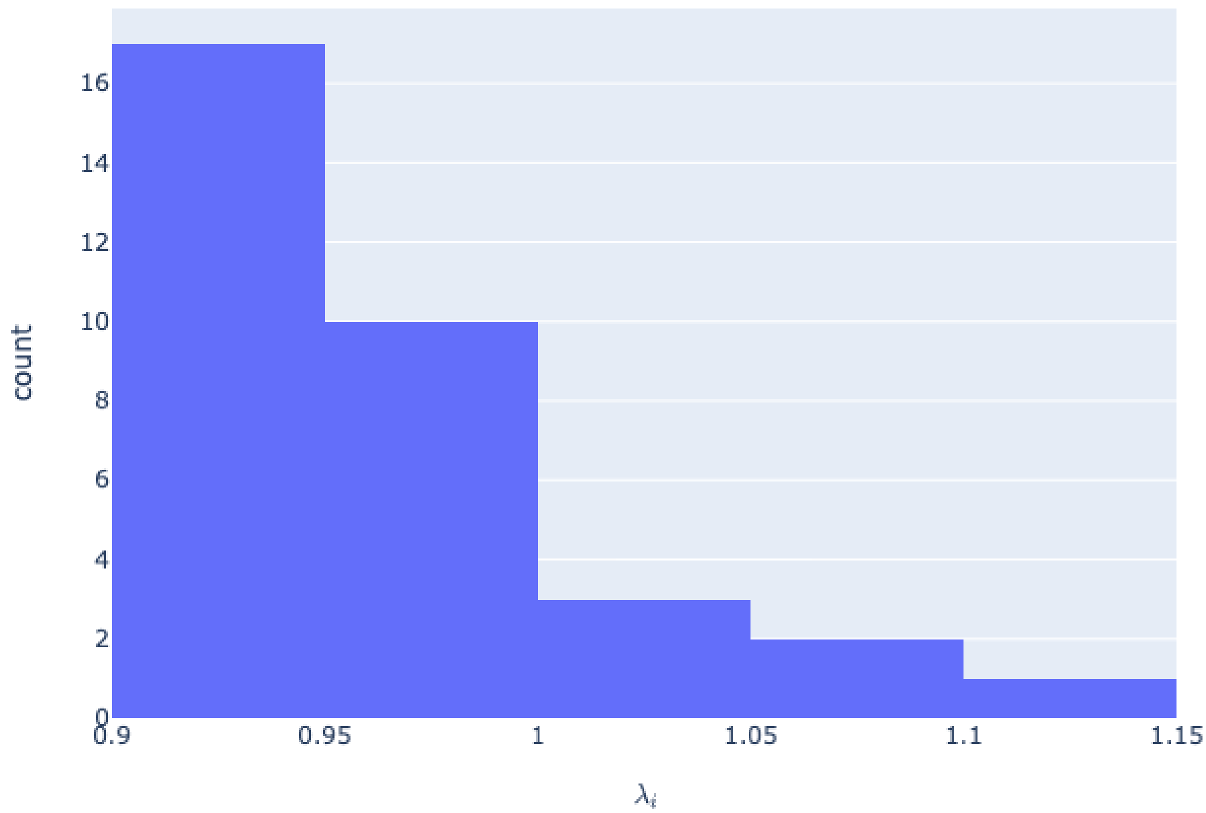
Figure 1: Alphas for 5×10 portfolios sorted on stock-level fund performance and CAPM beta



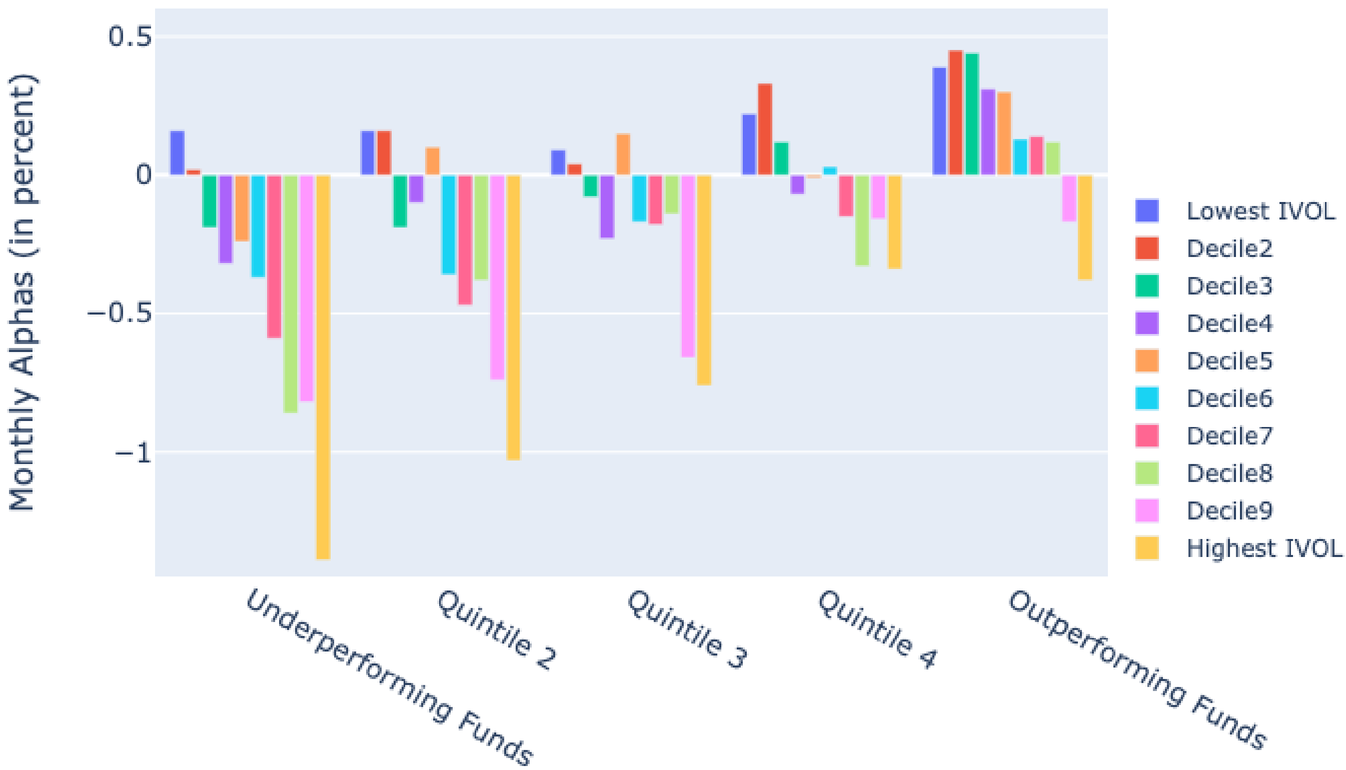
This figure plots the monthly alphas for 5×10 portfolios formed by sorting on the stock-level fund performance and the CAPM beta. Alphas are computed with respect to the Fama-French three-factor model (Fama and French (1993)). We first sort stocks into quintile portfolios based on the stock-level fund performance, defined as the weighted-average of the year-to-date excess returns (relative the benchmark index) of funds that hold the stock. Because of the change in the Morningstar rating method, we use the S&P 500 index as the benchmark before June 2002 and the Russell index as the benchmark after June 2002. Within each of the five fund-performance quintile portfolios, we sort stocks into ten decile portfolios based on betas. Stocks' betas are measured from the regressions of their returns on the market excess returns.

Figure 2: Sensitivity of S&P 500 index funds' stock holdings to price



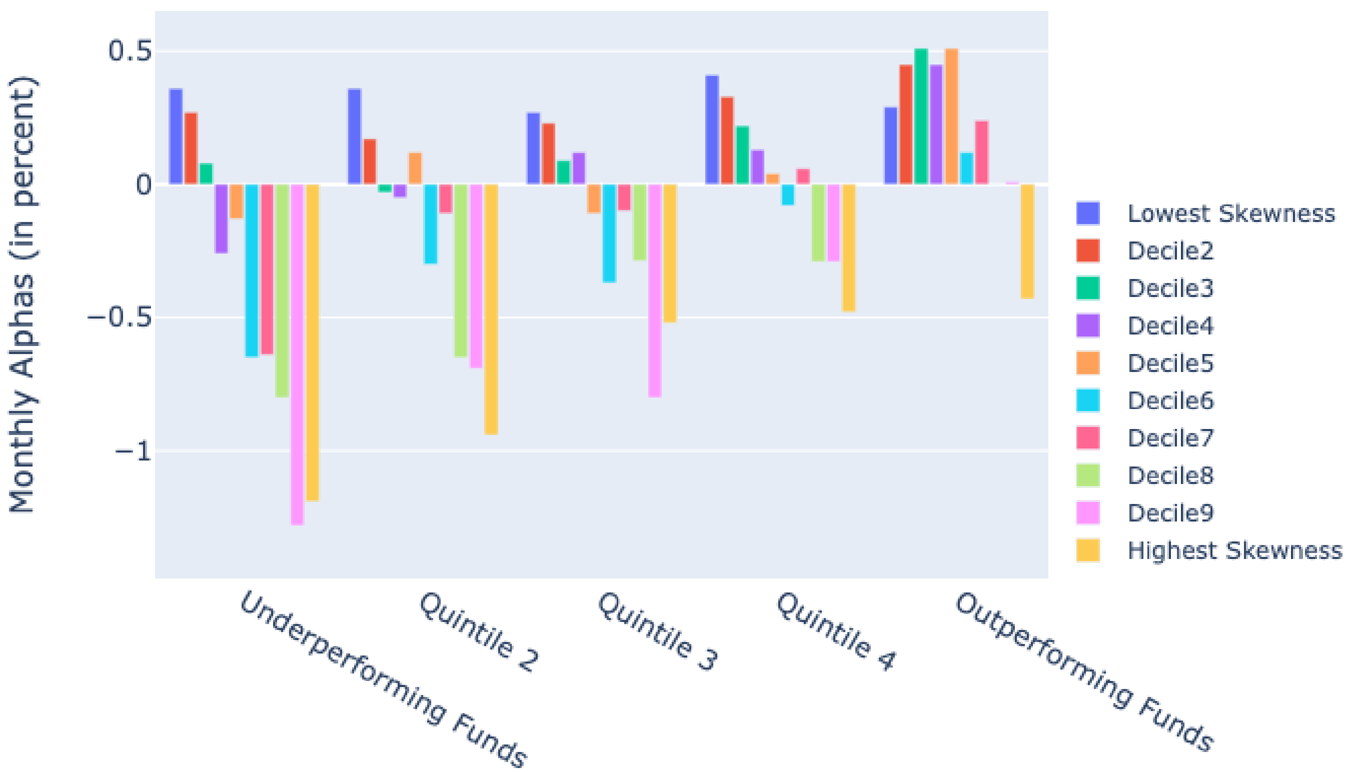
This figure plots the histogram of the point estimates of the sensitivity of holdings to price, λ_i, for each S&P 500 index fund in 2002; "count" indicates the total number of funds in each bin.

Figure 3: Alphas for 5×10 portfolios sorted on stock-level fund performance and IVOL



This figure plots the monthly alphas for 5×10 portfolios formed by sorting on the stock-level fund performance and idiosyncratic volatility (IVOL) . Alphas are computed with respect to the Fama-French three-factor model. We first sort stocks into quintile portfolios based on stock-level fund performance, defined as the weighted-average of the year-to-date excess returns (relative the benchmark index) of funds that hold the stock. Because of the change in the Morningstar rating method, we use S&P 500 index as the benchmark before June 2002 and the Russell index as the benchmark after June 2002. Within each of the five fund-performance quintile portfolios, we sort stocks into ten decile portfolios based on IVOL. The monthly IVOL for individual stocks is calculated as the standard deviation of the residuals from the regression of the most recent month's daily returns on the Fama-French three factors (Ang et al. (2006)).

Figure 4: Alphas for 5×10 portfolios sorted on stock-level fund performance and return skewness



This figure plots the monthly alphas for 5×10 portfolios formed by sorting on the stock-level fund performance and return skewness. Alphas are computed with respect to the Fama-French three-factor model. We first sort stocks into quintile portfolios based on the stock-level fund performance, defined as the weighted-average of the year-to-date excess returns (relative the benchmark index) of funds that hold the stock. Because of the change in the Morningstar rating method, we use the S&P 500 index as the benchmark before June 2002 and the Russell index as the benchmark after June 2002. Within each of the five fund performance quintile portfolios, we sort stocks into ten decile portfolios based on return skewness. Following Bali et al. (2011), a stock's return skewness (lottery payoff) is defined as the average of its five highest daily returns in each month.

Table 1: Summary statistics of fund-level variables

This table presents the summary statistics of the fund-level variables (at the monthly frequency) for the merged CRSP and Thomson Reuters fund sample. The variables include the monthly gross return (net return plus annual expense ratio divided by 12), the total net asset (TNA), the expense ratio, the turnover ratio, and the fund age (defined as months since funds appear in the database). YTD_SP and YTD_Russell represent funds' year-to-date excess returns to the S&P500 index and the Russell category indices, respectively. P1, Q1, Q3, and P99 represent the first percentile, the first quartile, the third quartile, and the 99th percentile of variables' sample distributions, respectively. The sample period is January 1982 to December 2018.

Variable	N	Mean	Std	P5	Q1	Median	Q3	P95
Gross Return	432644	0.008	0.176	-0.081	-0.018	0.012	0.038	0.082
TNA (Million)	435006	1433.4	5864.58	11.3	62.2	230.2	873.6	5550.2
Exp Ratio	432644	0.012	0.005	0.005	0.009	0.012	0.014	0.020
Turn Ratio	432484	0.810	0.892	0.110	0.330	0.610	1.024	2.080
Age (month)	435621	168	136	20	66	133	230	461
YTD_SP	432448	0.018	0.101	-0.077	-0.014	0.011	0.043	0.131
YTD_Russell	427822	0.004	0.089	-0.069	-0.020	0.000	0.021	0.085

Table 2: Double sorts

This table reports monthly alphas for 5×10 portfolios formed by sorting on the stock-level fund performance relative to the benchmark index and the CAPM beta. Alphas are computed with respect to the Fama-French three-factor model. We first sort stocks into quintile portfolios based on the stock-level fund performance, defined as the weighted-average of the year-to-date excess returns (relative the benchmark index) of funds that hold the stock. Because of the change in the Morningstar rating method, we use the S&P 500 index as the benchmark before June 2002 and the Russell index as the benchmark after June 2002. Within each of the five fund-performance quintile portfolios, we sort stocks into ten decile portfolios based on betas. Stocks' betas are measured from the regressions of their returns on the market excess returns. The t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is January 1982 to December 2018.

Panel A: Alphas											
	Beta Decile										
Performance quintile	1	2	3	4	5	6	7	8	9	10	10-1
1	0.29	0.01	-0.03	-0.09	-0.28	-0.34	-0.52	-0.55	-0.61	-0.47	-0.76
t-stat	1.98	0.07	-0.24	-0.68	-1.68	-2.19	-2.68	-2.97	-2.98	-2.15	-2.76
2	0.18	0.24	0.04	0.01	0.07	-0.14	-0.16	-0.31	-0.58	-0.43	-0.61
t-stat	1.32	1.87	0.31	0.06	0.48	-1.00	-1.06	-1.99	-3.31	-2.15	-2.38
3	0.13	0.05	0.05	-0.14	0.11	-0.06	-0.32	-0.14	-0.34	-0.43	-0.57
t-stat	0.94	0.39	0.37	-1.22	0.84	-0.42	-2.32	-1.01	-2.00	-2.18	-2.10
4	0.24	0.34	0.42	0.37	-0.15	0.27	0.08	-0.15	-0.40	-0.14	-0.38
t-stat	1.72	2.62	2.93	2.89	-1.04	1.92	0.54	-1.05	-2.50	-0.82	-1.59
5	0.32	0.45	0.46	0.58	0.43	0.16	0.24	0.25	-0.07	0.12	-0.19
t-stat	1.96	2.69	2.85	3.28	2.33	0.91	1.49	1.42	-0.38	0.55	-0.74
5-1	0.03	0.44	0.49	0.68	0.70	0.50	0.76	0.80	0.54	0.59	0.56
t-stat	0.16	1.83	2.06	2.72	2.47	1.86	2.67	2.79	1.82	1.83	1.73
All Stocks	0.18	0.21	0.20	0.21	-0.04	0.02	-0.02	-0.22	-0.26	-0.33	-0.52
t-stat	1.90	2.44	2.45	2.74	-0.52	0.29	-0.21	-2.53	-2.45	-2.22	-2.40
Panel B: Estimated CAPM beta											
1	0.24	0.54	0.73	0.88	1.03	1.17	1.33	1.51	1.74	2.19	1.95
2	0.23	0.53	0.72	0.87	1.01	1.16	1.31	1.49	1.73	2.19	1.97
3	0.23	0.54	0.72	0.88	1.02	1.16	1.32	1.50	1.74	2.21	1.98
4	0.24	0.55	0.74	0.89	1.03	1.18	1.33	1.52	1.75	2.22	1.98
5	0.26	0.58	0.77	0.92	1.06	1.21	1.37	1.55	1.78	2.26	2.00
All Stocks	0.20	0.50	0.69	0.85	0.99	1.15	1.30	1.49	1.73	2.21	2.01

Table 3: Beta anomaly with different benchmarks

This table reports alphas (with respect to the Fama-French three-factor model) of the beta anomaly for each of the five quintile portfolios formed on the stock-level fund performance. We first sort stocks into quintile portfolios based on the stock-level fund performance, defined as the weighted-average of the year-to-date excess returns (relative the benchmark index) of funds that hold the stock. Within each of the five fund performance quintile portfolios, we then compute the alpha of the strategy that buys stocks in the highest beta decile and sells stocks in the lowest beta decile. Stocks' betas are measured from the regressions of their returns on the benchmark index. The benchmark index includes the S&P 500 index, Large Value (Russell 1000 Value), Large Growth (Russell 1000 Growth), Small Value (Russell 2000 Value), and Small Growth (Russell 2000 Growth). The t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). We split the sample into two periods based on the Morningstar rating method change in June 2002. In Panel A, the sample period is January 1982 and June 2002 for all benchmarks but that of the small-cap value category, which starts from July 1996. In Panel B, the sample period is July 2002 and December 2018.

	Performance quintile				
Benchmarks	1	2	3	4	5
Panel A: Pre-June 2002					
S&P 500	-0.72	-0.41	-0.22	-0.39	0.21
t-stat	-1.83	-1.29	-0.59	-1.16	0.53
Large Value	0.05	-0.11	-0.21	-0.01	-0.40
t-stat	0.13	-0.30	-0.59	-0.03	-0.96
Large Growth	-0.76	-0.24	-0.26	-0.27	0.11
t-stat	-1.58	-0.52	-0.66	-0.67	0.19
Small Value	-0.86	-0.04	-1.13	0.24	1.22
t-stat	-0.96	-0.05	-1.15	0.35	1.54
Small Growth	-0.34	-0.83	-0.72	0.26	0.47
t-stat	-0.61	-1.69	-1.49	0.52	0.74
Panel B: Post-June 2002					
S&P 500	-0.16	-0.54	-0.96	-0.66	-0.50
t-stat	-0.43	-1.36	-2.88	-1.96	-1.34
Large Value	-1.16	-0.54	-0.21	-0.25	-0.11
t-stat	-3.14	-1.40	-0.61	-0.66	-0.28
Large Growth	-0.42	-0.33	-0.34	-0.52	-0.16
t-stat	-0.99	-0.89	-0.77	-1.29	-0.38
Small Value	-0.82	-0.69	-0.60	0.06	-0.39
t-stat	-2.18	-2.11	-1.95	0.20	-1.04
Small Growth	-0.91	-0.47	-0.68	-0.48	-0.47
t-stat	-2.20	-1.22	-1.95	-1.26	-1.22

Table 4: Morningstar rating change and risk shifts by underperforming funds in 2002

This table reports the cross-sectional regressions of changes of funds' holding beta on funds' ranking changes in 2002. We define changes of funds' holding beta as the difference between the beta of the change of stock holdings (relative to the second quarter) in the fourth quarter and the beta of stock holdings in the second quarter. Stocks' betas are measured from the regressions of their returns on the benchmark index including the S&P 500 index, Large Value (Russell 1000 Value), Large Growth (Russell 1000 Growth), Small Value (Russell 2000 Value), and Small Growth (Russell 2000 Growth). Fund's ranking change in 2002 is measured as the difference between its ranking within a fund category using its first-half year performance and its ranking within the fund universe. (1) and (2) look at the regressions with and without control variables, respectively. The control variables include the total net asset, the fund age, the turnover ratio, and the expense ratio. The t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is 2002.

$$Beta\_Change_i = \alpha + \beta Rank\_Change_i + \gamma_k \sum_{k=1}^{4} Control_{k,i} + \epsilon_i$$

	Decile Ranking		Vigintile ranking	
	(1)	(2)	(1)	(2)
Intercept	0.016	-0.000	0.015	-0.005
t-stat	1.28	-0.00	1.24	-0.12
Rank Change	-0.058	-0.058	-0.030	-0.029
t-stat	-15.31	-14.97	-15.24	-14.95
Net Asset		1.021		0.708
t-stat		0.37		0.27
Expense Ratio		1.915		2.084
t-stat		0.75		0.82
Turnover		-3.029		-2.922
t-stat		-2.42		-2.35
Age		1.305		1.399
t-stat		1.54		1.66
Adjusted R-sqr (%)	22.939	23.526	23.628	24.186

Table 5: Risk shifting by underperforming funds

This table reports the pooled cross-sectional time-series regressions of changes of funds' holding beta on their first-half-year performance, defined as the cumulative excess monthly returns (relative the Russell index) in the first-half-year. We define changes in funds' holding beta as the difference between the beta of change of stock holdings (relative to the second quarter) in the fourth quarter and the beta of stock holdings in the second quarter. Stocks' betas are measured from the regressions of their returns on the benchmark index including the S&P 500 index, Large Value (Russell 1000 Value), Large Growth (Russell 1000 Growth), Small Value (Russell 2000 Value), and Small Growth (Russell 2000 Growth). (1) and (2) look at the regressions with and without control variables, respectively. The control variables include the total net asset, the fund age, the turnover ratio, and the expense ratio, The t-statistics are based on the standard errors clustered at the fund level. The sample period is 1982 to 2018.

$$Beta\_Change_{i,t} = \alpha + \beta Fund\_Performance_{i,t} + \gamma_n \sum_{k=1}^{4} Control_{k,i,t} + \epsilon_{i,t}$$

	S&P 500		LV		LG		SV		SG	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	0.020	0.017	0.015	0.017	0.018	0.021	0.021	0.011	0.019	-0.007
t-stat	8.85	2.31	4.47	1.61	4.76	1.71	3.59	0.50	5.65	-0.52
Performance	-0.075	-0.076	-0.012	-0.012	-0.317	-0.311	-0.442	-0.446	-0.158	-0.160
t-stat	-1.92	-1.94	-1.59	-1.67	-3.36	-3.35	-3.66	-3.69	-1.86	-1.87
Net Asset		-0.155		-0.617		-0.253		2.755		-0.596
t-stat		-0.83		-1.30		-1.26		0.88		-0.39
Expense Ratio		0.836		0.495		0.724		1.063		1.431
t-stat		1.58		0.66		0.79		0.67		1.61
Turnover		-1.301		-1.365		-1.430		-1.431		-0.498
t-stat		-3.95		-1.84		-2.74		-2.84		-2.06
Age		0.238		0.085		0.076		0.262		0.792
t-stat		1.55		0.35		0.32		0.55		2.72
R-sqr (%)	0.064	0.243	-0.019	0.009	0.218	0.355	1.162	1.397	0.163	0.393

Table 6: Morningstar rating change and risk shifts by underperforming funds

This table reports the pooled cross-sectional time-series regressions of changes of funds' holding beta on their first-half-year performance, defined as the cumulative excess monthly returns (relative the Russell index) in the first a-half year. We define changes of funds' holding beta as the difference between the beta of changes of stock holdings (relative to the second quarter) in the fourth quarter and the beta of stock holdings in the second quarter. The control variables include the total net asset, the fund age, the turnover ratio, and the expense ratio, The t-statistics are based on the standard errors clustered at the fund level. Panel A looks at the period from 1982 to 2001, and Panel B looks at the period from 2003 to 2018.

$$Beta\_Change_{i,t} = \alpha + \beta Fund\_Performance_{i,t} + \gamma_k \sum_{k=1}^{4} Control_{k,i,t} + \epsilon_{i,t}$$

	S&P 500	LV	LG	SV	SG
		Panel A: Pre-2002			
$\widehat{\beta}$	-0.180	0.154	-0.181	0.036	-0.326
t-stat	-2.55	0.79	-1.18	0.19	-2.81
		Panel B: Post-2002			
$\widehat{\beta}$	-0.060	-0.014	-0.394	-0.625	0.035
t-stat	-1.86	-1.63	-3.28	-4.04	0.35

Table 7: Beta coefficient and demand elasticity

This table reports coefficients on stock betas with the benchmark in the demand system, $\eta_{i,t}$, sensitivities of holdings to price $\lambda_{i,t}$, and the implied demand elasticities for different groups of investors. We sort active mutual funds into five quintile portfolios based on their performance relative to their peers in the same category. We use GMM to estimate Equation 12 for each investor group. Panel A and B display the $\eta_{i,t}$ coefficients and $\lambda_{i,t}$ sensitivities, respectively. Panel C reports the demand elasticity of investors. We first measure an investor's elasticity on a given stock using Equation 13. We measure the investor-level elasticity as the weighted-average of her elasticity on stocks she holds (weighted by the holding value). The sample period covers the third and the fourth quarters in 2002.

	Active Mutual Fund					Other Investors		
Fund Rank	1	2	3	4	5	IF	IO	HH
Panel A: Demand system coefficient on stock beta, $\eta_{i,t}$								
2002 Q3	0.172	-0.140	-0.107	-0.113	-0.175	-0.021	-0.077	-0.261
t-statistic	2.88	-3.84	-1.69	-3.15	-4.88	-7.40	-10.36	-3.92
2002 Q4	0.140	-0.075	-0.137	-0.012	-0.169	-0.004	-0.083	-0.145
t-statistic	3.21	-2.41	-4.28	-0.38	-6.94	-0.49	-14.80	-2.74
Panel B: Sensitivity of holdings to price, $\lambda_{i,t}$								
2002 Q3	0.831	0.270	0.377	0.272	0.255	0.944	0.848	0.198
t-statistic	5.27	2.73	1.86	2.45	2.03	71.08	20.07	0.547
2002 Q4	0.636	0.212	-0.128	0.373	0.208	0.999	0.664	0.352
t-statistic	4.58	2.15	-1.34	2.54	1.89	22.26	16.65	0.996
Panel C: Demand elasticity								
2002 Q3	-0.175	-0.732	-0.625	-0.73	-0.748	-0.058	-0.152	-0.801
2002 Q4	-0.37	-0.789	-1.127	-0.629	-0.794	-0.002	-0.336	-0.647

Table 8: Counterfactual analysis in 2002

This table reports the impacts of underperforming funds by reallocating underperforming funds' AUM proportionally to all other investors. The repricing statistic ζ is caculated as, $\frac{\Sigma_{n=1}^{N}|ME_t^{CF}(n)-ME_t(n)|}{\Sigma_{n=1}^{N}ME_t(n)}$ in which CF denotes counterfactual market values and n denotes a stock that underperforming funds hold. We sort stocks into ten portfolios based on their betas, and calculate the repricing statistic (in percentage) for each beta decile portfolio. Panel A and B look at the third and the fourth quarters in 2002, respectively.

Beta Decile	1	2	3	4	5	6	7	8	9	10	10-1
Panel A: 2002 Q3											
LV	-0.34	-0.45	-0.38	-0.0	-0.25	-0.26	-0.68	-0.83	-0.51	-0.5	-0.16
LG	0.15	0.09	-0.99	-0.14	-0.49	-0.13	-0.82	-1.28	-1.94	-2.29	-2.44
SV	-0.4	-0.26	-0.41	-0.51	-0.63	-0.74	-0.97	-1.35	-1.82	-1.31	-0.91
SG	-0.25	-0.21	-0.24	-0.14	-0.37	-0.59	-0.65	-0.48	-1.06	-1.24	-0.99
Panel B: 2002 Q4											
LV	0.07	-0.09	-0.1	-0.2	-0.01	-0.11	-0.29	-0.29	-0.24	-0.21	-0.28
LG	0.07	0.04	0.05	-0.13	-0.02	-0.53	-0.38	-0.64	-0.43	-1.06	-1.13
SV	-0.07	-0.12	-0.16	-0.12	-0.24	-0.28	-0.33	-0.41	-0.48	-0.5	-0.43
SG	0.01	-0.01	-0.01	-0.17	-0.27	-0.20	-0.14	-0.22	-0.57	-0.55	-0.56

Table 9: Realized vs. Counterfactual style-level beta anomaly

This table reports realized and counterfactual monthly alphas for decile portfolios sorted on stocks' beta with the Russell index including Large Value (Russell 1000 Value), Large Growth (Russell 1000 Growth), Small Value (Russell 2000 Value), and Small Growth (Russell 2000 Growth). For each style-level beta anomaly, we look at the stocks held by funds in that category. Counterfactual returns in month t are computed as $\frac{P_t+D_t-P_{t-1}}{P_{t-1}}$, in which P denotes the monthly counterfactual share price and D denotes monthly dividend per share. Alphas are computed with respect to the Fama-French three-factor model. The t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is July 2002 to December 2018.

Decile	1	2	3	4	5	6	7	8	9	10	10-1
Panel A: Large Value											
Realized Alpha	0.21	0.05	0.23	0.05	0.08	0.00	-0.07	-0.09	-0.21	-0.16	-0.36
t-stat	1.86	0.51	1.79	0.47	0.61	0.02	-0.43	-0.55	-1.00	-0.71	-1.23
Counterfactual Alpha	0.21	0.07	0.23	0.10	0.09	0.01	-0.03	-0.08	-0.09	0.03	-0.18
t-stat	1.85	0.71	1.77	0.87	0.72	0.09	-0.19	-0.54	-0.43	0.12	-0.56
Panel B: Large Growth											
Realized Alpha	0.23	0.17	0.15	-0.08	0.01	0.01	-0.07	-0.05	-0.06	-0.26	-0.49
t-stat	1.89	1.58	1.43	-0.64	0.12	0.04	-0.48	-0.31	-0.28	-1.01	-1.44
Counterfactual Alpha	0.24	0.18	0.18	-0.09	0.03	0.00	-0.02	0.01	-0.01	-0.10	-0.35
t-stat	1.97	1.62	1.68	-0.78	0.23	0.03	-0.15	0.05	-0.06	-0.36	-0.95
Panel C: Small Value											
Realized Alpha	0.16	0.30	0.04	0.09	-0.11	-0.21	-0.12	-0.16	-0.40	-0.48	-0.64
t-stat	1.14	2.41	0.29	0.66	-0.78	-1.64	-0.89	-1.08	-2.17	-2.24	-2.23
Counterfactual Alpha	0.16	0.28	0.03	0.08	-0.14	-0.13	-0.03	-0.05	-0.20	-0.10	-0.26
t-stat	1.16	2.16	0.23	0.58	-0.98	-0.95	-0.20	-0.27	-0.93	-0.38	-0.78
Panel D: Small Growth											
Realized Alpha	0.28	0.30	0.11	-0.05	-0.01	-0.08	0.05	-0.22	-0.21	-0.43	-0.71
t-stat	1.83	2.27	0.70	-0.31	-0.09	-0.46	0.33	-1.24	-0.99	-1.76	-2.05
Counterfactual Alpha	0.26	0.30	0.22	-0.06	-0.02	-0.02	0.12	-0.09	0.04	-0.15	-0.41
t-stat	1.68	2.23	1.34	-0.42	-0.13	-0.10	0.75	-0.54	0.18	-0.50	-1.05

Table 10: Double sorts based on stock-level fund performance and return IVOL

The table reports monthly alphas for 5×10 portfolios formed by sorting on the stock-level fund performance and idiosyncratic volatility (IVOL). Alphas are computed with respect to the Fama-French three-factor model. We first sort stocks into quintile portfolios based on the stock-level fund performance, defined as the weighted-average of the year-to-date excess returns (relative the benchmark index) of funds that hold the stock. Because of the change in the Morningstar rating method, we use the S&P 500 index as the benchmark before June 2002 and the Russell index as the benchmark after June 2002 . Within each of the five fund performance quintile portfolios, we sort stocks into ten decile portfolios based on IVOL. The monthly IVOL for individual stock is calculated as the standard deviation of the residuals from the regression of the most recent month's daily returns on the Fama-French three factors (Ang et al. (2006)). The t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is January 1982 to December 2018.

Panel A: Alphas											
	IVOL Decile										
Performance quintile	1	2	3	4	5	6	7	8	9	10	10-1
1	0.16	0.02	-0.19	-0.32	-0.24	-0.37	-0.59	-0.86	-0.82	-1.39	-1.55
t-stat	1.35	0.12	-1.20	-2.04	-1.33	-1.92	-2.85	-3.89	-3.43	-5.23	-5.83
2	0.16	0.16	-0.19	-0.10	0.10	-0.36	-0.47	-0.38	-0.74	-1.03	-1.19
t-stat	1.41	1.47	-1.57	-0.74	0.69	-2.52	-2.96	-1.98	-3.51	-4.20	-4.38
3	0.09	0.04	-0.08	-0.23	0.15	-0.17	-0.18	-0.14	-0.66	-0.76	-0.84
t-stat	0.81	0.36	-0.61	-1.93	1.16	-1.12	-1.14	-0.78	-3.49	-3.47	-3.28
4	0.22	0.33	0.12	-0.07	-0.01	0.03	-0.15	-0.33	-0.16	-0.34	-0.56
t-stat	1.68	2.71	1.00	-0.60	-0.09	0.21	-0.91	-2.09	-0.90	-1.56	-2.01
5	0.39	0.45	0.44	0.31	0.30	0.13	0.14	0.12	-0.17	-0.38	-0.77
t-stat	3.35	2.76	2.23	1.88	1.65	0.75	0.78	0.65	-0.74	-1.50	-2.79
5-1	0.24	0.43	0.62	0.64	0.54	0.51	0.73	0.99	0.66	1.02	0.78
t-stat	1.35	1.80	2.13	2.40	1.76	1.74	2.39	3.12	1.86	2.71	2.24
All Stocks	0.21	0.17	0.00	-0.06	-0.00	-0.09	-0.23	-0.20	-0.61	-0.93	-1.14
t-stat	2.75	2.72	0.07	-0.75	-0.03	-1.05	-2.21	-1.65	-4.20	-4.96	-5.08
Panel B: Estimated IVOL											
1	0.008	0.011	0.013	0.016	0.018	0.020	0.024	0.027	0.033	0.049	0.042
2	0.007	0.010	0.012	0.014	0.016	0.019	0.022	0.025	0.031	0.046	0.039
3	0.007	0.010	0.012	0.014	0.016	0.018	0.021	0.025	0.030	0.046	0.039
4	0.007	0.010	0.012	0.014	0.017	0.019	0.022	0.025	0.031	0.046	0.038
5	0.008	0.011	0.014	0.016	0.019	0.021	0.024	0.028	0.034	0.051	0.043
All Stocks	0.007	0.010	0.012	0.015	0.017	0.020	0.023	0.027	0.034	0.051	0.044

Table 11: Double sorts based on stock-level fund performance and return skewness

The table reports monthly alphas for 5×10 portfolios formed by sorting on the stock-level fund performance and return skewness. Alphas are computed with respect to the Fama-French three-factor model. We first sort stocks into quintile portfolios on the stock-level fund performance, defined as the weighted-average of the year-to-date excess returns (relative the benchmark index) of funds that hold the stock. Because of the change in the Morningstar rating method, we use the S&P 500 index as the benchmark before June 2002 and the Russell index as the benchmark after June 2002. Within each of the five fund performance quintile portfolios, we sort stocks into ten decile portfolios based on return skewness. Following Bali et al. (2011), stocks' return skewness (lottery payoff) is defined as the average of its five highest daily returns in each month. The t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is January 1982 to December 2018.

	Skewness Decile										
Performance quintile	1	2	3	4	5	6	7	8	9	10	10-1
Panel A: Alphas											
1	0.36	0.27	0.08	-0.26	-0.13	-0.65	-0.64	-0.80	-1.28	-1.19	-1.55
t-stat	2.83	1.99	0.51	-1.58	-0.80	-3.67	-2.96	-4.13	-5.25	-4.60	-5.38
2	0.36	0.17	-0.03	-0.05	0.12	-0.30	-0.11	-0.65	-0.69	-0.94	-1.29
t-stat	2.79	1.42	-0.27	-0.41	0.77	-1.92	-0.60	-2.98	-3.28	-3.65	-4.22
3	0.27	0.23	0.09	0.12	-0.11	-0.37	-0.10	-0.27	-0.80	-0.52	-0.79
t-stat	2.44	2.07	0.78	0.96	-0.77	-2.57	-0.63	-1.54	-4.14	-2.18	-2.80
4	0.41	0.33	0.22	0.13	0.04	-0.08	0.06	-0.29	-0.29	-0.48	-0.89
t-stat	3.34	2.69	1.81	1.01	0.28	-0.51	0.37	-1.69	-1.63	-1.99	-2.98
5	0.29	0.45	0.51	0.45	0.51	0.12	0.24	0.00	0.01	-0.43	-0.73
t-stat	2.33	3.44	2.81	2.71	2.97	0.70	1.32	0.02	0.07	-1.71	-2.55
5-1	-0.07	0.19	0.43	0.71	0.64	0.77	0.87	0.81	1.30	0.76	0.83
t-stat	-0.40	1.00	1.66	2.59	2.31	2.73	2.80	2.45	3.83	2.07	2.30
All Stocks	0.30	0.28	0.12	0.06	-0.12	-0.08	-0.15	-0.26	-0.61	-0.93	-1.23
t-stat	3.40	3.52	1.79	0.86	-1.35	-0.89	-1.41	-2.03	-3.65	-4.92	-5.07
Panel B: Estimated Skewness											
1	0.011	0.017	0.020	0.024	0.028	0.032	0.036	0.042	0.051	0.075	0.064
2	0.011	0.016	0.019	0.022	0.026	0.029	0.034	0.039	0.048	0.070	0.059
3	0.011	0.016	0.019	0.022	0.025	0.029	0.033	0.039	0.047	0.069	0.058
4	0.011	0.016	0.020	0.023	0.026	0.030	0.034	0.040	0.048	0.070	0.058
5	0.012	0.017	0.022	0.025	0.029	0.033	0.038	0.044	0.053	0.077	0.065
All Stocks	0.010	0.015	0.019	0.023	0.027	0.031	0.036	0.042	0.052	0.076	0.066

Internet Appendix for "Mutual Fund Risk Shifting and Risk Anomalies"

A1. Style-level beta anomaly

Motivated by Barberis and Shleifer (2003), in this section, we show that the beta anomaly exists at the style-investing level. More specially, Table A1 reports the style-level beta anomaly. Similar to the results in Panel A, row "All Stocks" of Table 2 where we use CAPM beta to sort portfolios, we find similar patterns when sorting on style beta.

A2. Are underforming funds just dumb and always holding overpricing stocks?

To rule out the possibility that our main finding (presented in Table 2) is driven by funds who are dumb and always invest into high-beta stocks that generate lower alphas, we conduct two tests. First, we check whether mutual funds who underperform previously will continue to hold overpricing stocks and therefore, underperform subsequently. To examine this, we use a mispricing measure constructed by Stambaugh and Yuan (2017). The mispricing score ranges from 1 to 100 and a higher score indicates more overpricing.

Table A2 reports the results. We find that funds who underperform previously are not always holding overpricing stocks. For example, funds who perform the worst in the last year tend to hold less overpricing stocks in the current year, as shown in the second column of Table A2. More importantly, underperforming funds perform better with more reduction of the overpricing score of their holdings. Overall, these findings suggest that underperforming funds are not always dumb and holding overpricing stocks.

In the second test, we calculate the alpha of the beta anomaly for stock portfolios formed on the stock-level fund-current-performance and stock-level fund-past-performance. If our finding in Table 2 is driven by funds who are dumb and always invest into high-beta stocks, then we should expect a more prominent beta anomaly among stocks held by funds who underperform in both current and past year. However, we find this is not the case. Table A3 indicates that there is little variation in the alpha of the beta anomaly across stock portfolios with different past performance.

A3. Robustness checks: Other beta measures

We check the robustness of the findings presented in Table 2 by using other beta measures. We consider the method using one year of daily returns with the Dimson correction (Hong and Sraer (2016) and Cederburg and O'doherty (2016)) and the method of Frazzini and Pedersen (2014) that estimates the correlations between stocks and market portfolio and the volatility of market portfolio separately.

For the first beta measurement, we use the past 12 months of daily returns to estimate the market beta for stock n in month t:

$$r_{n,t} = a_n + \beta_{n,1} r_{m,t} + \beta_{n,2} r_{m,t-1} + \beta_{n,3} \frac{r_{m,t-2} + r_{m,t-3} + r_{m,t-4}}{3} + \epsilon_{n,t}.$$

The stock's time-series beta estimate is computed as:

$$\hat{\beta}^{ts}_{n,t} = \hat{\beta}_{n,1} + \hat{\beta}_{n,2} + \hat{\beta}_{n,3}.$$

Regarding the method of Frazzini and Pedersen (2014), the estimated beta of stock n is give by:

$$\hat{\beta}^{ts}_{n} = \hat{\rho} \frac{\hat{\sigma_n}}{\hat{\sigma_m}}$$

Following Frazzini and Pedersen (2014), we estimate volatilities using a one-year rolling standard deviation and require at least 120 trading days with non-missing data. We estimate correlations using a five-year rolling window and overlapping three-day log returns, requiring at least 750 trading days for non-missing data. Finally, we shrink the time-series beta estimates to reduce the influence of outliers (see Section 2.2 for details).

Table A5 and A4 report the robustness check with the beta estimated from one-year daily returns and the beta of Frazzini and Pedersen (2014), respectively. Overall, we find consistent results that the beta anomaly is more significant among stocks held by underperforming funds.

A4. Beta anomaly in the first and second half of a year

Chevalier and Ellison (1997) find that funds who underperform in the first-half year increase their portfolio risk to catch up toward the year end. If our findings in Table 2 are driven by this mechanism, we expect that the beta anomaly across the stocks held by underperforming funds is more significant in the second-half year. Table A6 reports the beta anomaly across the stocks held by underperforming funds for the first half (panel A) and second half (panel B) of the year following the same procedures as in Table 2. Indeed, we find a stronger beta anomaly in the second half of the year.

A5. Fund flow and beta anomaly

Prior studies find that flow-induced trading has significant impacts on stock prices (Coval and Stafford (2007) and Lou (2012)). The beta anomaly could arise from the selling pressure of underperforming funds resultant from investor redemption. To explore this explanation, we sort stocks into 3×3 portfolios based on the stock-level fund performance and the stock-level fund flow (sequentially); we further examine the beta anomaly of each portfolio. Funds' monthly flows are calculated as $\frac{TNA_t}{TNA_{t-1}} - (1 + ret_t)$. The stock-level fund flow is defined as the weighted-average of flows of funds that hold the stock, and a smaller value of this measure indicates the stock is mainly held by funds who have smaller or potentially negative flows. Table A7 reports the monthly alpha of the beta anomaly for each portfolio. We find little variation in the beta-anomaly alphas across portfolios with different flows and the beta anomaly is only dependent on the fund performance.

A6. Exogenous downgrade and risk shifting

Table 4 shows that there exists a negative relation between rank change and beta change. However, this finding could be well driven by the outperforming funds' incentives to lower their risk. To investigate whether it is indeed mainly the downgrading funds engaging in risk shifting, we redo the regression in Equation (5) excluding the funds who experienced ranking increase after the Morningstar rating method change. Table A8 provides the results. We find that there still exists a negative relation between rank change and beta change in the sense that funds experience more downward changes in their ranks do more risk shifting which rule out the alternative story.

A7. Risk shifting across funds with different past performance

It is possible that underperforming funds and outperforming funds engage in risk-shifting in different manners. We group funds based on their performance in the first half of a year and report the changes in the betas of funds' portfolios with their respective benchmarks in the second half of the year. Table A9 Panel A reports the demeaned beta changes for fund quintile portfolios sorted on their first half-year year-to-date excess returns within a category. The beta change is computed the same way as in Table 6. We find that funds that underperform in the first half of the year tend to increase their portfolio betas in the second half of the year; while the outperforming funds tend to reduce their betas. The difference in the beta changes between underperforming and outperforming funds is 0.015.

In Table A9 Panel A, we investigate the heterogeneous response of risk-shifting to *relative* past performance. In Table A9 Panel B, we focus on the heterogeneous response of risk-shifting to *absolute* past performance. More specifically, we group funds using cutoffs based on the cross-sectional standard deviation of the performance. Each year we sort funds into groups based on their year-to-date excess returns (relative to the appropriate benchmark). We then group them into five portfolios with breakpoints equal to -1, $-\frac{1}{2}$, $\frac{1}{2}$, and one standard deviation around zero, since zero indicates that a fund has the same year-to-date return as the benchmark. We find that funds in the second group, i.e. funds that just underperform the benchmark by small amount (with average returns of -2.1% in the first half of a year) have the strongest incentive to risk shift, with demeaned beta changes of 0.005.

A8. Morningstar rating change and fund flows in 2002

We investigate whether the downgrades caused by Morningstar rating change in June 2002 could lead to outflows from those funds due to investors' "star"-chasing behaviors using the following specification:

$$Flow_i = \alpha + \beta Rank\_Change_i + \gamma_k \sum_{k=1}^{5} Control_{k,i} + \epsilon_i,$$

in which fund i's flow is defined as $\frac{TNA_{Dec}}{TNA_{Jun}} - 1 - Cum\_ret$, where TNA_{Dec} and TNA_{Jun} are total net assets in December and June of 2002, respectively.[22] Cum_ret is fund i's cumulative returns from June to December of 2002.

Table A10 reports the regression results. We find a significantly negative relation between fund flows and ranking changes: a one unit decrease in the decile ranking after the Morningstar rating method change results in 0.007 lower flows in the second half year of 2002. Further, The results remain robust when including standard control variables and when using vigintile ranking to rank funds.

A9. Tests of weak identification

The instrument that we proposed in Section 5.2.2 needs to satisfy the relevance and free of weak identification problems. We report the minimum eigenvalue statistics (i.e., Cragg Donald statistics) for the first-stage regression of log market equity onto the instrument and other firm characteristics. We find that the first-stage minimum eigenvalue statistics are all above the critical value proposed by Stock and Yogo (2005).

A10. Identifying S&P 500 index funds

We identify the S&P 500 index funds using two criteria. First, we lowercase all fund names and select funds whose name contains "s&p 500 index". Second, for the above identified potential funds, we check the Thomson Reuters s12 files to verify if the number of stocks a S&P 500 index fund holds each quarter is around 500. If a fund passes the two criteria, we label it as a S&P 500 fund. Notice that, the number of stocks held by S&P funds might not be exactly 500 due to the index reconstitution.

[22]For funds with extreme flows of more than 5 or less than -0.9, we exclude them in the regressions.

A11. Repricing statistics for the post-2002 period

Table A14 reports the repricing statistics of underperforming funds in each category by allocating underperforming funds' AUM proportionally to all other investors' in the post-2002 period. We find that underperforming funds in each investing category have larger impacts on stocks that have a high beta with respect to the category benchmarks.

A12. The relationship between repricing and alpha decay

How does this decline of the alpha from the beta anomaly relate to the repricing that occurs in the counterfactual equilibrium? In this section, we provide a parsimonious framework to analyze this question.

To begin with, we denote the log of price-dividend ratio of an asset as $z_t = \log\left(\frac{P_t}{D_t}\right)$. For the ease of notation, we omit all the asset specific subscripts. Next, we use Campbell-Shiller approximation (Campbell and Shiller (1988)) to decompose the log return:

$$r_{t+1} \approx \kappa_0 + \kappa_1 z_{t+1} - z_t + g_{t+1}.$$

Solving forward for z_t, we have

$$z_t = \frac{\kappa_0}{1-\kappa_1} + \left[\sum_{j=0}^{\infty} \kappa_1^j \left(g_{t+1+j} - r_{t+1+j}\right)\right].$$

To facilitate the analysis, we make some simplifying assumptions:

1. The asset return follows a factor structure: $r_{t+1} = \alpha_{t+1} + \beta' f_{t+1} + \epsilon_{t+1}$, where $\beta' f_{t+1}$ represents the compensation for exposure to systematic risk factor(s) f. The decay in mispricing α_{t+1} is captured by an autoregressive process: $\alpha_{t+1} = \phi\alpha_t + \varepsilon_{t+1}$. For a given asset, the exposures to the risk factors are the same in both the counterfactual and the realized world and it is time invariant.

2. In both the counterfactual and the realized world, g_{t+1} is fixed at 0. (This assumption can be easily relaxed.)

Based on the above assumptions, we can express the realized z_t as

$$
\begin{aligned}
z_t &= \frac{\kappa_0}{1-\kappa_1} + \left[\sum_{j=0}^{\infty} \kappa_1^j \left(0 - (\alpha_{t+1+j} + \beta f_{t+1+j} + \epsilon_{t+1+j})\right)\right] \\
&= \frac{\kappa_0}{1-\kappa_1} - \left[\sum_{j=0}^{\infty} \kappa_1^j \left(\alpha_{t+1+j} + \beta f_{t+1+j} + \epsilon_{t+1+j}\right)\right] \\
&= \frac{\kappa_0}{1-\kappa_1} - \frac{\alpha_{t+1}}{1-\phi\kappa_1} - \beta\left[\sum_{j=0}^{\infty} \kappa_1^j f_{t+1+j}\right].
\end{aligned}
$$

Similarly, we have the counterfactual log of price-dividend ratio

$$
z_t^{CF} = z_t + \frac{\alpha_{t+1}^{dif}}{1-\phi\kappa_1},
$$

where α_{t+1}^{dif} is the alpha difference between realized beta anomaly and counterfactual beta anomaly using the returns (at $t+1$) following the formation period (at t).

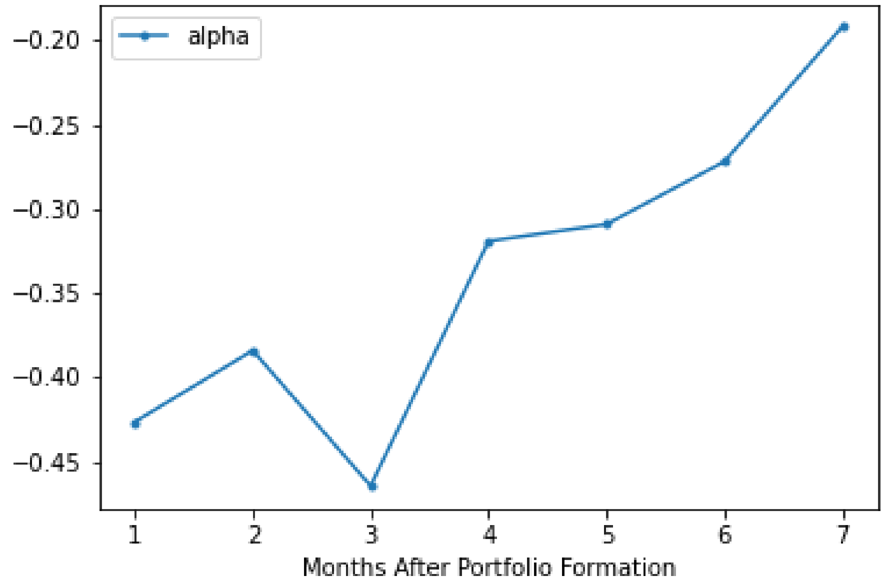
Now if we define the asset specific repricing measure ζ in a given time period t as $\frac{P_t^{CF}-P_t}{P_t}$. Further, if we assume the current dividend D_t is the same in both the counterfactual and the real world, then we have

$$
\begin{aligned}
\zeta_t(n) &= \frac{P_t^{CF} - P_t}{P_t} \\
&= \frac{P_t(n)^{CF}/D_t - P_t/D_t}{P_t/D_t} \\
&= \frac{\exp(z_t^{CF}) - \exp(z_t)}{\exp(z_t)} \\
&= \exp\left(\frac{\alpha_{t+1}^{dif}}{1-\phi\kappa_1}\right) - 1
\end{aligned}
$$

The above expression explicitly links the (stock-level) repricing with (stock-level) alpha. When we need to link the portfolio-level repricing with portfolio-level alpha, we can simply value-weight the two variables.

Now, let's take the high-beta stock portfolio in Small Growth fund category (beta is measured with the Small Growth category benchmark) as an example. By looking at the alpha of the high-beta stock for different horizons, we find an estimate of 0.50 for ϕ using an AR(1) model. If we plug in the value of $\kappa_1 = 0.96$ (4% dividend price ratio), $\phi = 0.50$ and

Figure A1: Alphas for different horizons



This figure plots the monthly alpha of a value-weighted portfolio with the highest beta with respect to the Small Growth category benchmark Russell 2000 Growth, for different horizons.

$\alpha_{t+1}^{dif} = -0.28\%$ (shown in Table 9) we have

$$\zeta = exp(-0.0058) - 1 = -0.58\%.$$

Therefore, the repricing of high-beta stocks must be more negative than -0.58%, so that it can produce an alpha decline of 0.28%. As shown by Table 8, the average repricing is -0.99% in 2002 Q3 for high-beta stocks in the Small Growth category.

A13. Robustness check: other low risk puzzles

Bali et al. (2011) and Ang et al. (2006) find negative return/IVOL and return/skewness relations, respectively. To check whether our results are consistent with those prior studies, we report value-weighted returns for 5×10 portfolios formed by sorting on stock-level fund performance and IVOL/return skewness. Table A15 and A16 report the results. Overall, we find that the return/IVOL relation and the return/skewness relation tend to be more significant among stocks that are largely held by underperforming funds.

A14. Robustness check: Morningstar rating

We check whether our main results presented in Tables 2, 10, and 11 are robust if we use the actual Mornningstar star ratings as a measure of the fund's performance instead of uinsg the year-to-date excess returns. Morningstar rating is assigned based on a relative ranking system, and a higher rating indicates the funds have better past performance, measured by Morningstar risk adjusted return (MRAR).[23] Before June 2002, Morningstar ranked all funds together based on their MRAR and assigned star ratings based on the estimated ranks. For example, the top 10% funds receive five stars, while the bottom 10% receive one star. After June 2002, funds are ranked against their peers in the same categories (investing styles).

Tables A17, A18, and A19 reports the results. Overall we find consistent results: the low-risk anomalies are more significant across stocks held by funds who are assigned lower Morningstar ratings (poorer past performance).

[23] See Evans and Sun (2021) and Ben-David et al. (2022) for more details about the Morningstar rating system.

Table A1: Style-level beta anomaly

This table reports monthly alphas for decile portfolios formed by sorting on betas with respect to the S&P500 index and the Russell index including Large Value (Russell 1000 Value), Large Growth (Russell 1000 Growth), Small Value (Russell 2000 Value), and Small Growth (Russell 2000 Growth). For each style-level beta anomaly, we look at the stocks held by funds in that category. Alphas are computed with respect to the Fama-French three-factor model. Stock's style betas are estimated in the same fashion as stock's CAPM beta as described in Section 2.2: we only replace market excess return with corresponding index excess returns. The t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is January 1982 to December 2018.

	Beta Decile										
	1	2	3	4	5	6	7	8	9	10	10-1
S&P 500	0.20	0.14	0.15	0.15	0.05	0.01	-0.07	-0.07	-0.23	-0.26	-0.47
t-stat	1.95	1.69	1.59	1.76	0.62	0.16	-1.10	-0.84	-2.15	-1.87	-2.16
Large Value	0.03	0.14	0.19	0.09	0.10	0.04	-0.14	-0.16	-0.24	-0.22	-0.25
t-stat	0.28	1.66	2.38	1.13	1.29	0.51	-1.65	-1.61	-2.00	-1.77	-1.29
Large Growth	0.14	0.22	0.08	-0.01	-0.01	-0.02	-0.00	-0.07	-0.17	-0.31	-0.44
t-stat	1.44	2.22	0.82	-0.11	-0.06	-0.23	-0.00	-0.70	-1.25	-1.80	-1.90
Small Value	0.23	0.27	0.14	0.15	-0.03	-0.01	-0.08	-0.09	-0.03	-0.24	-0.47
t-stat	1.70	2.59	1.29	1.31	-0.28	-0.05	-0.68	-0.86	-0.23	-1.80	-2.25
Small Growth	0.30	0.17	0.23	0.16	-0.06	-0.04	-0.15	-0.16	-0.38	-0.43	-0.73
t-stat	2.64	1.43	1.95	1.43	-0.56	-0.38	-1.17	-1.19	-2.31	-2.21	-2.85

Table A2: Change of mispricing score

This table reports the change of mispricing scores of 3×3 fund portfolios sorted on current performance and past performance, independently. Funds' current (past) performance is defined as the year-to-date excess return relative to benchmarks in the current (past) year. We use a cutoff of 12 months as the month gap between measuring current and past performance. Mispricing score is measured as in Stambaugh and Yuan (2017) in which a higher value indicates more overpricing. We first measure the mispricing score at the fund level. We then sort funds into 3×3 portfolios based on their current and past performance. Finally, we calculate the mispricing score of each fund portfolio, value-weighted by funds' asset under management. The change of mispricing score is measured as the difference between the mispricing score of holdings in the current quarter and the mispricing score of holdings four quarters ago. The sample period is January 1982 to December 2018.

	Past-year Performance		
Current-year Performance	Underperform	Medium	Outperform
Underperform	-0.35	0.19	0.46
t-stat	-1.96	1.16	2.68
Medium	-0.64	-0.10	0.31
t-stat	-4.21	-0.66	1.89
Outperform	-0.97	-0.63	-0.10
t-stat	-5.83	-4.09	-0.63

Table A3: Beta anomaly and funds' past performance

This table reports the monthly alpha (with respect to the Fama-French three-factor model) of the beta anomaly for each 3×3 stock portfolios sorted on the stock-level fund current performance and the stock-level fund past performance. Funds' current (past) performance is defined as the year-to-date excess return relative to benchmarks in the current (last) year. We use a cutoff of 12 months as the month gap between measuring current and past performance. The t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is January 1982 to December 2018.

	Past-year Performance		
Current-year Performance	Underperform	Medium	Outperform
Underperform	-0.38	-0.70	-0.91
t-stat	-1.28	-2.51	-3.06
Medium	-0.55	-0.49	-0.47
t-stat	-1.87	-1.83	-1.62
Outperform	-0.00	-0.43	-0.25
t-stat	-0.01	-1.46	-0.82

Table A4: Double sorts on stock-level fund performance and betas measured with daily returns

This table reports monthly alphas for 5×10 portfolios formed by sorting on the stock-level fund-performance and the CAPM beta. Alphas are computed with respect to the Fama-French three-factor model. We first sort stocks into quintile portfolios based on the stock-level fund-performance, defined as the weighted-average of the year-to-date excess returns (relative the benchmark index) of funds that hold the stock. Because of the change in the Morningstar rating method, we use the S&P 500 index as the benchmark before June 2002 and the Russell index as the benchmark after June 2002. Within each of the five fund-performance quintile portfolios, we sort stocks into ten decile portfolios based on betas. Stocks' betas are measured from the regressions of the past one-year daily returns on the market excess returns. For more details regarding the beta estimation, please refer to Hong and Sraer (2016). The t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is January 1982 to December 2018.

	Beta Decile										
Performance quintile	1	2	3	4	5	6	7	8	9	10	10-1
1	0.14	0.01	0.04	0.05	-0.07	-0.10	-0.43	-0.51	-0.84	-1.15	-1.29
t-stat	0.73	0.05	0.28	0.35	-0.43	-0.60	-2.41	-2.48	-3.30	-4.23	-3.67
2	0.03	0.12	0.24	0.20	-0.01	-0.21	0.03	-0.44	-0.18	-0.88	-0.91
t-stat	0.20	0.82	1.83	1.44	-0.07	-1.63	0.21	-2.68	-1.00	-3.85	-3.07
3	-0.06	0.17	0.13	-0.01	0.01	0.13	-0.06	-0.10	-0.44	-0.69	-0.63
t-stat	-0.35	1.30	1.00	-0.11	0.08	1.05	-0.42	-0.70	-2.60	-3.46	-2.15
4	0.33	0.25	0.37	0.43	0.07	0.06	0.02	0.20	-0.23	-0.38	-0.71
t-stat	2.01	1.76	2.82	3.33	0.56	0.47	0.12	1.46	-1.29	-1.82	-2.47
5	0.02	0.28	0.40	0.32	0.56	0.26	0.30	0.31	0.21	-0.40	-0.43
t-stat	0.15	1.78	3.08	2.39	3.70	1.39	1.48	1.56	0.97	-1.70	-1.42
5-1	-0.11	0.27	0.36	0.27	0.63	0.36	0.73	0.83	1.05	0.75	0.87
t-stat	-0.52	1.32	1.83	1.27	2.45	1.25	2.28	2.55	2.78	2.19	2.33
All Stocks	0.12	0.10	0.15	0.19	0.06	0.06	-0.15	-0.13	-0.05	-0.67	-0.78
t-stat	0.79	0.93	1.57	2.13	0.92	0.71	-2.01	-1.20	-0.38	-3.37	-2.66

Table A5: Double sorts on stock-level performance and beta measured as in Frazzini and Pedersen (2014)

This table reports monthly alphas for 5×10 portfolios formed by sorting on the stock-level fund-performance and the CAPM beta. Alphas are computed with respect to the Fama-French three-factor model. We first sort stocks into quintile portfolios based on the stock-level fund-performance, defined as the weighted-average of the year-to-date excess returns (relative the benchmark index) of funds that hold the stock. Because of the change in the Morningstar rating method, we use the S&P 500 index as the benchmark before June 2002 and the Russell index as the benchmark after June 2002. Within each of the five fund-performance quintile portfolios, we sort stocks into ten decile portfolios based on betas. Stocks' betas are measured as in Frazzini and Pedersen (2014). The t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is January 1982 to December 2018.

	Beta Decile										
Performance quintile	1	2	3	4	5	6	7	8	9	10	10-1
1	0.34	0.32	0.20	0.18	0.13	-0.05	-0.34	-0.44	-0.46	-1.17	-1.51
t-stat	2.18	2.31	1.37	1.16	0.95	-0.28	-2.31	-2.53	-2.24	-4.41	-4.81
2	0.35	0.29	0.28	0.07	0.04	-0.07	-0.06	-0.02	-0.36	-1.05	-1.40
t-stat	2.27	1.86	2.34	0.57	0.32	-0.50	-0.38	-0.15	-2.04	-5.02	-5.11
3	0.27	0.44	0.11	0.17	0.14	-0.12	-0.21	-0.27	-0.29	-0.76	-1.04
t-stat	1.65	3.50	1.01	1.32	1.17	-0.95	-1.61	-1.99	-1.80	-3.83	-3.52
4	0.21	0.28	0.26	0.53	0.28	0.17	0.13	-0.20	-0.17	-0.44	-0.64
t-stat	1.31	2.15	1.84	3.49	2.17	1.23	1.04	-1.44	-1.14	-2.25	-2.31
5	0.16	0.41	0.28	0.14	0.49	0.42	0.43	0.13	-0.01	-0.18	-0.34
t-stat	1.00	3.16	1.85	1.00	3.28	2.75	2.78	0.65	-0.03	-0.74	-1.11
5-1	-0.18	0.09	0.08	-0.04	0.35	0.47	0.77	0.57	0.45	0.98	1.16
t-stat	-0.94	0.54	0.39	-0.19	1.64	1.95	3.21	1.90	1.23	2.64	2.95
All Stocks	0.30	0.38	0.31	0.15	0.10	0.03	-0.09	-0.19	-0.29	-0.58	-0.89
t-stat	1.97	3.30	3.25	1.56	1.17	0.31	-1.01	-2.12	-2.87	-3.63	-3.33

Table A6: Beta anomaly in the first and second half of a year

The table reports monthly alphas for 5×10 portfolios formed by sorting on the stock-level fund-performance relative to the benchmark index and the CAPM beta. The sorting variables are the same as those described in Table 2. Panel A and B looks at the first and second half of a year, respectively. The sample period is January 1982 to December 2018.

	Beta Decile										
Performance quintile	1	2	3	4	5	6	7	8	9	10	10-1
Panel A: First-half year											
1	0.27	-0.18	0.03	-0.09	-0.02	-0.05	-0.25	-0.35	-0.18	-0.10	-0.37
t-stat	1.28	-0.86	0.12	-0.48	-0.10	-0.20	-0.91	-1.25	-0.61	-0.30	-0.92
2	0.02	0.36	0.16	0.09	-0.11	-0.16	-0.05	-0.19	-0.29	-0.41	-0.43
t-stat	0.09	1.92	0.80	0.45	-0.58	-0.79	-0.24	-0.85	-1.15	-1.34	-1.13
3	0.08	-0.03	0.14	-0.21	-0.15	0.04	-0.31	-0.08	-0.02	-0.53	-0.61
t-stat	0.38	-0.16	0.75	-1.14	-0.81	0.23	-1.71	-0.37	-0.08	-2.05	-1.58
4	0.18	0.36	0.22	0.42	-0.09	0.32	0.15	-0.00	-0.40	-0.32	-0.50
t-stat	0.88	2.25	1.13	2.21	-0.51	1.69	0.63	-0.02	-1.68	-1.25	-1.46
5	0.33	0.26	0.29	0.43	0.12	0.09	0.30	0.12	-0.58	-0.19	-0.51
t-stat	1.46	1.06	1.17	1.72	0.54	0.41	1.32	0.52	-2.52	-0.68	-1.48
5-1	0.06	0.44	0.26	0.52	0.14	0.14	0.56	0.47	-0.40	-0.09	-0.14
t-stat	0.19	1.41	0.71	1.44	0.41	0.36	1.33	1.18	-1.00	-0.20	-0.33
All Stocks	0.16	0.24	0.21	0.15	-0.03	0.07	0.05	-0.23	-0.07	-0.36	-0.52
t-stat	1.17	1.94	1.77	1.48	-0.27	0.69	0.52	-1.83	-0.43	-1.62	-1.70
Panel B: Second-half year											
1	0.25	0.23	0.04	-0.00	-0.36	-0.42	-0.65	-0.62	-0.84	-0.75	-0.99
t-stat	1.28	1.12	0.23	-0.01	-1.51	-2.23	-2.63	-2.67	-3.05	-2.66	-2.70
2	0.37	0.20	-0.02	0.02	0.28	-0.14	-0.19	-0.27	-0.70	-0.34	-0.71
t-stat	1.91	1.15	-0.12	0.12	1.40	-0.68	-0.86	-1.37	-3.00	-1.33	-2.09
3	0.17	0.05	0.06	-0.09	0.34	-0.16	-0.27	-0.17	-0.75	-0.23	-0.41
t-stat	0.88	0.27	0.31	-0.50	2.11	-0.90	-1.27	-0.96	-2.98	-0.81	-1.10
4	0.28	0.36	0.58	0.36	-0.14	0.26	0.04	-0.32	-0.35	-0.01	-0.30
t-stat	1.59	1.75	2.86	2.07	-0.60	1.20	0.23	-1.64	-1.65	-0.05	-0.90
5	0.15	0.45	0.47	0.50	0.65	0.06	0.13	0.29	0.28	0.21	0.06
t-stat	0.71	2.00	2.19	2.23	2.00	0.29	0.55	1.20	1.06	0.66	0.15
5-1	-0.09	0.22	0.42	0.51	1.01	0.48	0.77	0.91	1.12	0.96	1.05
t-stat	-0.35	0.63	1.39	1.67	2.17	1.55	2.13	2.47	2.72	2.21	2.25
All Stocks	0.20	0.20	0.24	0.31	-0.05	-0.01	-0.05	-0.17	-0.47	-0.30	-0.50
t-stat	1.46	1.61	2.06	2.65	-0.47	-0.12	-0.42	-1.53	-3.42	-1.43	-1.65

Table A7: Beta anomaly and fund flow

The table reports the monthly alpha (with respect to the Fama-French three-factor model) of the beta anomaly for each 3×3 stock portfolios sorted on the stock-level fund performance and the stock-level fund flow. The stock-level fund performance is defined as the weighted-average of the year-to-date excess returns (relative the benchmark index) of funds that hold the stock. The stock-level fund flow is defined as the weighted-average of flows of funds that hold the stock. Funds' monthly flows are calculated as $\frac{TNA_t}{TNA_{t-1}} - (1 + ret_t)$. The t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is January 1982 to December 2018.

		Fund Flow	
Fund Performance	Small	Medium	Large
Underperform	-0.79	-0.79	-1.11
t-stat	-2.21	-1.95	-3.21
Medium	-0.08	-0.68	-0.57
t-stat	-0.26	-2.14	-1.79
Outpeform	-0.03	-0.03	0.14
t-stat	-0.10	-0.09	0.40

Table A8: Morningstar rating change and risk shifts by underperforming funds in 2002

This table reports the cross-sectional regressions of changes of funds' holding beta on funds' ranking changes in 2002. We define changes of funds' holding beta as the difference between the beta of the change of stock holdings (relative to the second quarter) in the fourth quarter and the beta of stock holdings in the second quarter. Stocks' betas are measured from the regressions of their returns on the benchmark index including the S&P 500 index, Large Value (Russell 1000 Value), Large Growth (Russell 1000 Growth), Small Value (Russell 2000 Value), and Small Growth (Russell 2000 Growth). Fund's ranking change in 2002 is measured as the difference between its ranking within a fund category using its first-half year performance and its ranking within the fund universe. We look at the regressions excluding the funds who experienced ranking increase after the Morningstar rating method change in June 2002. The control variables include the total net asset, the fund age, the turnover ratio, and the expense ratio. The t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is 2002.

$$Beta\_Change_i = \alpha + \beta Rank\_Change_i + \gamma_k \sum_{k=1}^{4} Control_{k,i} + \epsilon_i$$

	Decile Ranking	Vigintile ranking
Intercept	0.117	0.072
t-stat	1.65	0.99
Rank Decline	-0.037	-0.014
t-stat	-4.23	-3.13
Net Asset	0.678	1.273
t-stat	0.28	0.54
Expense Ratio	-1.592	3.784
t-stat	-0.38	0.90
Turnover	-4.282	-2.968
t-stat	-2.76	-2.58
Age	2.627	2.001
t-stat	1.82	1.37
Adjusted R-sqr (%)	10.429	6.061

Table A9: Risk shifting across funds with different performance

This table reports beta changes of fund portfolios sorted on their first half-year year-to-date excess returns (relative the benchmark index) within a category. In Panel A, we sort funds into quantile portfolios based on their performance. In Panel B, we sort funds into portfolios using the standard deviation of the performance. Each year we break funds into outperform (underperform) groups if their year-to-date excess returns are larger (smaller) than zero plus (minus) one standard deviation of funds' year-to-date excess returns in the same category. The cutoff of the middle three portfolios is a half of the one standard deviation of funds' year-to-date excess returns. The first, the second, and the third rows in each panel look at the equal-weighted average of year-to-date excess returns, beta changes defined as in Table 6, and number of funds in each fund portfolio, respectively. We demean the beta changes each year for funds in each category. The sample period is 2003 to 2018.

Performance	Underperform	2	3	4	Outperform
Panel A: Quintile Sort					
YTD Excess Returns	-0.036	-0.012	0.001	0.015	0.046
Beta Change	0.004	0.003	0.004	0.000	-0.011
Number of Funds	94	96	96	96	95
Panel B: Standard-deviation Sort					
YTD Excess Returns	-0.046	-0.021	0.000	0.022	0.057
Beta Change	0.002	0.005	0.002	0.002	-0.014
Number of Funds	66	70	203	64	75

Table A10: Morningstar rating change and fund flows in 2002

This table reports the cross-sectional regressions of fund flows in the second half year of 2002 on fund's ranking change. We define fund i's flow as $\frac{TNA_{Dec}}{TNA_{Jun}} - (1 + Cum\_ret)$ where TNA_{Dec} and TNA_{Jun} are total net asset in December and June, respectively. Cum_ret is funds' cumulative returns from June to December. Stocks' betas are measured from the regressions of their returns on the benchmark index including Large Value (Russell 1000 Value), Large Growth (Russell 1000 Growth), Small Value (Russell 2000 Value), and Small Growth (Russell 2000 Growth). Fund's ranking change in 2002 is measured as the difference between its ranking within the fund universe and its ranking within a fund category using its first-half year performance. (1) and (2) look at the regressions with and without control variables, respectively. The control variables include the total net asset, the fund age, the turnover ratio, the expense ratio and the year-to-date excess returns. The t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is in 2002.

$$Flow_i = \alpha + \beta Rank\_Change_i + \gamma_j \sum_{j=1}^{5} Control_{j,i} + \epsilon_i$$

	Decile Ranking		Vigintile ranking	
	(1)	(2)	(1)	(2)
Intercept	0.041	0.218	0.041	0.218
t-stat	4.23	5.35	4.23	5.35
Rank Change	-0.007	-0.009	-0.003	-0.004
t-stat	-2.09	-2.68	-1.93	-2.54
Net Asset		-1.966		-1.909
t-stat		-1.20		-1.17
Expense Ratio		-7.278		-7.297
t-stat		-3.22		-3.23
Turnover		-2.602		-2.582
t-stat		-4.35		-4.32
Age		-3.807		-3.816
t-stat		-5.30		-5.30
Return		-0.006		-0.006
t-stat		-0.19		-0.21
Adjusted R-sqr (%)	0.293	4.401	0.231	4.333

Table A11: First-stage regression: Minimum eigenvalue statistics

This table reports the minimum eigenvalue statistics (i.e., Cragg Donald statistics) for the first-stage regression of log market equity onto the instrument and other firm characteristics. The detailed definition of our instrument can be found in Section 5.2.2.

	Minimum eigenvalue statistics				
Performance qunintile	1	2	3	4	5
Q3 2002	66.41	103.76	31.74	136.25	67.00
Q4 2002	62.69	113.67	199.37	64.52	97.89

Table A12: Elasticity across beta deciles

This table reports the average elasticity of stock decile portfolios formed on beta measured with respect to the Russell index including Large Value (Russell 1000 Value), Large Growth (Russell 1000 Growth), Small Value (Russell 2000 Value), and Small Growth (Russell 2000 Growth) in 2002 Q3. We first measure an investor's demand elasticity of a given stock using Equation 13. For a given stock, we take the average of the elasticity of across all investors that hold the stock, weighted by their holding values.

Beta Decile	1	2	3	4	5	6	7	8	9	10
Large Value	-0.52	-0.476	-0.468	-0.463	-0.444	-0.447	-0.427	-0.432	-0.404	-0.384
Large Growth	-0.498	-0.488	-0.443	-0.452	-0.431	-0.449	-0.43	-0.428	-0.413	-0.432
Small Value	-0.504	-0.481	-0.453	-0.449	-0.453	-0.423	-0.437	-0.446	-0.416	-0.403
Small Growth	-0.482	-0.474	-0.458	-0.446	-0.428	-0.444	-0.43	-0.441	-0.428	-0.434

Table A13: Elasticity for overpriced and underprcied high-beta stocks

This table reports the average elasticity of overpriced and underprcied high-beta stock portfolios formed on beta measured with the Russell index including Large Value (Russell 1000 Value), Large Growth (Russell 1000 Growth), Small Value (Russell 2000 Value), and Small Growth (Russell 2000 Growth) in 2002 Q3. If a high-beta stock's realized price is higher (lower) than its counterfactual price estimated by reallocating underperforming funds' AUM to all other investors, we define it as an overpriced (underpriced) high-beta stock.

	Overpriced	Underpriced
Large Value	-0.304	-0.390
Large Growth	-0.373	-0.451
Small Value	-0.390	-0.418
Small Growth	-0.384	-0.488

Table A14: Counterfactual analysis post-2002

This table reports the price impacts of underperforming funds in each category by allocating underperforming funds' AUM proportionally to other investors' in the post-2002 period. The repricing statistic ζ is caculated as, $\frac{\Sigma_{n=1}^{N}|ME_t^{CF}(n)-ME_t(n)|}{\Sigma_{n=1}^{N}ME_t(n)}$ in which CF denotes counterfactual market values and n denotes a stock that underperforming funds hold. We sort stocks into ten portfolios based on the style-level betas, and calculate the repricing statistic (in percentage) for each beta decile portfolio.

Beta Decile	1	2	3	4	5	6	7	8	9	10	10-1
Panel A: Large Value											
Repricing	0.03	0.02	0.0	0.01	-0.04	-0.07	-0.09	-0.16	-0.26	-0.28	-0.32
Panel B: Large Growth											
Repricing	0.05	0.03	0.02	-0.02	-0.03	-0.07	-0.1	-0.18	-0.2	-0.3	-0.34
Panel C: Small Value											
Repricing	0.09	0.06	0.01	-0.03	-0.09	-0.13	-0.2	-0.33	-0.45	-0.4	-0.48
Panel D: Small Growth											
Repricing	0.09	0.06	0.03	-0.05	-0.1	-0.11	-0.17	-0.22	-0.4	-0.53	-0.62

Table A15: Double sorts based on stock-level fund performance and IVOL

This table reports monthly value-weighted returns for 5×10 portfolios formed by sorting on the stock-level fund-performance and idiosyncratic volatility (IVOL). We first sort stocks into quintile portfolios based on the stock-level fund-performance, defined as the weighted-average of the year-to-date excess returns (relative the benchmark index) of funds that hold the stock. Because of the change in the Morningstar rating method, we use the S&P 500 index as the benchmark before June 2002 and the Russell index as the benchmark after June 2002 . Within each of the five fund-performance quintile portfolios, we sort stocks into ten decile portfolios based on IVOL. The monthly IVOL for individual stocks is calculated as the standard deviation of the residuals from the regression of the most recent month's daily returns on the Fama-French three factors (Ang et al. (2006)). The t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is January 1982 to December 2018.

	IVOL Decile										
Performance quintile	1	2	3	4	5	6	7	8	9	10	10-1
1	0.70	0.68	0.56	0.50	0.60	0.42	0.30	0.04	0.08	-0.50	-1.20
t-stat	3.64	3.07	2.14	1.77	1.97	1.35	0.88	0.10	0.20	-1.18	-3.56
2	0.76	0.86	0.56	0.68	0.92	0.46	0.32	0.40	0.11	-0.06	-0.83
t-stat	3.92	3.96	2.41	2.79	3.45	1.63	1.08	1.22	0.30	-0.16	-2.50
3	0.68	0.70	0.61	0.49	0.91	0.64	0.64	0.70	0.24	0.11	-0.57
t-stat	3.57	3.28	2.72	2.06	3.59	2.29	2.10	2.13	0.65	0.29	-1.70
4	0.78	0.97	0.85	0.65	0.69	0.87	0.57	0.51	0.66	0.51	-0.27
t-stat	3.78	4.54	3.54	2.74	2.63	2.89	1.85	1.52	1.85	1.29	-0.81
5	1.02	1.06	1.09	1.00	1.01	0.87	0.90	0.85	0.62	0.38	-0.64
t-stat	4.88	4.13	3.65	3.43	3.13	2.66	2.63	2.26	1.56	0.86	-1.76
5-1	0.32	0.38	0.53	0.50	0.42	0.45	0.60	0.82	0.54	0.88	0.56
t-stat	1.83	1.56	1.81	1.85	1.36	1.55	1.91	2.57	1.56	2.41	1.63
All Stocks	0.76	0.82	0.71	0.67	0.78	0.69	0.55	0.59	0.22	-0.07	-0.83
t-stat	4.25	4.23	3.37	3.02	3.10	2.55	1.87	1.79	0.60	-0.17	-2.51

Table A16: Double sorts based on stock-level fund performance and return skewness

This table reports monthly value-weighted returns for 5×10 portfolios formed by sorting on the stock-level fund performance and return skewness. We first sort stocks into quintile portfolios on the stock-level fund-performance, defined as the weighted-average of the year-to-date excess returns (relative the benchmark index) of funds that hold the stock. Because of the change in the Morningstar rating method, we use the S&P 500 index as the benchmark before June 2002 and the Russell index as the benchmark after June 2002. Within each of the five fund-performance quintile portfolios, we sort stocks into ten decile portfolios based on return skewness. Following Bali et al. (2011), stocks' return skewness (lottery payoff) is defined as the average of its five highest daily returns in each month. The t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is January 1982 to December 2018.

	Skewness Decile										
Performance quintile	1	2	3	4	5	6	7	8	9	10	10-1
1	0.86	0.85	0.76	0.51	0.63	0.25	0.28	0.14	-0.34	-0.24	-1.10
t-stat	4.69	4.06	3.13	1.93	2.29	0.78	0.79	0.38	-0.88	-0.57	-3.07
2	0.89	0.82	0.68	0.71	0.85	0.54	0.71	0.26	0.20	-0.07	-0.97
t-stat	4.84	3.92	3.14	3.01	3.39	1.91	2.44	0.76	0.56	-0.17	-2.64
3	0.81	0.84	0.76	0.79	0.66	0.44	0.70	0.58	0.17	0.32	-0.49
t-stat	4.49	4.26	3.56	3.50	2.61	1.64	2.54	1.88	0.47	0.78	-1.36
4	0.93	0.97	0.93	0.81	0.76	0.71	0.82	0.59	0.49	0.35	-0.58
t-stat	5.23	4.55	4.05	3.54	2.95	2.54	2.85	1.80	1.41	0.84	-1.51
5	0.85	1.13	1.15	1.14	1.21	0.85	0.94	0.75	0.77	0.35	-0.50
t-stat	4.30	4.94	4.23	4.01	4.10	2.72	2.82	2.02	1.91	0.81	-1.41
5-1	-0.01	0.27	0.39	0.63	0.57	0.60	0.67	0.62	1.11	0.59	0.60
t-stat	-0.09	1.45	1.52	2.30	2.11	2.04	2.17	1.89	3.23	1.66	1.73
All Stocks	0.79	0.88	0.77	0.76	0.63	0.67	0.65	0.57	0.25	-0.08	-0.88
t-stat	5.02	4.90	4.01	3.56	2.68	2.71	2.35	1.79	0.68	-0.21	-2.47

Table A17: Double sorts based on stock-level Morningstar ratings and CAPM beta

This table reports monthly alphas for 5×10 portfolios formed by sorting on the stock-level Morningstar ratings and the CAPM beta. Alphas are computed with respect to the Fama-French three-factor model. We first sort stocks into quintile portfolios based on the stock-level Mornningstar ratings, defined as the holding-asset-weighted Morningstar ratings of funds that hold the stock. Within each of the five fund-rating quintile portfolios, we sort stocks into ten decile portfolios based on betas. Stocks' betas are measured from the regressions of their returns on the market excess returns. The t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is January 1986 to December 2018.

	Beta Decile										
Performance quintile	1	2	3	4	5	6	7	8	9	10	10-1
Low Star Rating	0.24	0.11	0.06	-0.05	-0.07	-0.20	-0.21	-0.40	-0.48	-0.37	-0.61
t-stat	1.47	0.71	0.39	-0.29	-0.48	-1.25	-1.18	-2.19	-2.40	-1.51	-1.95
2	0.26	0.21	0.06	0.11	0.19	0.19	-0.03	-0.11	-0.01	-0.14	-0.40
t-stat	1.86	1.43	0.44	0.73	1.29	1.26	-0.18	-0.68	-0.05	-0.63	-1.43
3	0.23	0.15	0.21	0.10	-0.12	0.26	-0.18	-0.00	-0.09	0.01	-0.22
t-stat	1.63	1.19	1.46	0.78	-0.79	2.14	-1.48	-0.02	-0.64	0.04	-0.78
4	0.11	0.14	0.24	0.26	0.07	0.13	-0.03	0.06	0.06	-0.02	-0.13
t-stat	0.74	1.15	1.92	1.86	0.51	0.94	-0.18	0.41	0.33	-0.10	-0.50
High Star Rating	0.36	0.37	0.20	0.37	0.15	0.19	0.16	0.11	-0.05	0.03	-0.33
t-stat	2.22	2.59	1.26	2.69	1.05	1.36	1.07	0.70	-0.27	0.13	-1.14
High-Low	0.12	0.26	0.14	0.41	0.22	0.40	0.36	0.51	0.43	0.39	0.28
t-stat	0.58	1.30	0.66	1.89	1.05	1.76	1.61	2.04	1.65	1.38	0.82
All Stocks	0.15	0.18	0.16	0.20	-0.04	0.06	0.03	-0.15	-0.19	-0.22	-0.37
t-stat	1.43	1.95	1.81	2.43	-0.52	0.82	0.33	-1.67	-1.70	-1.33	-1.56

Table A18: Double sorts based on stock-level Mornningstar ratings and IVOL

This table reports monthly alphas for 5×10 portfolios formed by sorting on the stock-level Mornningstar ratings and idiosyncratic volatility (IVOL). Alphas are computed with respect to the Fama-French three-factor model. We first sort stocks into quintile portfolios based on the stock-level Mornningstar ratings, defined as the holding-asset-weighted Morningstar ratings of funds that hold the stock. Within each of the five fund-rating quintile portfolios, we sort stocks into ten decile portfolios based on IVOL. The monthly IVOL for individual stocks is calculated as the standard deviation of the residuals from the regression of the most recent month's daily returns on the Fama-French three factors (Ang et al. (2006)). The t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is January 1986 to December 2018.

	IVOL Decile										
Performance quintile	1	2	3	4	5	6	7	8	9	10	10-1
Low Star Rating	0.20	0.12	-0.04	-0.30	-0.13	-0.19	-0.35	-0.77	-0.80	-1.27	-1.47
t-stat	1.52	0.89	-0.24	-1.77	-0.67	-1.00	-1.78	-3.26	-3.66	-4.56	-4.58
2	0.21	0.11	-0.02	0.31	0.03	0.09	0.12	-0.19	-0.20	-0.57	-0.77
t-stat	1.75	0.96	-0.19	2.11	0.21	0.53	0.64	-0.89	-0.97	-2.13	-2.44
3	0.14	0.15	0.18	0.01	0.05	-0.20	0.18	-0.25	-0.51	-0.60	-0.74
t-stat	1.35	1.38	1.55	0.04	0.38	-1.23	1.14	-1.43	-2.46	-2.24	-2.33
4	0.21	0.17	0.05	-0.07	0.07	0.06	0.15	-0.29	0.15	-0.48	-0.69
t-stat	1.78	1.51	0.40	-0.57	0.44	0.36	0.97	-1.67	0.66	-1.99	-2.39
High Star Rating	0.30	0.08	0.25	0.38	0.19	0.08	-0.16	-0.05	-0.12	-0.72	-1.02
t-stat	2.45	0.69	2.03	2.66	1.15	0.47	-0.86	-0.23	-0.54	-2.66	-3.41
5-1	0.10	-0.04	0.29	0.68	0.31	0.27	0.18	0.72	0.69	0.54	0.45
t-stat	0.55	-0.23	1.46	2.82	1.17	1.00	0.62	2.13	2.28	1.50	1.20
All Stocks	0.14	0.15	0.01	-0.03	0.02	-0.09	-0.21	-0.17	-0.59	-0.86	-1.00
t-stat	1.76	2.25	0.22	-0.39	0.17	-1.01	-1.88	-1.31	-3.70	-4.22	-4.12

Table A19: Double sorts based on stock-level Morningstar ratings and return skewness

This table reports ex-post monthly alphas for 5×10 portfolios formed by sorting on the stock-level Morningstar ratings and return skewness. Alphas are computed with respect to the Fama-French three-factor model. We first sort stocks into quintile portfolios based on the stock-level Mornningstar ratings, defined as the holding-asset-weighted Morningstar ratings of funds that hold the stock. Within each of the five fund-rating quintile portfolios, we sort stocks into ten decile portfolios based on return skewness. Following Bali et al. (2011), stocks' return skewness (lottery payoff) is defined as the average of its five highest daily returns in each month. The *t*-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). The sample period is January 1986 to December 2018.

	Skewness Decile										
Performance quintile	1	2	3	4	5	6	7	8	9	10	10-1
Low Star Rating	0.33	0.46	0.01	-0.18	-0.25	-0.15	-0.36	-0.45	-0.68	-1.52	-1.85
t-stat	2.41	3.36	0.08	-1.07	-1.43	-0.80	-1.87	-2.17	-3.18	-5.36	-5.29
2	0.39	0.37	0.19	-0.14	0.29	0.05	0.14	-0.27	-0.59	-0.70	-1.09
t-stat	3.38	3.01	1.37	-1.00	1.76	0.31	0.79	-1.43	-2.35	-2.43	-3.08
3	0.40	0.22	0.02	0.21	-0.07	-0.23	-0.06	0.15	-0.46	-0.63	-1.03
t-stat	3.51	1.99	0.15	1.76	-0.55	-1.59	-0.39	0.82	-2.00	-2.41	-3.21
4	0.27	0.28	0.21	-0.04	0.12	0.08	0.08	-0.42	-0.39	-0.15	-0.43
t-stat	2.21	2.21	1.68	-0.30	0.86	0.57	0.47	-2.20	-1.98	-0.57	-1.30
High Star Rating	0.39	0.31	0.12	0.48	-0.00	-0.05	-0.12	-0.14	-0.24	-0.24	-0.62
t-stat	2.86	2.45	0.93	3.48	-0.02	-0.34	-0.65	-0.59	-1.02	-0.79	-1.81
5-1	0.06	-0.15	0.11	0.65	0.24	0.10	0.24	0.31	0.43	1.28	1.23
t-stat	0.33	-0.88	0.54	2.97	0.95	0.38	0.89	0.93	1.35	3.57	3.25
All Stocks	0.29	0.24	0.11	0.03	-0.11	-0.05	-0.14	-0.24	-0.58	-0.86	-1.15
t-stat	3.10	2.91	1.39	0.37	-1.14	-0.54	-1.18	-1.71	-3.20	-4.24	-4.44