Mutual Fund Strategy: Swing for the Fences or Bat for Average

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Abstract

We document two distinct mutual fund strategies: "Swinging for the Fences" (SF), where managers hold stocks with extreme style-adjusted returns on either tail of the return distribution, and "Batting for Average" (BA), where managers seek stocks with consistent moderate performance. We provide evidence that these strategies are persistent and deliberate. Existing measures of active management and known asset pricing factors do not explain the strategies. SF attracts more flow, particularly when funds mention specific stock holdings in shareholder reports. SF funds charge higher fees and hold riskier portfolios; yet, they fail to deliver higher risk-adjusted returns. In falsification tests, SF strategies are not present in passive funds, supporting our conclusion that SF and BA are intentional strategies.

Keywords: Mutual Fund Performance, Performance Persistence, Mutual Fund Holdings, Investment Skill, Stock Picking Ability.

JEL Classifications: G11, G23.

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I Introduction

We document two contrasting mutual fund strategies that have implications for mutual fund selection and offer insight into fund managers' stock selections. Colloquially, and descriptively, we label these strategies as "Swinging for the Fences" (SF) and "Batting for Average" (BA). Swinging for the fences describes funds that hold a relatively large number of stocks that are "homeruns" and/or "strikeouts," which we define as holdings with extreme relative returns. In contrast, Batting for Average describes funds that try to beat the market with the most holdings possible regardless of the amount by which they beat the market.[1] We provide evidence that SF and BA are mutual fund strategies that impact flows, expenses, and volatility, but not risk-adjusted returns, providing insight into the incentives and decisions made by fund managers.

Our hypothesis is that a fund strategy that picks stocks that beat the market more often is different from a strategy that leads to a small number of stocks that end up as big winners or big losers. Consistent with our hypothesis, we find that the SF and BA strategies are persistent strategies at funds through time and after conditioning on other fund characteristics.[2] Furthermore, we find that SF and BA are not explained by common measures of active management and a comprehensive list of 211 asset pricing factors, leading us to conclude that SF and BA are likely to be deliberate and distinct stock–picking strategies. Our paper makes several contributions to the large literature on

[1]Baseball enthusiasts will recognize an analogy that compares Tony Gwynn, who "hit for average" to Reggie Jackson who "swung for the fences." Gwynn had one of the highest batting averages of all time at 0.338, but hit few homeruns (132) and infrequently struck out (434). In contrast, Reggie Jackson had a substantially lower batting average at 0.262, but hit about four times more homeruns (563) and had five times more strikeouts (2,596) than Tony Gwynn (Source: MLB.com).

[2]While other studies (e.g., Koijen and Yogo (2019) and Hartzmark (2015)) find persistence in mutual fund holdings, we document persistence in stock investment strategy despite frequent changes in holdings.

mutual fund managers' portfolio choices.[3]

We show that swinging for the fences is a persistent fund strategy that leads to extreme relative returns of select holdings. While SF and BA do not offer superior risk–adjusted returns, gross or net-of-fees, we do find that SF is related to higher fund volatility. Specifically, one standard deviation increase in our measure of swinging for the fences leads to 23 bps increase in monthly fund return volatility. Funds with no homerun or strikeout holdings have 4 bps lower monthly volatility. At a portfolio level, we find that the portfolio of funds that swing for the fences has monthly volatility of 3.49% while the portfolio of funds that do not swing for the fences has volatility of 2.44%, a statistically significant difference of 1.05% (*t-statistic* of 8.69). These results are consistent with and help to identify a stock level strategy that generates higher idiosyncratic fund volatility like that found in Clifford, Fulkerson, Jame, and Jordan (2021), which shows that fund investors are attracted to funds with high idiosyncratic volatility, even though chasing idiosyncratic volatility does not deliver superior performance.

Our paper also complements the literature on lottery-like returns and mutual fund flows. In particular, Agarwal, Jiang, and Wen (2020) find that the disclosure of right tail "lottery stocks" leads to increased fund flows. Similarly, Solomon, Soltes, and Sosyura (2014) show that funds holding stocks with high returns receive higher fund flows, especially when catalyzed by media attention. At the mutual fund portfolio level, Akbas and Genc (2020) show that, controlling for last year's performance, extreme fund returns in one month during the year are associated with higher mutual fund flows in the future.

[3]See, e.g., Cremers and Petajisto (2009), Kacperczyk, Sialm, and Zheng (2005), Hong and Kostovetsky (2012), Hong and Kacperczyk (2009), Giannetti and Simonov (2006), Hartzmark and Sussman (2019), Coval and Moskowitz (1999), Pool, Stoffman, and Yonker (2012), and Cohen, Frazzini, and Malloy (2008).

While complementary, we provide evidence of a mutual fund strategy choice, in contrast to investors' reactions to lottery-like returns. We also employ a distinct definition of extreme holdings' performance. We consider a stock to be a homerun if its *quarterly* relative performance is exceptional, defined as being in the 90^{th} percentile relative to its Fama-French peers. In contrast, Agarwal et al. (2020) define lottery-like performance as an extreme *daily* holdings' return regardless of quarter-end performance, while Akbas and Genc (2020) focuses on an extreme monthly fund return. These differences matter. We show that just one out of every seven homeruns would be defined as a lottery stock, confirming that SF is measuring something distinct relative to prior measures of lottery stocks.

We also find that SF funds are more likely to specifically mention their homeruns and strikeouts in their annual shareholder reports, particularly when these holdings have a larger positive economic impact on fund returns. These disclosures of specific homeruns and strikeouts in their annual reports lead to even higher flows into their funds. This suggests a role for salience, similar to that created by the media in Solomon et al. (2014), generated by fund managers' disclosures of homeruns and strikeouts. Our SF measure also extends the literature by showing that investors not only chase funds with more homeruns but also withdraw capital from funds with too many strikeouts, which contrasts with the lottery stock/fund literature that has naturally focused on *positive* extreme performance.

Consistent with the hypothesis that younger funds and early–career managers have stronger incentives to stand out among the competition, we find that younger funds and, in some of our tests, early-career managers are more likely to employ the more flamboyant SF strategy. This complements findings in Chuprinin and Ruf (2018) that mutual fund flows are sensitive to portfolio composition in the years immediately after fund inception. Furthermore, as funds grow older, the likelihood of holding stocks that are strikeouts decreases at a significantly higher rate than the rate of hitting homeruns, suggesting that funds learn to pick potential homeruns more efficiently. This finding highlights the role of experience in mutual fund performance (Chevalier and Ellison (1999), Kempf, Manconi, and Spalt (2017)).

Moreover, we find that SF and BA strategies both suffer from diseconomies of scale. Berk and Green (2004) argue that liquidity constraints challenge active managers and lead to decreasing returns to scale in active mutual funds.[4] Yan (2008) and Pollet and Wilson (2008) identify factors that contribute to diseconomies. Yan (2008) finds larger diseconomies among funds that primarily invest in small-cap stocks and funds with higher turnover, while Pollet and Wilson (2008) show that large growing funds diversify their portfolios to reduce the negative effect of portfolio size on performance. In larger funds, we observe more frequent strikeouts relative to smaller funds. This is consistent with large fund managers having to select less favored stocks in order to fully invest more total net assets.

We also find that funds with a focus on institutional clients are less likely to swing for the fences relative to funds that focus on retail clients. This finding is consistent with Del Guercio and Reuter (2014) and Barber, Huang, and Odean (2016) who find that investors in funds that are directly sold are more sophisticated than investors in broker-sold funds. Retail funds' tendency to swing for the fences is consistent with the

[4]In addition, Pástor, Stambaugh, and Taylor (2015) offer evidence of decreasing returns at the industry level, showing that as the size of the active mutual fund industry increases, a fund's ability to outperform passive benchmarks declines. Zhu (2018) finds a significant negative impact of fund size on performance.

well-documented fact that retail investors are attracted to stocks with extreme returns (Kumar (2009), Kumar, Page, and Spalt (2011), Conrad, Kapadia, and Xing (2014), and Bali, Brown, Murray, and Tang (2017)).

The economic impact on flows associated with the SF strategy is meaningful. A one-standard deviation increase in SF is associated with 18 bps increase in fund flows. For the average size fund, the effect translates to $8.4 million in additional fund flow each quarter. Furthermore, the effect of homeruns and strikeouts on capital flows is more than twice as large when funds specifically mention the stocks that were large contributors or detractors to performance in the managerial commentary section of the annual shareholder report. This is consistent with the SF strategy providing managers with salient talking points that influence flows.

The SF strategy may also help to understand mutual fund fees. It is puzzling that actively-managed equity funds generally have higher fees and commonly generate poor net-of-expense performance relative to low-fee funds (Sheng, Simutin, and Zhang (2023) and Cooper, Halling, and Yang (2021)). Yet funds with high fees continue to exist and to do so must attract investors' attention (Elton, Gruber, and Busse (2004), Hortaçsu and Syverson (2004), and Christoffersen and Musto (2002)). Gil-Bazo and Ruiz-Verdú (2009) offer a model of the mutual fund industry in which high-fee funds strategically target unsophisticated investors who are more responsive to advertising. We contribute by showing that swinging for the fences is a common strategy among funds that target retail investors who are more likely to respond to a simple signal like a homerun. We also finding SF funds have meaningfully higher expense ratios. A one-standard deviation increase in swinging for the fences is associated with 3.7 bps higher fees.

Our paper also contributes to the literature that studies the determinants of capital flows to mutual funds. Del Guercio and Tkac (2008) show that Morningstar ratings changes lead to changes in fund flows, while Kaniel and Parham (2017) finds that investors allocate more flow to funds that are featured in the media than funds with otherwise similar performance. Hillert, Niessen-Ruenzi, and Ruenzi (2023) show that fund flows are influenced by tone and writing style of funds' annual shareholder letters. Ben-David, Li, Rossi, and Song (2022) show that mutual fund investors rely on simple signals such as fund rankings and likely do not engage in sophisticated risk-adjustments when allocating their capital. Our paper adds to this literature by showing that the simple presence of past homeruns and strikeouts in the funds' portfolio significantly affects fund flows and manager disclosures of the specific homeruns magnify the impact.

Finally, we conduct falsification tests in a sample of passively-managed funds to rule out the conjecture that our measures are artifacts of the data. If swinging for the fences and batting for average are two intentional active investment strategies, then passive funds with no incentives to pursue stock picking strategies should not exhibit the relations we find among actively-managed funds. We find no robust evidence that returns, volatility, flows or fees are related to the SF or BA measures in passive funds. These tests support the hypothesis that SF and BA strategies are intentional strategies among actively managed mutual funds and not merely artifacts of the data.

Our paper is organized as follows. Section II explains the data and variables and reports the descriptive statistics. Section III examines the persistence and marketing of the strategies as well as their relation with other fund characteristics and active management metrics. Section IV examines the performance implications of the strategies. Section V studies funds' incentives to pursue the strategies, including fund flows and fees. Section VI provides our falsification tests that use passively-managed fund data. Section VII concludes.

II Data, Variable Construction, & Summary Statistics

A Data & Sample Construction

Our sample includes quarterly observations for actively-managed US equity mutual funds appearing in the CRSP Mutual Funds dataset and Morningstar Direct between 1993 and 2020. Following Pástor et al. (2015), we cross-check returns and size using CRSP and Morningstar. To be included in our sample, funds must appear in both CRSP and Morningstar, and their returns and size must correspond closely.[5] For funds with multiple share classes, we aggregate the data at the fund level by asset-weighting across share classes. We restrict the sample to funds whose Morningstar category falls within the Morningstar 3×3 style box.[6] This restriction excludes non-equity funds, international equity funds, and industry-sector funds. We exclude funds that have less than 12 quarters of data and have less than $15 million in assets under management. We compute benchmark-adjusted returns as a fund's returns in excess of returns on its benchmark assigned by Morningstar. Since the benchmark assignments are made by Morningstar

[5] We remove funds that differ by more than one percent of the amount reported in CRSP. For cases which differ by small amounts, we use values reported in CRSP.

[6] The Morningstar style box is created by the interaction of small/mid/large-cap with growth/blend/value.

rather than the funds themselves, there is less concern for manipulation of self-reported benchmarks in the fund's prospectus (Sensoy, 2009).

We obtain mutual fund portfolio holdings from Thomson Reuters Mutual Fund Holdings S12 database, which reports quarterly snapshots of fund holdings in our sample. We use quarterly holdings to construct our strategy measures. Ideally, we would like to observe the precise timing of funds' trading activity to identify homeruns and strikeouts at the trade level: a pair of buy – sell trades with extreme gains or losses, respectively. However, since the data are limited to quarterly holdings reports, we define our strategy measures using portfolio holdings at the beginning of a quarter that are followed by extreme performance in the subsequent quarter. We are confident that holding-level measures capture mutual funds' strategy. First, holdings reflect the managers' intentional portfolio choices and their *ex ante* expectation of future performance. Second, changes in quarterly holdings are the direct result of trades made by the fund during the quarter.

B Swing for the Fences and Bat for Average Strategy Measures

At the end of each quarter, we estimate homeruns (HR), strikeouts (SO), and batting average (BA) as a fraction of total stocks held by the fund at the beginning of that quarter. For each fund at the end of each quarter, HR, SO, and BA are defined as the number of stocks held by the fund, at the beginning of the quarter, that become homeruns, strikeouts, and hits by the end of that quarter. A stock is identified as a homerun or a strikeout if its portfolio-adjusted quarterly return is in the 90^{th} or 10^{th} percentile of the return distribution in the calendar quarter, respectively. A stock is identified as a hit if its portfolio-adjusted quarterly return is positive, meaning it beats its benchmark portfolio. The benchmark portfolio for each stock is its corresponding Fama–French 25 "FF25" portfolio, which is determined by the book-to-market ratio and market capitalization. The FF25 benchmark controls for the fact that small-cap and growth firms are naturally more likely to deliver extreme returns. As a result, stocks that are designated HR, SO or as beating their benchmark, are doing so with respect to peer stocks with similar market capitalization and book-to-market ratios.

We also define three additional variables. First, we define HR+SO in a quarter as a measure of swinging for the fences. Second, we define HR-SO, as the spread between the two measures. HR-SO measures how successful a fund is at swinging for the fences by delivering more homeruns than strikeouts. Last, we define $\mathbb{1}(\text{HR+SO} = 0)$ as a dummy variable that takes the value of 1 if the fund has no homeruns and strikeouts in the portfolio. $\mathbb{1}(\text{HR+SO} = 0)$ measures a fund's tendency to just bat for average.

[Insert Figure 1 approximately here]

Figure 1 illustrates the timing and construction of our measures. Our primary objective is to examine whether past homeruns and strikeouts in a fund's portfolio predict future performance or capital flows. In doing so, we estimate the effect of HR and SO at quarter $t-1$ on fund outcomes at quarter t. The construction of our strategy variables at quarter $t-1$ is designed to mitigate the impact of potential window dressing on our measures. Specifically, we designate stock j as a homerun in quarter $t-1$ if it's FF25 adjusted return in quarter $t-1$ is in the 90^{th} percentile. We only count stock j as a homerun or strikeout ($HR_{i,t-1}$, $SO_{i,t-1}$) for fund i, if fund i holds stock j at quarter-end

$t-2$, prior to stock j's extreme performance during quarter $t-1$. In other words, construction of $HR_{i,t-1}$ and $SO_{i,t-1}$ is based on portfolio holdings at quarter $t-2$, preventing funds from receiving credit for purchasing stock j during or after the extreme relative returns.

Our results are robust to a variety of alternative definitions for our variables. First, we define homeruns and strikeouts using alternative thresholds[7] and find that our estimation results remain very similar regardless of which thresholds are used to define the strategy measures. Second, our conclusions are robust to the adoption of alternative risk adjustments including using a simple market adjustment and Fama-French 6 portfolios, in place of the FF25 portfolios to identify extreme adjusted-returns in funds' stock holdings. Given that homeruns and strikeouts identify extreme realized returns, it is not surprising that the specific model of expected returns does not meaningfully impact the stocks that we define as homeruns or strikeouts.

We focus on equally weighted measures of homeruns and strikeouts, which puts more emphasis on small holdings. We believe this simple characterization of extreme performers is consistent with how investors might notice that a homerun is held in the portfolio. For robustness and further insight, we provide additional evidence using alternative weights at the fund-level for HR, SO, and BA. We employ three weighting alternatives that emphasize larger holdings and more extreme returns. Specifically, we define value-weighted HR, SO, and BA using portfolio weights, putting more emphasis on larger portfolio holdings. Second, we use holdings' returns as weights to compute our

[7] We use $20^{th}/80^{th}$, $15^{th}/85^{th}$, and $5^{th}/95^{th}$ as alternative thresholds. More extreme cut offs such as $1^{st}/99^{th}$ yield a small sample of homeruns and strikeouts, reducing statistical power. On the other hand, less extreme cut offs identify more modest returns as homeruns or strikeouts, rendering them less salient.

measures, allowing more salient extreme performances to carry more weight. Third, we limit the calculation of strategy measures to the top–20 largest holdings to credit funds for holding a homerun only if that homerun is among the biggest holdings. We find that our results are consistent across these methods.

C Disclosure Data & Measures

To examine whether mutual funds disclose and advertise their homeruns and strikeouts to their investors, we collect N-CSR filings of all mutual funds between 2003 and 2020. Form N-CSR was introduced as part of the SEC's rule making following the Sarbanes-Oxley Act of 2002, which sought to enhance corporate responsibility and financial disclosure.[8] Form N-CSR filing is required for all registered management investment companies, including mutual funds, and provides investors with detailed information about a fund's performance, holdings, expenses, as well as a management discussion of results.

We are particularly interested in characterizing how fund managers discuss their performance. In the Management Discussion of Fund Performance, fund managers explain in narrative form the key factors that influenced performance. Managerial discussion often covers market and economic conditions, investment strategy, and comparison with benchmarks. The key factors that managers attribute to performance vary wildly. While some managers limit their discussion to industry trends and/or macroeconomic conditions as key factors, some managers will mention specific holdings that were notable contributors or detractors to fund performance. To test the idea that SF strategies can influence flows,

[8]We thank the anonymous referee who encouraged us to explore the mechanism through which HR and SO might influence flows.

we extract from these management discussions cases where fund managers mention individual stocks they hold in their management discussion. To do so, we collect form N-CSR filings of all mutual funds in our sample after 2003 from directEDGAR. N-CSR filings are filed at the fund advisor level, meaning that some filings comprise multiple mutual funds' disclosures. We break these files into fund specific disclosures. For each filing, we machine read the Management Discussion of Fund Performance to identify whether the fund managers discussed their homerun and strikeout holdings as key contributors and detractors to performance. We achieve that by comparing these narrative discussions against the names and ticker symbols of homeruns and strikeouts in the fund portfolio. We then define two indicator variables: MENTIONED_HR and MENTIONED_SO, which take values of 1 if the fund mentions at least one homerun as a contributor and at least one strikeout as a detractor in that year, respectively, and zero otherwise. In Online Appendix C, we provide an example of an N-CSR filing in which the management does not mention holdings as key contributors and an example of an N-CSR filing in which the management specifically highlights homeruns.

D Summary Statistics

Our sample of active mutual funds includes 2,312 unique funds and 114,935 fund-quarter observations from 1993 to 2020. Table 1 reports descriptive statistics for the variables used in our analysis. Consistent with the mutual fund literature, mutual funds deliver 2.65% quarterly gross returns and 2.34% in net-of-fees returns. The sample funds deliver 0.12% and -0.19% in Morningstar benchmark-adjusted quarterly gross and net returns, respectively. Carhart (1997) four-factor quarterly α is -0.07%. The average funds' benchmark-adjusted monthly volatility is 1.68%. The average factor-adjusted monthly volatility is 1.59%.[9]

[Insert Table 1 approximately here]

The share of fund holdings that are homeruns and strikeouts average 5.16% and 4.30%, respectively. The standard deviations of these measures are 7.72% and 6.43%, suggesting considerable variation in funds' ability or willingness to swing for the fences. HR + SO is 9.47% with a standard deviation of 7.35%. HR-SO is 0.85%, suggesting that an average fund hits slightly more homeruns than strikeouts. In a given quarter, 9% of the fund–quarters have no homeruns and strikeouts holdings in their portfolio. In addition, the average BA is 49.15%, suggesting slightly below half of the stocks held by mutual funds exceed their FF 25 portfolio returns in any given quarter. On average, 46.52% of funds mention at least one homerun holding as a factor that contributed to the fund's annual performance, whereas 39.25% of funds mention at least one strikeout holding as a factor that detracted from the fund's performance.

The average fund size and fund family size are $4.6 billion and $128.3 billion, respectively. However, the median fund has only $435 million and the median fund family has $11.74 billion in AUM. Funds, on average, attract 3.19% of their AUM in additional capital each quarter. Funds' expense ratios average 1.23% and average turnover is 82%. Funds in our sample average 15 years old and hold an average of 126 different securities in each quarter. Thirty-one percent of funds have an institutional focus while 67% are

[9] Volatility is the standard deviation of the fund's monthly adjusted-returns over the prior 12 months.

retailed-focused.[10] The fund managers in the sample average slightly less than 10 years of experience as manager, and 59% of funds are managed by a team of managers.

E Homeruns vs. other Forms of Extreme Returns

The Swing-for-the-Fences strategy is a distinctive form of risk taking. SF funds display an ability to pick stocks that can deliver extreme returns in future quarters. As mentioned above, we define a homerun stock to be a stock that delivers a portfolio-adjusted quarterly return that is in the top 10% of its peer stocks. As described earlier in Section B, we use the FF25 portfolios constructed based on market capitalization and book-to-market ratios to define the universe of peer stocks. In this section, we describe the distinctions between our homeruns and other forms of extreme returns studied in the literature. Specifically, we focus on measures of "lottery stocks" (e.g., Kumar (2009), Bali, Cakici, and Whitelaw (2011), Bali et al. (2017), Agarwal et al. (2020), and Bali, Hirshleifer, Peng, and Tang (2021)), "high volatility" (Clifford et al. (2021)), and "high skewness" (Bessembinder (2018) and Farago and Hjalmarsson (2023)).

To identify lottery stocks, we first calculate MAX as a stock's return on the best day of the quarter.[11] Then, we designate a stock as a lottery stock in a quarter if its MAX is larger than the 90^{th} percentile of all stocks in that quarter. We use a 90% cutoff to correspond to our definitions of homeruns. Homeruns are different from lottery stocks in at least two ways. First, we define homeruns by a stock's cumulative returns over a quarter, whereas lottery stocks' definition is based on a single day's return. Second, homeruns'

[10] We define the focus of the fund based on its biggest share class, which is unidentified for 2% of the sample because the biggest share class is not clearly retail or institutional.

[11] While Agarwal et al. (2020) construct the MAX measure at the monthly frequency, we construct MAX at the quarterly level to be comparable to our quarterly homeruns.

extreme performance is relative to each stock's market capitalization and book-to-market peers, while lottery-like performance is based on raw returns. Similarly, we calculate each stock's volatility and skewness of daily portfolio-adjusted returns for 250 trading days. Then, we designate a stock as a high–volatility (high–skewness) stock in a quarter if its volatility (skewness) is larger than the 90^{th} percentile of all stocks in that quarter.

In each quarter we measure a stock's average probability of being defined as 1) a homerun only, 2) a lottery stock only, 3) both a homerun and a lottery stock and 4) neither a homerun nor a lottery stock. We measure these probabilities by dividing the number of stocks in each of these four groups by the total number of stocks in the CRSP universe.[12] We then average these probabilities across all quarters in our sample and repeat the same exercise for high-volatility and high-skewness stocks.

Panel A of Table 2 reports these probabilities. In our sample, 83% of stocks are neither a homerun nor a lottery stock in a given quarter. On average, 6.8% of stocks are lottery stocks and 8.54% are homeruns. More importantly, only 1.41% of stocks are identified as both a homerun and a lottery stock. The probabilities of being both a homerun and a high-volatility or a high-skewness stock in the same quarter is very similar at 1.91% and 1.37%, respectively. If homeruns and other extreme returns designations were randomly assigned, the unconditional probability of a stock being a homerun and one other designation (Lottery, high-volatility, or high-skewness) would be 1%. Hence, the probabilities of 1.37 – 1.91% suggest that there is little overlap between homeruns and these measures of extreme performance.

[12]For example, if our sample includes 100 stocks in a given quarter and there are 7 homeruns and 9 lottery stocks, the probability of being a homerun is 7% and the probability of being a lottery stock is 9%. If 2 stocks out of the 16 stocks are identified as both a lottery and a homerun, then the probability of being both is 2%.

[Insert Table 2 approximately here]

In Panel B of Table 2, we report the share of homeruns that are also designated as one other extreme performer in a given quarter.[13] Panel B of Table 2 shows that only 14% of all homeruns are also designated as lottery stocks, 19% are also high-volatility stocks, and only 13% are also high-skewness stocks. This analysis implies that the stock picking strategy that we call swinging for the fences captures a different feature of stock holdings than lottery-ness, volatility, and skewness.[14]

III Swing for the Fences vs. Bat for Average

In this section, we present evidence on the persistence of the SF and BA strategies in equity mutual funds. We also provide evidence on mutual funds' homerun and strikeout disclosures. Next, we offer some stylized facts regarding strategy choice and fund characteristics. Finally, we evaluate whether SF is related to documented investment strategies such as momentum or value.

A Persistence

A steppingstone to exploring whether SF and BA are indeed strategies is to determine whether they demonstrate persistence from one quarter to the next. We estimate auto-correlations of SF and BA strategy measures with up to four quarterly lags.

[13]For example, if our sample includes 20 homeruns in a quarter and 3 of them are also designated as lottery stocks, then we measure this share as 15% for that quarter.

[14]We repeat this analysis using volatility and skewness of raw returns and factor-adjusted returns as well as MAX5 as an alternative measure of lottery-like returns and find nearly identical results. Following Agarwal et al. (2020), we define MAX5 as cumulative returns of the five best days of the quarter.

Because homeruns and strikeouts are potentially more likely in funds with more aggressive styles (e.g. small stocks), we account for style (market capitalization and book-to-market) in two ways. First, when defining homeruns and strikeouts at the stock level, we evaluate a stock's return relative to the comparable FF25 portfolio to control for size and value at the stock level. Second, in all our model specifications, we include Morningstar category fixed effects to control for the mutual funds' style. Therefore, our inferences are drawn from variation within each of the 9 style categories. These mutual fund style fixed effects allows us to compare like funds and avoids drawing inferences from comparisons between, for example, a small-cap fund and a large-cap fund.

[Insert Table 3 approximately here]

Table 3 reports the estimation results for our strategy variables. We believe that HR+SO, HR, SO reflect a SF strategy. In contrast, we define an indicator variable, $\mathbb{1}(\text{HR+SO} = 0)$, that takes the value of one when the fund has neither homeruns nor strikeouts in a quarter. We believe this indicator variable reflects the strategy choice to not Swing for the Fences. For each of these four variables, the autocorrelation coefficients on four quarterly lags are positive and highly statistically significant,[15] suggesting that the strategy to swing for the fences, or not, is a persistent feature that we interpret as an investment strategy. We interpret HR-SO, BA and benchmark-adjusted returns to reflect performance measures. In other words, does the manager have more HR than SO, have a majority of stocks that beat the market, or have positive benchmark adjusted returns. We do not find evidence of persistence in these performance measures (i.e., HR-SO, BA or benchmark-adjusted returns), which is consistent with fund performance being

[15]In unreported results, lagged values are statistically significant beyond 12 quarters.

unpredictable. Throughout the paper we will refer to $\mathbb{1}(\text{HR+SO} = 0)$ as a measure of a fund's strategy to bat for average or "not" be a SF fund. BA captures the fund's success in trying to bat for average.

As another assessment of persistence, we calculate transition matrices for our measures in Table A.2 in Online Appendix A. At quarter-end t, we sort all funds into five portfolios based on one of the strategy measures (e.g., HR). We then sort the funds at quarter-ends $t+1$ and $t+4$, into an updated set of five portfolios. Table A.2 reports the transition rates for each fund's strategy portfolio in quarter t to the fund's strategy portfolio in quarters $t+1$ and $t+4$. We observe that the numbers on the diagonals are significantly larger than the numbers off the diagonals, implying that both HR and SO are persistent in funds. For example, 32% of funds in the low-HR portfolio in each quarter stay in the low-HR portfolio in the next quarter while only 6% of those funds move to the high-HR portfolio. This pattern is observed for funds in each of the five portfolios and persists for four quarters. Moreover, we find similar transition rates when we sort funds based on SO or HR+SO.

B Marketing Swinging for the Fences

In this section, we examine the Management Discussion of Fund Performance section in mutual funds' N-CSR filings between 2003[16] and 2020 to test whether mutual funds disclose their homerun and strikeout holdings to their investors. As described above in Section C, reading these sections, we identify whether the fund managers discussed their

[16] Form N-CSR was introduced as part of the SEC's rule making following the Sarbanes-Oxley Act of 2002.

homerun and strikeout holdings as key contributors and detractors. We define two indicator variables MENTIONED_HR and MENTIONED_SO, taking value of 1 if the fund mentions at least one homerun as a contributor and at least one strikeout as a detractor, respectively.

Between 2003 and 2020, 46.5% of funds mentioned at least one homerun holding as a contributing factor to the fund's performance while 39.5% of funds mentioned a strikeout holding as a factor that detracted from their portfolio's performance in that year. We also find that the likelihood of mentioning holdings as performance factors is associated with swinging for the fences. Specifically, we sort funds into five quintiles based on HR and compute the average likelihood that a fund mentions homeruns as performance factors (MENTIONED_HR) for the funds in each quintile. We repeat these sorts for strikeouts, calculating the average likelihood of mentioning strikeouts as performance factors (MENTIONED_SO). Figure 2 calculates for each HR and SO quintile the likelihood that fund management mentions specific holdings in the managerial discussion section of the fund's N-CSR.

[Insert Figure 2 approximately here]

Figure 2 documents two interesting facts. First, funds in the first quintile with the lowest HR or SO have the lowest likelihood of mentioning holdings as performance factors. As the propensity to swing for the fences increases, the likelihood to mention holdings in the managerial discussion of performance increases monotonically. This fact is consistent with the hypothesis that SF funds deliberately pick stocks with potential to deliver extreme performance and are more likely to discuss these holdings as factors that affected the fund's performance, either as a contributor or a detractor. Second, the propensity to mention holdings is asymmetric. In every quintile, managers are more likely to mention their homeruns than their strikeouts. This asymmetry is largest for quintile 5 funds that most aggressively pursue the SF strategy. In a given year, a fund in HR quintile 5 has a 57% likelihood of mentioning specific homeruns, while SO quintile 5 funds have a 44% likelihood of mentioning specific strikeouts.

While Figure 2 shows that funds with higher HR and SO are more likely to disclose their homerun and/or strikeout holdings as performance factors in their managerial discussion of performance, it does not account for differences across other fund attributes such as fund size, fund age, managerial experience, etc., that are also related to HR and SO. In Table 4 we estimate the relation between managers' mentions of specific holdings and SF strategy measures in a multivariate regression. In column 1, we regress MENTIONED_HR on HR and other characteristics. In column 2, we regress MENTIONED_SO on SO and other characteristics. First, higher HR and SO are related to higher likelihood of mentioning homeruns and strikeouts in the N-CSR. This is consistent with the pattern in Figure 2. Second, funds with higher returns are more likely to discuss holdings as performance factors. Not surprisingly, the point estimate is larger for homeruns relative to strikeouts. Third, funds from larger families are more likely to mention holdings. Last, we find that younger funds and funds with a retail focus are more likely to discuss homerun and strikeout holdings as performance factors.

Our next test regarding disclosure of homeruns and strikeouts investigates whether funds are more likely to mention their homeruns or strikeouts when they are more meaningful economically. A homerun may be more salient if it accounts for a larger portion of the portfolio and if it delivers a very large quarterly return. We calculate *Contribution* of homerun (strikeout) holdings to be the fraction of the fund's portfolio returns that the homerun (strikeout) holdings deliver in each quarter. The magnitude of *Contribution* is increasing in both the portfolio weight as well as the quarterly return of the homerun (strikeout) holdings, with larger values when the fund has more economically salient homeruns (strikeouts). We then define HIGH–CONTRIBUTION_HR as an indicator variable taking value of one if the fund's homeruns have a contribution to portfolio return that is larger than the median contribution for all sample funds in all quarters. Similarly, we define HIGH–CONTRIBUTION_SO when the fund's strikeouts have a contribution to portfolio return that is below the sample median.[17]

[Insert Table 4 approximately here]

To examine whether more important homeruns and strikeouts are more likely to be discussed in managerial commentary, we include in our regressions an interaction term between HR and SO and High–Contribution indicators and report the estimates in Table 4. In column 3, we interact HR with HIGH–CONTRIBUTION_HR and find that managers are more likely to mention their homerun holdings when the homeruns have a larger impact on performance. Specifically, while a one-percent increase in HR is associated with 3.17% (7.718×0.41) increase in the likelihood of mentioning homeruns, the same increase in HR among funds with more impactful homeruns leads to 7.79% ($7.718 \times (0.41 + 0.60)$) increase in the likelihood of a being mentioned. In column 4, we investigate the effect of important strikeouts. Similarly, high–contribution SOs are more than twice as likely to be

[17] Contribution's sign for each holding is determined by its return. Its sign at the fund level is determined by the sum of the contribution of homeruns (strikeouts). While both positive and negative values are possible for contribution, contribution of homerun holdings at the fund level are always positive and contribution of strikeouts are always negative in our sample. So, economically meaningful homeruns have large, positive contributions while salient strikeouts have large, negative contributions.

mentioned relative to low–contribution SOs.

In our analysis of fund disclosures, we find that mutual funds that swing for the fences are more likely to mention the specific names of the stocks that delivered homeruns and strikeouts in their performance disclosures, particularly when these holdings have a greater economic impact on returns. This tendency is stronger for homeruns than strikeouts, revealing an asymmetric disclosure pattern, suggesting that marketing incentives are likely to influence fund managers' communications to investors. We believe this provides evidence of a credible mechanism that connects SF to fund flows, which we examine below in Section A.

C Which Funds Swing for the Fences?

To identify the mutual fund characteristics that are associated with swinging for the fences and batting for average, we regress these strategies on lagged fund characteristics and report the results in Table 5. These predictive regressions reveal some interesting patterns and provide some new stylized facts about mutual funds.

First, we find that funds with higher turnover and expense ratios are more likely to swing for the fences. In column 1, we find that one standard deviation increase in the turnover ratio is associated with 0.82% increase in HR+SO,[18] our measure of swinging for the fences. Column 2 shows a significantly negative relationship between turnover in the fund and the batting for average strategy as measured by $\mathbb{1}(\text{HR+SO} = 0)$. In columns 3 and 4, we find consistent evidence that funds with higher portfolio turnover are more likely to have homeruns and strikeouts in their portfolio. This conforms to the notion that funds

[18]We arrive at this estimation by 0.007×117. Turnover ratio's standard deviation is 117%.

cannot swing for the fences without frequently making changes to their portfolios. Furthermore, we find evidence that higher fees are positively associated with swinging for the fences. We explore the relation to fees in more detail in Section B.

Second, we find that a fund's investor base is related to its strategy choice. Specifically, funds that primarily sell to institutional investors are less likely to swing for the fences. Column 1 shows that funds with institutional focus have 46 bps fewer homerun and strikeout holdings in their portfolios. Columns 3 and 4 examine homeruns and strikeouts separately and show that the decrease in HR+SO is driven by both homeruns and strikeouts.

[Insert Table 5 approximately here]

Third, we find that both strategies suffer from decreasing returns to scale. Berk and Green (2004) argue that, due to liquidity constraints, diminishing returns to scale erode funds' performance as they grow larger. Whereas a small fund can put all of its capital in its best ideas, a large fund has to invest in its second-best ideas and/or take larger positions in its existing stock holdings relative to what is optimal.[19] In Table 4, column 3, in the HR regression, the coefficient on SIZE is positive, but not significant. In Column 4, SO increases significantly with fund size. Consistent with these coefficients, in column 5 the spread between HR and SO decreases in fund size. In other words, as funds get larger, they are less successful at swinging for the fences. An increase of one log magnitude in SIZE translates to 14.7 bps increase in strikeouts and ultimately a decrease of 9 bps in

[19] Empirical evidence on diseconomies of scale in the active management industry is mixed. Chen, Hong, Huang, and Kubik (2004), Chen, Hong, Jiang, and Kubik (2013), Reuter and Zitzewitz (2021), Edelen, Evans, and Kadlec (2007), Yan (2008), and Zhu (2018) find decreasing returns to scale while Pástor et al. (2015), Elton, Gruber, and Blake (2012), and Gutierrez, Maxwell, and Xu (2009) don't.

HR-SO, which represents the performance of SF. For brevity we don't tabulate, but this effect is significantly stronger at 38 bps when we include fund fixed effects, suggesting that when a fund grows by one log magnitude, its ability to successfully swing for the fences declines by 38 bps. These results are consistent with the hypothesis that the probability of a strikeout increases as asset size increases since funds must dig deeper into their preferred stock picks. Moreover, column 6 shows that larger funds tend to have a lower BA as well. A one-log increase in fund size is associated with 10.1 bps decrease in the fund's BA. The effect of fund size on HR, SO, and BA suggests that both strategies are likely to suffer from diseconomies of scale.

Furthermore, we find that younger funds and younger managers are more likely to swing for the fences. Specifically, as FUND_AGE increases, HR+SO decreases, suggesting older funds engage less in SF. Likewise, $\mathbb{1}(\text{HR+SO} = 0)$ increases in probability as funds grow older, suggesting older funds prefer to bat for average or not SF. This relationship is consistent with the hypothesis that younger funds have stronger incentives to stand out in the competition at the earlier stages of their life cycle. Figure A.1 in Online Appendix A illustrates the relationship between fund age and SF as a strategy by showing average HR+SO, HR, SO, and HR-SO for funds at different ages. It appears that funds aggressively swing for the fences in the first few years after their inception. Average HR+SO for funds under 5 years is 10.8%, average HR is 6.1%, and average SO is 4.9%, all of which are significantly higher than the full sample averages. Subsequently, HR and SO experience a modest yet steady drop for about 20 years. For comparison, average HR+SO, HR, and SO for funds older than 20 years are 8.6%, 4.5%, and 3.9%, respectively. These averages correspond to 21, 26, and 21% decrease in these measures, respectively. We find evidence that as fund managers' experience increases, SO decreases at a significantly higher rate than HR, suggesting that managers learn to pick potential homeruns as they gain more experience and have fewer strikeouts for each homerun. This is consistent with the role of experience in mutual fund performance (Chevalier and Ellison (1999) and Kempf et al. (2017)).

Last, Table 5 shows that funds that are managed by a team of managers (TEAM_MANAGED) are less likely to swing for the fences than solo-managed funds. Specifically, column 1 shows that HR + SO is 51 basis points lower for team-managed funds and column 2 shows that team-managed funds are 2.05% more likely to have neither homerun nor strikeout holdings in their portfolios. This effect could be driven by the fact that a manager that is trusted to operate solo may have enough human capital or confidence to take the risk to swing for the fences.

D Fund Strategies vs. other Measures of Active Management

A fund's stock picking strategy is an active investment decision. Therefore, it is natural to ask whether SF and BA are related to other measures of active investment. For example, funds with high levels of active share (Cremers and Petajisto (2009)) potentially deviate from the passive benchmark in hopes of picking outperforming stocks. Moreover, (Kacperczyk et al. (2005)) argue that funds with concentrated portfolios within industries pick outperforming stocks and thus deliver higher returns. To address potential overlap between existing measures of active management and the SF strategy, we include ACTIVE_SHARE and INDUSTRY_CONCENTRATION_INDEX (ICI) as control variables in the regression models in Table 5. The estimates are reported in columns 7 and 8.[20] Comparing column 1 to column 7, and column 2 to column 8, we find that the inclusion of ACTIVE_SHARE and ICI does not change the inferences drawn from the estimated coefficients on other fund characteristics. Moreover, we find that both ACTIVE_SHARE and ICI are positively related to both SF and BA as captured by $\mathbb{1}(\text{HR}+\text{SO} = 0)$.

We conclude from these estimates that the distinction between SF and BA strategies are not driven by these measures of active investment. Both strategies are positively correlated with active share. This positive correlation is not surprising because the SF and BA are active investment strategies. A fund can actively pick stocks that are expected to have extreme returns (i.e., swing for the fences) while another fund can be equally active in picking stocks that are expected to have moderate returns (i.e., batting for average). Therefore, both groups are active managers deviating from the passive benchmark to seek alpha and thus exhibit a positive relation to active share.

Another potential active investment strategy is momentum. In the presence of a static fund portfolio that holds momentum stocks, we may observe persistence in homerun and strikeout holdings in those momentum stocks. In other words, a fund that holds a certain homerun stock may choose to continue to hold that stock over the next quarter and that stock may happen to be a homerun again, leading to persistence in the fund's HR even in the absence of an intentional strategy of swinging for the fences. We don't believe this to be the case. First, Hartzmark (2015) shows that mutual funds are more likely to promptly sell their best and worst performers in their portfolios. So, if a fund experiences a homerun,

[20] We do not include ACTIVE_SHARE and ICI in all columns because both variables are missing for a portion of our observations. We report full sample estimates in columns 1-6, and estimates that include ACTIVE_SHARE and ICI in columns 7 and 8.

it is more likely to sell it by the end of the following quarter than keep it in the portfolio. Second, Table 5 shows that funds with higher HR and SO tend to have higher turnover ratios, suggesting that they have less static portfolios than peers that bat for average.

Nonetheless, we directly investigate whether funds that swing for the fences systematically chase momentum relative to other funds. Our hypothesis is that if SF funds simply follow a momentum strategy and hold their homeruns over multiple quarters, then their quarterly returns are expected to correlate with the momentum factor. To test this hypothesis, we regress SF and BA strategy measures on the fund's loading on the momentum factor[21] alongside other control variables and report our estimation results in Table A.4 in Online Appendix A. The results show that the coefficients on the momentum factor are not statistically significant for SF or BA variables. We conclude that the persistence in HR and SO is unlikely to be an artifact in the data brought about by momentum in stock returns. Rather, we believe that our evidence supports the hypothesis that fund managers are deliberate in picking stocks that are part of a SF strategy.

Although we show that swinging for the fences is inherently different from active share, industry concentration, and momentum, the existing literature has documented many other factors that predict future abnormal returns (McLean and Pontiff (2016), Harvey, Liu, and Zhu (2016), and Feng, Giglio, and Xiu (2020)). Therefore, mutual funds may actively exploit these factors in hopes of generating abnormal returns. It is possible that swinging for the fences is not a deliberate stock picking strategy and may simply result from exposure to one or more of the known factors. Using a comprehensive list of

[21]We measure each fund's loading on the momentum factor in each quarter by estimating the Carhart (1997) factor model using a 36-quarter rolling window prior to the quarter.

factors from The Open Asset Pricing Project,[22] we address this question at both the stock and fund return level.

At the stock level, we estimate each homerun stock's exposures to all factors[23] and identify its top five. If certain factor(s) drive homerun outcomes, they should appear frequently among these top exposures. Instead, we find that the 10 most common factors, on average are relevant to only 6.7% of homerun stocks, indicating no single factor explains their homerun performance. At the fund level, we sort funds into HR quintiles and measure how often each factor is relevant within each group. Again, the 10 most common factors appear for only 15.7% of funds. More importantly, if loading on a factor causes high HR, exposure to the factor should concentrate in the High–HR group. Contrary to this expectation, we find that each factor's prevalence is similar across quintiles, suggesting that while funds are exposed to certain factors, this exposure is not related to their tendency to swing for the fences.

We provide, in Online Appendix B, a more detailed description of this analysis, including the estimation of factor exposures, the top factors, and the results to further address that swinging for the fences is different from exposure to existing factors found to predict returns.

[22] Chen and Zimmermann (2022) provide data and code that reproduces 212 factors that finance research has shown to provide cross-sectional stock return predictability. The code, data, and description of the factors are publicly available at https://www.openassetpricing.com.

[23] In our estimations, we use 250 daily returns preceding the homerun quarter.

IV Fund Performance

In this section, we investigate the performance implications of SF and BA strategies. We first examine whether either of these strategies generate superior risk-adjusted returns, and then we examine whether these strategies are associated with fund volatility.

A Returns

We focus on benchmark-adjusted net returns, ADJUSTED_RETURNS, which we define as the fund's quarterly net-of-fee returns in excess of its Morningstar designated benchmark index. Benchmark adjustment accounts for fund style and risk but, unlike factors that are long-short portfolios, index portfolios are easily implemented by mutual fund managers, which makes them appropriate benchmarks. In addition, Cremers, Petajisto, and Zitzewitz (2008) argue that factor adjustment produces biased assessments of fund performance. Nonetheless, we show in Online Appendix A that our performance results are robust to using Carhart (1997) Four-Factor alpha as an alternative measure of performance.

We regress ADJUSTED_RETURNS on our strategy measures while controlling for other fund characteristics. The fund characteristics that we include in these regressions are lagged ADJUSTED_RETURNS, SIZE, FAMILY_SIZE, TURNOVER, EXPENSE_RATIO, INSTITUTIONAL, FLOW, AGE, EXPERIENCE, and STOCKS_HELD. Furthermore, we include three additional control variables that we call *Style Premiums* to control for the effect of potential exposures to particular styles.[24]

[24]For each fund at quarter $t-2$, we identify the top three factors the fund has the highest exposure to and calculate the premiums to those factors in quarter $t-1$. These premiums are the return of the long-short

We identify homeruns and strikeouts at the stock level based on their returns relative to one of the FF25 benchmark portfolios. As discussed above, this mitigates the concern that the presence of homeruns and strikeouts in a fund's portfolio is due to market capitalization or growth/value. In addition, we include Morningstar style category fixed effects in our regressions to further control for any fund-level style effects. Therefore, our inference regarding the effect of the strategies on performance is drawn from variation within the style categories. We also include calendar date fixed effects to absorb any macro-level market conditions that may affect performance.

[Insert Table 6 approximately here]

We report the estimation results in Table 6. First, as documented in the literature, we confirm that past returns do not predict future returns (Elton, Gruber, and Blake (1996), Carhart (1997), French (2008), Fama and French (2010), Del Guercio and Reuter (2014), and Glode (2011)). The coefficient on past returns is not significant in any of the specifications. Furthermore, none of the coefficients on the strategy measures are significant, suggesting that these measures do not carry information about future returns. Column 1 shows that higher tendency to swing for the fences, measured by HR+SO, does not translate to higher returns. Similarly, column 2 shows that higher tendency to bat for average, as measured by $\mathbb{1}(\text{HR+SO} = 0)$, does not translate to higher performance either. Columns 3 to 6 estimate the effect of HR, SO, HR–SO, and BA on performance and report insignificant effects. These results imply that neither of the two strategies benefit fund investors through superior returns beyond the benchmarks of similar risk.

strategy according to each factor. When we identify relevant factors and measure premiums at $t-1$ or $t-2$ we find similar results.

In Table A.5 in Online Appendix A, we show that our results are robust to alternative model specifications as well as alternative measures of performance. First, we replace style category fixed effects with fund fixed effects. In columns 1 to 6, we show that these strategies are not associated with superior fund returns. Next, we replace our dependent variable with the Carhart (1997) four-factor alpha. In columns 6 to 12, we continue to find qualitatively similar results.

Our primary strategy measures used in Table 6 are weighted equally and thus put more emphasis on small holdings. It is possible that the lack of performance implications may be the result of the fact that small holdings, when becoming homeruns and strikeouts, do not affect portfolio outcomes significantly. We replicate our analysis in Table 6 with alternative fund-level HR, SO, and BA using three weighting schemes that emphasize larger holdings and more extreme returns and report our results in column 1-3 of Table A.6 in Online Appendix A.[25] In sum, the SF strategy does not generate superior returns using a number of reasonable weights for the strategy metrics.

The results in Tables 6 and Table A.5 in Online Appendix A show that the strategy to swing for the fences does not deliver superior net-of-fee returns to investors. However, net-of-fee performance, while useful to evaluate investor value, fails to directly measure the fund's ability to select better-performing stocks via a selection strategy such as swinging for the fences. This is particularly important because Table 5 shows that SF funds are associated with higher fees.

[25]Panel A defines value-weighted HR, SO, and BA using portfolio weights, putting more emphasis on larger portfolio holdings. Panel B uses holdings' returns as weights to compute HR, SO and BA, allowing more salient extreme performances to carry more weight in the calculations. Panel C limits the calculation of strategy measures to the top–20 largest holdings to credit funds for holding a homerun only if the homerun is among the biggest holdings. We fail to find significant performance implications after using any of these differing weights.

Therefore, SF funds may lack net-of-fee performance simply because the strategy does not outperform their benchmarks. Alternatively, SF funds may lack net-of-fee performance despite the strategy generating positive gross performance for SF funds. We posit that SF funds may generate higher gross returns through their stock picking ability but charge investors higher fees, allowing managers to capture the benefits of superior performance. In a competitive mutual fund industry, it is expected that much of the benefit of stock picking abilities would naturally accrue to the fund managers rather than investors (Berk and Green (2004)).

We test this hypothesis by repeating our analysis in Table 6 with benchmark-adjusted gross returns. Specifically, we regress benchmark-adjusted gross returns on the strategy measures while controlling for fund characteristics as well as category and date fixed effects. The estimated coefficients are reported in Table A.7 in Online Appendix A. We find that neither of the two strategies is able to deliver superior gross returns. Overall, we conclude that the strategy choice between SF and BA does not deliver superior risk-adjusted mutual fund returns.

B Volatility

We now turn to an analysis of fund volatility. We assess the risk associated with the SF and BA strategies using two methods. First, we examine the cross-sectional standard deviation of fund returns in portfolios of funds sorted on the strategy measures. We sort funds into 5 portfolios in each quarter and compute the standard deviation of quarterly fund returns across all funds in each portfolio. We report time series averages of the cross-sectional standard deviations for each portfolio along with a 5% confidence interval in Figure 3. The figure shows that cross-sectional volatility is significantly higher for portfolios that have higher HR+SO, HR, and SO. In other words, dispersion in returns is much higher for SF funds than for BA funds. Figure 3 also reports these average standard deviations of fund returns for these strategy portfolios during our sample. We find that the difference in cross-sectional standard deviation between the highest and lowest HR+SO portfolios (High–Low) is 1.05%, which is statistically significant at 1% confidence. The same spread is 0.77% and 0.80% for portfolios sorted on HR and SO, respectively. We show in Figure A.2 in Online Appendix A that the results are very similar when we use cross-sectional standard deviations of four-factor alphas in lieu of benchmark-adjusted returns.

[Insert Figure 3 approximately here]

In our second analysis of portfolio risk, we regress fund-level return volatility on lagged measures of SF and BA strategies while controlling for fund characteristics. We calculate, BENCHMARK-ADJUSTED_VOLATILITY, in each quarter, as the standard deviation of the fund's monthly benchmark-adjusted return over the previous 12 months. The regression results are reported in Table 7 where the dependent variable is our main measure of volatility based on benchmark-adjusted net returns. In column 1, we examine whether HR+SO is positively associated with return volatility in the fund. The coefficient estimate indicates that one percent increase in HR+SO is associated with 3.09 bps increase in the volatility of the fund. One standard deviation increase in HR+SO leads to an economically large increase of 22.71 bps (3.088×7.352). Column 2 indicates that BA funds with $\mathbb{1}(\text{HR+SO} = 0)$ have 4 bps lower volatility than SF funds. Columns 3 and 4 show that homeruns and strikeouts are both associated with higher fund volatility. Interestingly, columns 5 and 6 show that the performance measures, HR-SO and BA, do not exhibit a robust relation to volatility. In Table A.8 in Online Appendix A, we repeat our analysis in Table 7 except that our dependent variable is volatility of a four-factor alpha. We find qualitatively similar results. Moreover, we show that the results are robust to the inclusion of fund fixed effects. Therefore, both across all funds within a style category and within funds, we find that swinging for the fences is a strategy that increases fund return volatility.

[Insert Table 7 approximately here]

While our primary strategy measures are weighted equally and thus put more emphasis on small holdings, we provide robustness tests using additional weighting schemes that emphasize larger holdings and more extreme returns and report our results in column 4 – 6 of Table A.6 in Online Appendix A. As in the weighted return analysis, we use three weighting measures and in all three panels, we find that SF funds have higher idiosyncratic volatility regardless of how the strategy metrics are weighted. Our findings in this section show that while swinging for the fences does not produce superior returns, it is a riskier strategy as funds with higher number of homeruns and strikeouts in their portfolios exhibit higher volatility.

V Management Incentives

Given that we find that the SF strategy incurs more risk, yet fails to deliver deliver superior risk-adjusted returns, we now turn to managers' incentives to pursue homeruns. Specifically, we ask two questions: First, do funds use homeruns to attract additional flows? Second, do fund managers use their homeruns to justify higher fees? Each of these hypotheses independently would lead to increased fund revenue. In this section we test these two hypotheses.

A Fund Flows

To examine the relationship between the SF strategy and fund flows, we regress flows on strategy measures, while controlling for fund characteristics, including past style premiums. Following the fund flow literature, we define QUARTERLY_Fund_FLOW in each quarter as the net flow into the fund divided by the lagged size of the fund. We control for past returns in our regressions by including lagged quarterly returns, returns for the past four quarters, and the returns for the past three years (Sirri and Tufano (1998)). In our regressions, we include category and calendar date fixed effects to further absorb the effects of fund investment style and general economic factors.

[Insert Table 8 approximately here]

In Table 8 we observe the well-documented flow-performance relation (Sirri and Tufano (1998)). Past performance up to three years prior is correlated with fund flows. However, we find that, above and beyond the role of returns, our strategy measures significantly explain fund flows. In column 1, we find that the SF strategy (having high HR+SO) attracts additional flow. Whereas, the BA strategy, $\mathbb{1}$(HR+SO $= 0$), attracts less flow. The magnitude of the effect is large. A one standard deviation increase in the tendency to swing for the fences, as measured by HR+SO, is associated with 0.18% (0.025×7.352) increase in fund flow. In contrast, column 2 shows that having no homeruns and strikeouts in the portfolio (HR+SO $= 0$) is associated with 0.04% decrease in flows. In terms of economic magnitude, the fund flow response to these strategies is meaningful. The average fund, for example, will receive \$8.39 million in additional fund flows for a one-standard deviation increase in swinging for the fences.

In columns 3 and 4, we examine the role of HR and SO separately. We find that having more homeruns leads to additional flows whereas more strikeouts lead to lower flows. Specifically, the estimates suggest that one standard deviation increase in HR is associated with 0.88% (0.114×7.718) increase in flow, while the same increase in SO is associated with 0.80% (-0.125×6.429) decrease in flows. Thus, while swinging for the fences attracts additional flows (column 1), investors reward managers for their homeruns and punish managers for strike outs.

In column 5, we include both HR and SO in the flow model and document that the point estimate of investors' response to strikeouts is slightly larger than it is for homeruns. Despite these estimates, column 1 documents a net positive flow to swinging for the fences. This positive relation that the SF strategy has with fund flows is due to the fact that managers, on average, score more homeruns than strikeouts. In fact, Table 1 shows that funds do have more HRs on average than SOs with both mean and median being higher for HR by 1%. Specifically, using the estimated coefficients in column 5, the net flow response for the average fund with average HR value of 5.16 and SO value of 4.31 is 0.20%.[26] This response is very similar in magnitude to the estimated coefficient in column 1.

In columns 6 - 8, we examine the effect of the performance metrics, HR–SO and

[26]We arrive at this number using $5.156 \times 0.124 - 4.304 \times 0.149$. The average values are from Table 1 and estimated coefficients are from column 5 of Table 8.

BA. Column 6 shows that a one-standard deviation increase in the spread (HR–SO) increases the additional fund flows by 0.70% (0.128×5.449). Moreover, the same increase in BA is associated with 0.66% (0.074×8.905) increase in flow. For comparison, one standard deviation increase in ADJUSTED_RETURNS leads to 1.19% ($0.004 \times 2.997 \times 100$) increase in subsequent fund flows. Thus, the effect of our measures on flow is economically meaningful after controlling for the flow-performance relation.[27]

Our primary strategy measures are weighted equally and thus put more emphasis on small holdings. We believe the simplicity of our extreme performers is in line with how an investor might notice that a homerun is held in the portfolio when selecting funds. However, investors' response to more impactful homeruns and strikeouts could be amplified. We replicate our analysis in Table 8 with alternative fund-level HR, SO, and BA using three weighting schemes that emphasize larger holdings and more extreme returns and report our results in column 7 – 9 of Table A.6 in Online Appendix A. Specifically, we define value–weighted measures using portfolio weights (Panel A), return–weighted measures using holdings' returns as weights (Panel B), and measured based on top–20 largest holdings (Panel C). In all three panels, we find the similar evidence that homeruns attract flows while strikeouts decrease flows with the SF strategy attracting a net positive flow regardless of how the strategy metrics are weighted and calculated. Furthermore, we find that strategy metrics that emphasize more economically valuable homeruns and strikeouts, particularly value–weighted alternatives, are associated with larger estimated

[27] As an additional robustness test, we repeat our analysis with FLOW_RANK as an alternative measure of fund flows and report our results in Table A.9 in Online Appendix A. At each quarter, we sort all funds based on their percentage flow and rank them from the lowest to highest. Then, we standardize the ranks over the [0,1] interval. We find qualitatively similar results, suggesting the relationship between our measures and fund flows is robust to other measures of fund flows.

coefficients, suggesting that investors respond to more salient holdings more strongly. Following this finding, we further investigate the role of salience, both marketing activity and economic impact, in the relationship between the SF strategy and flows.

[Insert Table 9 approximately here]

As noted above, Table 8 document investors' reactions to homeruns and strikeouts, implying that these are salient measures that affect flows. Given that the strategy to swing for the fences delivers a net positive capital flow to SF funds, managers have incentives to swing for the fences and promote their homeruns to attract more flows. The evidence in Section B shows that fund managers that swing for the fences indeed highlight their homeruns and strikeouts in their performance commentary. We now investigate whether homerun and strikeout holdings have a larger effect on flows when mutual funds mention their specific holdings in their managerial discussion of performance. To do so we interact strategy measures with the indicators of whether the fund mentions holdings.[28] In Table 9, column 1, we interact HR with MENTIONED_HR and find that capital flows are more responsive to homerun holdings when the fund mentions the specific stocks in its performance discussion as factors that contributed to the fund's performance. The economic impact is meaningful. A one-percent increase in HR is associated with 7.1 bps increase in flows, while the same increase in HR among funds that mention homeruns leads to 15.3 bps increase in flows. In column 2, we investigate the effect of being mentioned for strikeouts. Similarly, strikeouts among funds that mention them detract more than twice

[28] The N-CSR disclosures are aligned prior to the flows they are used to explain in our regressions. Since our regressions are quarterly but N-CSR disclosures are annual, we use the latest N-CSR filing available prior to the quarter. For example, in a regression of flow in 2015Q3 on SF strategy measures in 2015Q2, the Mentioned variable is from the N-CSR filings in 2014Q4.

the flow relative to strikeouts in funds that don't mention them. The magnitude of these effects are comparable to flow/performance sensitivity. For example, one standard deviation increase in HR in funds that mention them in the N-CSR is associated with 1.18% (0.153×7.718) increase in flow, which is comparable to the 1.49% ($0.005 \times 2.997 \times 100$) effect observed in response to the same increase in benchmark-adjusted net returns.

Section B, documents that homeruns and strikeouts are more likely to be named in shareholder reports when the holdings are larger or the returns are more extreme, and, therefore economically more impactful. In column 4, we examine whether these more salient holdings have a larger effect on flows. We interact HR with HIGH–CONTRIBUTION_HR and find that HR attracts more flow when the homeruns have a larger impact on performance. Specifically, while a one-percent increase in low–contribution HR is associated with 0.43% (0.056×7.718) increase in flows, the same increase in HR among funds with more impactful homeruns leads to 1.22% (0.158×7.718) increase in capital flows to the fund. In column 5, we investigate the effect of important strikeouts. Similarly, high–contribution SOs detract almost twice as much flows that low–contribution SOs do.

Our last piece of analysis on fund flows focuses on funds with primarily retail investor clients. The findings in Table 5 show that funds that primarily sell to institutional investors are less likely to swing for the fences, whereas retail-focused funds tend to invest in homeruns and strikeouts more frequently. This finding is consistent with the notion that less sophisticated investors tend to interpret holding stocks with extreme performance as a measure of skill among fund managers. We now test whether the subsequent flow of capital from these investors is more responsive to past HR and SO by interacting strategy measures with RETAIL_FUND, an indicator of whether the fund primarily sells to retail clients. We report our estimation results in Table A.10 in Online Appendix A. In sum, although the effect of strategy measures on subsequent flows is still statistically and economically significant for institutional funds, this effect is 65 – 86% stronger among retail-focused funds.

The results in Tables 8, 9, and A.10, show that investors reward funds with more flow when they have more HRs and withdraw flows from funds with more SOs, though on net the average SF strategy leads to higher flows. These flow effects are significantly stronger when holdings are highlighted in shareholder reports and when they have greater economic impact on fund performance. Moreover, this effect is stronger among funds with a focus on retail investors. Our findings suggest that investors interpret homeruns as signals of managerial skill, especially when managers emphasize them in disclosures, creating incentives for managers to swing for the fences and strategically highlight homeruns to attract capital flows.

B Fund Fees

Fund fees charged by mutual funds directly generate revenue for mutual fund companies. These fees are meaningful and vary substantially across funds. For example, Sheng et al. (2023) document that in the United States in 2019, fees amounted to tens of billions of dollars and ranged from 0.5% per year for the "cheapest" decile of actively managed funds to 2% for the most "expensive" decile. Given the magnitude of fee-based revenue for mutual fund families, another incentive for active mutual funds to swing for the fences is to use homerun holdings to justify higher fees.

[Insert Figure 4 approximately here]

To test this hypothesis, we sort funds into 5 portfolios based on their tendency to swing for the fences as measured by HR+SO in each quarter. Then, we follow two *High* and *Low* portfolios in the following quarter and examine their expense ratios. In Figure 4, we draw the distribution of expense ratios for the funds in these two portfolios. The figure shows that funds in the portfolio of High HR+SO, those who tend to swing for the fences, charge substantially higher fees relative to funds in the portfolio of Low HR+SO.

One potential concern with the sorting analysis in Figure 4 is that funds in the small-cap categories generally charge higher fees. This fact is relevant because our measures, HR and SO, are both naturally higher in small-cap categories. Therefore, it is possible that the result above is just an artifact of sorting funds into style categories. To address this concern, we regress fund EXPENSE_RATIO in basis points on lagged values of our strategy measures while controlling for prominent fund characteristics and style categories. We report the results in Table 10. There are several takeaways.

[Insert Table 10 approximately here]

First, our regressions confirm previously known facts about fees: larger, older funds within larger families have lower expense ratios. Moreover, there is a negative relation between net-of-fee returns and expense ratios. What is new is that funds that swing for the fences have higher expense ratios. Moreover, this relationship is robust to the inclusion of category and date fixed effects. In terms of economic magnitude, estimates in column 1 imply that one standard deviation increases in HR+SO is associated with 3.7

(0.503×7.352) bps increase in fund fees. This is roughly equivalent to one-tenth of standard deviation increase in expense ratios. In contrast, column 2 shows that BA funds with $\mathbb{1}(\text{HR+SO} = 0)$ charge 1.91 bps lower fees. Moreover, columns 3 and 4 show the effect of HR and SO on expense ratios. Presence of both homeruns and strikeouts in the portfolio is associated with higher fees. This is not surprising given that HR and SO tend to happen simultaneously in the portfolio.[29]

Furthermore, in columns 5 - 7, we examine whether performing well under either of the strategies is related to the fees and find that none of the coefficient estimates are significant. Specifically, HR–SO, a measure of high performance in hitting homeruns, is unrelated to fees. Similarly, BA seems to be unrelated to expense ratios. It appears that funds that pursue SF as a strategy charge higher fees. However, fees do not seem to be sensitive to how well funds perform the strategy and hit homeruns. This lack of sensitivity is not surprising given the fixed, sticky nature of fund fees.

[Insert Table 11 approximately here]

Last, we investigate whether the association between the SF strategy and higher expense ratios is stronger when mutual funds mention their specific holdings in their managerial discussion of performance. To do so we interact strategy measures with the indicators of whether the fund mentions holdings and report our results in Table 11. In column 1, we interact HR with MENTIONED_HR and report a positive coefficient on the interaction term. In column 2, we investigate the effect of highlighting strikeouts. Similarly,

[29] We provide robustness tests using value–weighted measures (Panel A), return–weighted measures (Panel B), and measured based on top–20 largest holdings (Panel C) in columns 10 – 12 of Table A.6 in Online Appendix A. In all three panels, we find higher associations between expense ratios and SF strategy measures regardless of how the strategy metrics are weighted and calculated.

SOs among funds that mention them are associated with higher fees more strongly relative to SOs in funds that don't mention them. In column 3, we include both interaction terms in our model and find similar results. While the statistical significance of these effects is small, the economic impact is meaningful. Specifically, the effect of SF measures on higher fees is 17 – 38% higher when the fund highlights holdings in its performance discussion.[30]

The results in tables 10, and 11, show that funds pursue the SF strategy tend to charge higher expense ratios. These flow effects are significantly stronger when holdings are highlighted in shareholder reports. Our findings suggest that investors interpret homeruns as signals of managerial skill, creating incentives for managers to swing for the fences and strategically highlight homeruns as justification for higher fees.

VI Evidence from Passive Funds

If swinging for the fences is an investment strategy that is utilized by actively-managed funds to stand out as skilled stock pickers, we would not expect to observe this behavior in passive funds. As a falsification test, we use a sample of passively-managed funds to investigate whether our SF and BA measures are meaningfully related to fund characteristics in passive funds. To construct our sample of passive funds, we follow the same procedure to construct our active sample. Our final sample of passive mutual funds consists of 218 unique funds and 7,826 fund-quarter observations from 1993 to 2020.

[Insert Table 12 approximately here]

[30] We arrive at these numbers by dividing the coefficients on the interaction terms by their corresponding baseline effects.

We begin our examination of our strategy measures in passive funds by repeating our analysis in Table 5. Specifically, we regress our measures on a set of fund characteristics and report our estimates in Table 12. In contrast to active funds, fund size has no relation with HR and SO, suggesting there is no decreasing returns to scale among passive funds. Furthermore, there is no significant difference between funds with institutional clients and retail clients. Fees and turnover ratio do not relate to the SF and BA strategies either. More importantly, contrary to actively-managed funds, where younger funds and younger managers were more likely to swing for the fences, no relation exists between the strategy measures and fund age or manager experience. Figure A.3 in Online Appendix A clearly shows this lack of relation between age and strategy. Specifically, all measures of swinging for the fences, HR+SO, HR, SO, and HR–SO, are fairly constant for all funds of various ages in our sample. This lends credence to our hypothesis that the negative relation between age and swinging for the fences is indeed a strategy for younger funds that allows managers to stand out among the competition and thus it is motivated by career concerns.

[Insert Table 13 approximately here]

The second part of our analysis of passive funds involves investigating the effect of our measures on performance, flows, and fees. Specifically, following the same specifications, we regress measures of performance, flows, and fees on lagged values of the strategy measures, past performance, and other fund characteristics for passive funds. In columns 1 - 4 of Table 13, where we regress fund benchmark-adjusted net returns and volatility on the two strategy measures, HR+SO and $\mathbb{1}(\text{HR+SO} = 0)$, we find no evidence that passive funds' returns or volatility are related to our measures of swinging for the fences or batting for average. This is important because, unlike active funds, HR and SO do do not explain portfolio risk. We study fund flows in columns 5 and 6. The coefficient estimates of both measures are statistically insignificant, suggesting that investors do not reward passive funds for having homeruns and strikeouts in their portfolios. In columns 7 and 8, we examine expense ratios for passive funds in columns 7 and 8 and find a similar result. Neither HR+SO nor $\mathbb{1}(\text{HR+SO} = 0)$ is associated with higher expense ratios among passive funds. These findings further suggest that homeruns and strikeouts that happen naturally in passive portfolios do not carry information for investors that alter fund flows or result in higher fees.

VII Conclusion

We characterize mutual funds' stock picking strategies by documenting that some funds swing for the fences in hopes of hitting homeruns, which we define as stocks with returns in the top decile of their FF25 portfolio of peers. These funds successfully hit homeruns but often strike out, defined as holding stocks with returns in the bottom decile of the FF25 adjusted return distribution. Other funds simply bat for average and avoid extreme stock performance.

We find strong evidence that SF and BA represent persistent, intentional strategies rather than variations in active management or exposure to known risk factors. The distinction between these two stock picking strategies helps to explain many of the stylized facts surrounding variables that are commonly used in the mutual fund literature.

We document that younger funds and early–career managers as well as funds with a focus on retail investors are more likely to swing for the fences. We also show that funds that swing for the fences deliver similar benchmark-adjusted returns while exhibiting higher return volatility. Despite this, SF funds attract higher future capital flows, especially when their homeruns are highlighted in shareholder reports, suggesting a marketing motive behind the strategy. Overall, it appears that investors are attracted to funds that swing for the fences, in spite of the fact that they do not receive superior risk–adjusted performance.

Using a set of falsification tests with passively managed funds that don't share the same stock–picking objectives, we confirm that the observed patterns are specific to active management decisions. Passive funds do not exhibit similar associations between strategy measures and performance, flows, or fees, supporting the interpretation that SF and BA are deliberate stock–selection strategies.

This paper makes three main contributions. First, it introduces and empirically validates the SF and BA frameworks as distinct, persistent mutual fund strategies. Second, it provides new insights into how fund characteristics, such as age, manager experience, client type, and fund size, shape strategic choices and investor responses. Third, it extends the literature on mutual fund flows and fees by showing that extreme past outcomes–both positive and negative–jointly affect capital allocation and may be used to justify higher fees. In doing so, we highlight how active fund managers use performance salience to compete for investor attention, even in the absence of superior risk–adjusted performance.

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Figure 1: Timing of Variable Construction and Estimation

This figure describes the timing and process of defining homeruns (HR), strikeouts (SO), and batting average (BA). In quarter $t-2$, we record fund holdings. Then, we observe each holding's portfolio-adjusted return during the following quarter (i.e. returns from $t-2$ to $t-1$). A stock holding is identified as homerun or strikeout if its portfolio-adjusted quarterly return is in the 90th or 10th percentile of the return distribution, respectively. A stock is identified as a hit if its portfolio-adjusted quarterly return is positive. For each stock, we use one of the FF25 portfolios which are based on the book-to-market ratio and market capitalization. Last, for each fund at quarter $t-1$, we define HR, SO, and BA as the number of holdings identified as homerun, strikeout, and hits during the quarter, scaled by the total number of stocks held by the fund at quarter $t-2$. In our estimates, we regress dependent variables of interest at quarter t on strategy variables at quarter $t-1$.

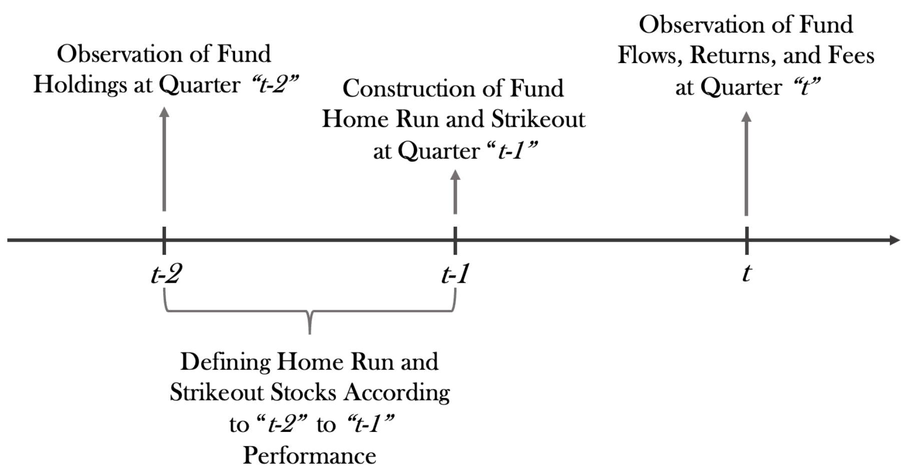


Table 1: Summary Statistics

This table reports descriptive statistics of all variables used in the analysis. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. All variables are reported at the fund-quarter level. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

Variable	Mean	Median	Std. Dev.
GROSS_RETURNS (%)	2.65	3.386	10.371
NET_RETURNS (%)	2.34	3.076	10.341
ADJUSTED_RETURNS (%)	−0.193	−0.027	2.997
FOUR-FACTOR_ALPHA (%)	−0.074	−0.066	2.841
ADJUSTED_RETURNS_VOLATILITY (%)	1.675	1.337	2.007
FOUR-FACTOR_ALPHA_VOLATILITY (%)	1.590	1.289	2.12
HR (%)	5.156	4.166	7.718
SO (%)	4.304	3.333	6.429
HR+SO (%)	9.473	8.000	7.352
HR–SO (%)	0.848	1.387	5.449
$\mathbb{1}(\text{HR+SO} = 0)$	0.083	0.000	0.276
BA	49.151	49.122	8.905
MENTIONED_HR	46.521	0.000	49.431
MENTIONED_SO	39.251	0.000	48.831
SIZE ($Billion)	4.664	0.435	29.321
FAMILY_SIZE ($Billion)	128.306	11.739	297.064
FLOW (%)	3.192	−1.037	11.862
EXPENSE_RATIO (%)	1.231	1.171	0.458
TURNOVER (%)	82.29	60.000	112.629
FUND_AGE (Years)	15.292	12.000	13.607
STOCKS_HELD	126.641	73.000	248.941
RETAIL_FUND	0.672	1.000	0.469
INSTITUTIONAL_FUND	0.308	0.000	0.462
EXPERIENCE (Years)	9.833	8.000	6.167
TEAM_MANAGED	0.587	1.000	0.492

Table 2: Homeruns and other Forms of Extreme Returns

This table reports the overlap between homeruns and other forms of extreme returns, including lottery stocks, high volatility stocks, and high skewness stocks. At quarter t, a stock is defined as a *homerun* if its quarterly portfolio-adjusted returns is above the 90^{th} percentile of its peers. At the same quarter, a stock is identified as a *Lottery Stock* if its highest one-day return (MAX) during the quarter is above the 90^{th} percentile of the CRSP universe. We calculate MAX following the methodology of Agarwal et al. (2020). Similarly, a stock is identified as a *High Volatility* and *High Skewness* if its volatility and skewness of its daily returns during the preceding 250 trading days is above the 90^{th} percentile of the CRSP universe, respectively. Panel A reports a stock's average probabilities of being defined as homerun, a lottery stock, a high-volatility stock, and/or a high-skewness stock. We measure these probabilities by dividing the number of stocks assigned to each of these four groups by total number of stocks in a given quarter and then averaging them over the sample period. Panel B reports the share of *homeruns* that are also identified as *Lottery Stock*, *High-volatility Stock*, and/or *High-skewness Stock*. We measure these shares at the quarterly level and then average across all quarters in the sample. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

Panel A: Probability of Being homerun and Other forms of Extreme Returns

	1	2	3	4	5	6
	Lottery Stock:		High Volatility:		High Skewness:	
Homerun:	0	1	0	1	0	1
0	83.24%	6.80	81.31	8.70	79.95	10.05
1	8.54	1.41	8.08	1.91	8.62	1.37

Panel B: Overlap of homeruns and Other forms of Extreme Returns

Share of homeruns being:	14.15%	19.10	13.72

Table 3: Auto-correlations of Strategy Measures

This table reports estimates from regressions of HR, SO, HR+SO, HR–SO, BA, and Risk-adjusted Returns on their lagged values for up to 4 quarters. *Lagged*$_t$ represents lagged value of the dependent variable for t quarters. All specifications include Morningstar Category fixed effects. All variables are defined in Section A as well as Table A.1 of Online Appendix A. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. *t-statistics* are based on two-way clustered standard errors at fund and year-quarter levels and are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	HR+SO	$\mathbb{1}$(HR+SO=0)$_t$	HR	SO	HR-SO	BA	Returns
	1	2	3	4	5	6	7
LAGGED_1	0.275∗∗∗	0.162∗∗∗	0.166∗∗∗	0.187∗∗∗	0.017	0.003	0.025
	(8.782)	(9.298)	(4.678)	(8.533)	(0.674)	(0.125)	(1.053)
LAGGED_2	0.235∗∗∗	0.163∗∗∗	0.149∗∗∗	0.197∗∗∗	0.035	−0.003	0.013
	(9.281)	(13.222)	(4.526)	(5.595)	(0.963)	(−0.100)	(0.423)
LAGGED_3	0.090∗∗∗	0.103∗∗∗	0.092∗∗∗	0.086∗∗∗	0.003	0.024	0.035
	(3.657)	(7.182)	(3.470)	(3.430)	(0.152)	(0.840)	(1.532)
LAGGED_4	0.095∗∗∗	0.089∗∗∗	0.071∗∗∗	0.121∗∗∗	0.015	−0.023	−0.021
	(3.394)	(5.967)	(3.285)	(6.504)	(0.649)	(−0.974)	(−1.042)
Observations	49,848	49,848	49,848	49,848	49,848	49,848	49,848
R-Squared	0.543	0.159	0.304	0.361	0.007	0.005	0.006
Fixed Effects:	Category	Category	Category	Category	Category	Category	Category

Figure 2: Likelihood of Mentions Across HR/SO Quintiles

This figure shows the likelihood that a fund manager mentions homerun and strikeout holdings in the managerial discussion of performance in its N-CSR form. We identify a fund as Mentioned if it mentions at least one homerun or strikeout holding when discussing factors that contributed to or detracted from performance of the fund. Then, we sort funds according to HR (Blue) and SO (Orange) into quintiles and calculate the average for the Mentioned indicator.

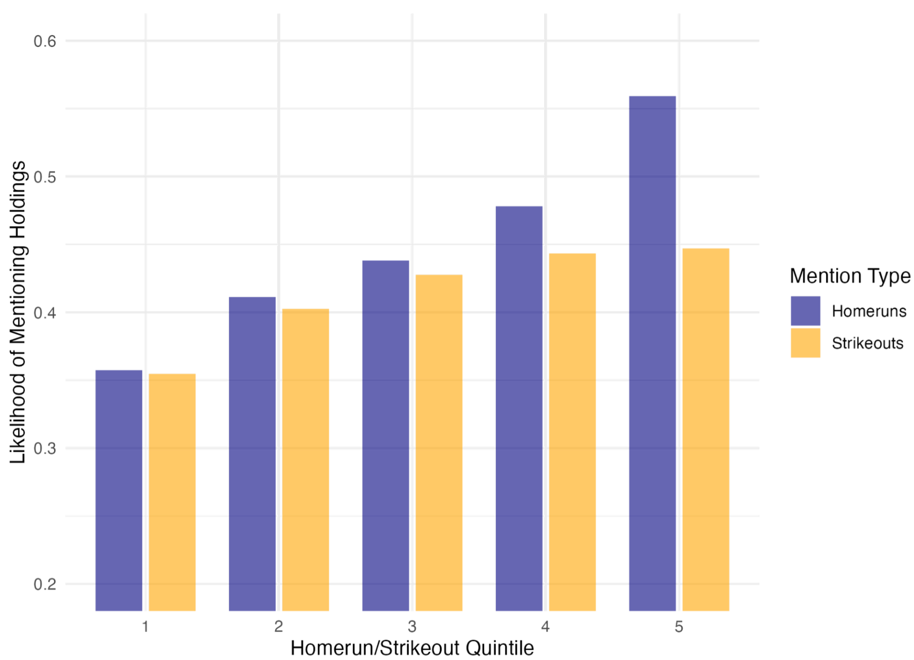


Table 4: Likelihood of Mentioning Homeruns and Strikeouts

This table reports the estimates from regressions of MENTIONED_HR and Mentioned_SO at quarter t on strategy measures and other fund characteristics at quarter $t-1$. MENTIONED_HR (MENTIONED_SO) is an indicator variable taking value of one if the fund mentions at least one homerun (strikeout) holding in its managerial discussion of performance in its N-CRS form and zero otherwise. HIGH–CONTRIBUTION_HR is an indicator variable taking value of one if the contribution of the fund's HRs to its performance is above the median and zero otherwise. Similarly, HIGH–CONTRIBUTION_SO is an indicator variable taking value of one if the contribution of the fund's SOs to its performance is above the median and zero otherwise. All specifications include Morningstar Category and calendar quarter fixed effects. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 2003 to 2020 that meet the inclusion criteria outlined in Section A. *t-statistics* are based on two-way clustered standard errors at fund and year-quarter levels and are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

Dep. Variable$_t$:	MENTIONED HR	MENTIONED SO	MENTIONED HR	MENTIONED SO
Variable$_{t-1}$	1	2	3	4
HR	0.690***		0.411**	
	(6.344)		(2.444)	
HR × HIGH–CONTRIBUTION_HR			0.602**	
			(2.328)	
SO		0.631***		0.373**
		(5.872)		(2.220)
SO × HIGH–CONTRIBUTION_SO				0.430***
				(2.697)
HIGH–CONTRIBUTION_HR			1.312***	
			(3.243)	
HIGH–CONTRIBUTION_SO				1.082***
				(2.912)
ADJUSTED_RETURNS	0.008***	0.005***	0.008***	0.005***
	(7.661)	(5.057)	(7.391)	(5.043)
SIZE	−0.179	−0.107	−0.19	−0.089
	(−0.394)	(−0.250)	(−0.423)	(−0.209)
FAMILY_SIZE	2.383***	3.089***	2.392***	3.039***
	(7.075)	(10.029)	(7.130)	(9.966)
EXPENSE_RATIO	−0.027	0.007	−0.054***	−0.012
	(−1.473)	(0.454)	(−2.708)	(−0.825)
TURNOVER	−0.001	0.013*	−0.003	0.009
	(−0.241)	(1.859)	(−0.581)	(1.443)
INSTITUTIONAL	−4.495***	−3.66***	−5.537***	−4.535***
	(−3.011)	(−3.067)	(−3.734)	(−3.494)
FLOW	0.014	−0.029	0.012	−0.031*
	(1.196)	(−1.633)	(1.039)	(−1.718)
FUND_AGE	−2.732**	−1.769*	−2.394**	−2.674***
	(−2.341)	(−1.848)	(−2.051)	(−2.546)
EXPERIENCE	−0.109	0.547	0.071	0.727
	(−0.127)	(0.737)	(0.083)	(0.989)
STOCKS_HELD	−0.005	−0.004	−0.008**	−0.006*
	(−1.495)	(−1.143)	(−2.175)	(−1.858)
Observations	58,769	58,769	58,769	58,769
R-Squared	0.094	0.090	0.097	0.091
fixed effects:	Category & Date	Category & Date	Category & Date	Category & Date

Table 5: Predictive Regressions of Strategies and Performance on Fund Characteristics

This table reports the estimates from regressions of HR+SO, $\mathbb{1}$(HR+SO = 0), HR, SO, HR–SO, and BA at quarter t on fund characteristics and other measures of active management, ACTIVE_SHARE (Cremers and Petajisto (2009)) and ICI (Kacperczyk et al. (2005)) at quarter $t-1$. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. *t-statistics* are based on two-way clustered standard errors at fund and year-quarter levels and are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

	HR+SO$_t$	$\mathbb{1}$(HR+SO=0)$_t$	HR$_t$	SO$_t$	HR-SO$_t$	BA$_t$	HR+SO$_t$	$\mathbb{1}$(HR+SO=0)$_t$
Variable$_{t-1}$	1	2	3	4	5	6	7	8
SIZE	0.205***	−0.401*	0.058	0.147***	−0.090**	−0.101**	0.163**	−0.597**
	(3.538)	(−1.925)	(1.624)	(4.119)	(−2.170)	(−2.005)	(2.439)	(−2.485)
FAMILY_SIZE	0.013	−0.998***	0.026	−0.012	0.038	0.063*	0.064	−0.694***
	(0.333)	(−7.053)	(1.032)	(−0.540)	(1.503)	(1.862)	(1.326)	(−4.270)
EXPENSE_RATIO	0.012***	−0.009	0.004***	0.007***	−0.003***	−0.002	0.009***	−0.017*
	(5.300)	(−1.028)	(3.248)	(6.342)	(−3.049)	(−0.791)	(3.699)	(−1.757)
INSTITUTIONAL	−0.465***	0.921*	−0.169*	−0.296***	0.126	0.136	−0.321*	−0.018
	(−3.089)	(1.662)	(−1.929)	(−3.393)	(1.419)	(1.158)	(−1.866)	(−0.028)
TURNOVER	0.007***	−0.013***	0.004***	0.003***	0.001	0.001	0.011***	−0.024***
	(6.192)	(−3.152)	(5.742)	(4.444)	(0.657)	(0.004)	(7.323)	(−5.258)
FLOW	0.005	−0.003	0.009***	−0.004	0.013***	−0.001	0.002	−0.002
	(1.400)	(−0.272)	(4.025)	(−1.649)	(3.831)	(−0.190)	(0.487)	(−0.189)
FUND_AGE	−0.536***	1.116**	−0.144	−0.392***	0.248**	0.237*	−0.405**	1.205**
	(−3.889)	(2.473)	(−1.611)	(−4.497)	(2.239)	(1.883)	(−2.567)	(2.280)
EXPERIENCE	−0.284**	0.642*	−0.093	−0.191***	0.098	0.125	−0.218	−0.012
	(−2.108)	(1.746)	(−0.912)	(−2.688)	(0.867)	(0.919)	(−1.355)	(−0.028)
STOCKS_HELD	0.004***	−0.009***	0.002***	0.002***	0.000*	−0.001***	0.006***	−0.006**
	(13.007)	(−5.238)	(11.754)	(11.152)	(1.878)	(−2.927)	(7.560)	(−2.214)
TEAM_MANAGED	−0.513***	2.048***	−0.210*	−0.303***	0.093	0.259*	−0.323*	1.889***
	(−3.124)	(3.740)	(−1.975)	(−3.527)	(0.911)	(1.707)	(−1.953)	−2.988
ACTIVE_SHARE							0.036***	0.302***
							(3.244)	(7.513)
ICI							13.348***	20.908**
							(5.255)	(2.437)
Obseervations	65,044	65,044	65,044	65,044	65,044	65,044	36,707	36,707
R-Squared	0.365	0.069	0.227	0.255	0.008	0.005	0.391	0.089
Fixed Effects:	Category	Category	Category	Category	Category	Category	Category	Category

Table 6: Benchmark–Adjusted Net Returns

This table reports the estimates from regressions of Benchmark-Adjusted Return, ADJUSTED_RETURNS, at quarter t on strategy measures and other fund characteristics at quarter $t-1$. Benchmark-Adjusted Return is quarterly fund return minus its Morningstar assigned benchmark. All specifications include Morningstar Category and calendar quarter fixed effects. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. *t-statistics* are based on two-way clustered standard errors at fund and year-quarter levels and are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

	Dep. Variable$_t$: Benchmark-Adjusted Net Returns (bps)					
Variable$_{t-1}$	1	2	3	4	5	6
HR + SO	0.156					
	(0.138)					
$\mathbb{1}$(HR+SO = 0)		−0.157				
		(−1.642)				
HR			1.102			
			(0.688)			
SO				−0.932		
				(−0.678)		
HR–SO					1.091	
					(1.103)	
BA						0.166
						(0.230)
ADJUSTED_RETURNS	0.028	0.028	0.028	0.028	0.028	0.028
	(0.832)	(0.828)	(0.822)	(0.836)	(0.824)	(0.836)
SIZE	−5.163***	−5.157***	−5.133***	−5.118***	−5.083***	−5.151***
	(−4.488)	(−4.483)	(−4.447)	(−4.455)	(−4.410)	(−4.454)
FAMILY_SIZE	3.458***	3.291***	3.414***	3.502***	3.451***	3.469***
	(4.122)	(3.953)	(3.998)	(4.085)	(3.951)	(3.957)
EXPENSE_RATIO	−0.225***	−0.224***	−0.228***	−0.217***	−0.221***	−0.223***
	(−4.335)	(−3.942)	(−4.173)	(−4.061)	(−3.893)	(−3.911)
TURNOVER	−0.031	−0.032	−0.033	−0.027	−0.030	−0.031
	(−0.962)	(−0.988)	(−1.042)	(−0.854)	(−0.946)	(−0.921)
INSTITUTIONAL	−3.543	−3.806	−3.455	−3.725	−3.621	−3.585
	(−1.076)	(−1.164)	(−1.058)	(−1.126)	(−1.104)	(−1.091)
FLOW	0.091	0.091	0.091	0.088	0.091	0.090
	(1.149)	(1.168)	(1.166)	(1.131)	(1.151)	(1.148)
FUND_AGE	−0.714	−0.704	−0.735	−0.792	−0.815	−0.74
	(−0.285)	(−0.282)	(−0.295)	(−0.314)	(−0.325)	(−0.294)
EXPERIENCE	−1.515	−1.531	−1.538	−1.474	−1.501	−1.497
	(−0.724)	(−0.734)	(−0.740)	(−0.702)	(−0.721)	(−0.715)
STOCKS_HELD	0.011	0.009	0.009	0.012*	0.011	0.011
	(1.364)	(1.325)	(1.195)	(1.713)	(1.471)	(1.509)
STYLE_PREMIUM_1	0.442	0.401	0.450	0.354	0.366	0.415
	(0.167)	(0.151)	(0.170)	(0.133)	(0.137)	(0.156)
STYLE_PREMIUM_2	2.777	2.781	2.805	2.751	2.784	2.779
	(0.953)	(0.956)	(0.965)	(0.943)	(0.958)	(0.956)
STYLE_PREMIUM_3	−3.285	−3.312	−3.240	−3.311	−3.260	−3.279
	(−1.409)	(−1.405)	(−1.399)	(−1.402)	(−1.391)	(−1.401)
Observations	69,829	69,829	69,829	69,829	69,829	69,829
R-Squared	0.491	0.491	0.491	0.491	0.491	0.491
Fixed Effects:	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date

Figure 3: Cross–Sectional Volatility of Fund Returns

This figure shows cross-sectional fund return volatility within portfolios sorted on HR+SO, HR, and SO. In each quarter, funds are sorted into 5 portfolios. For each portfolio, standard deviation of the return distribution is calculated. Then, the time series average of the cross-sectional standard deviations are reported in the Figure. Error bars report 95% confidence intervals. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

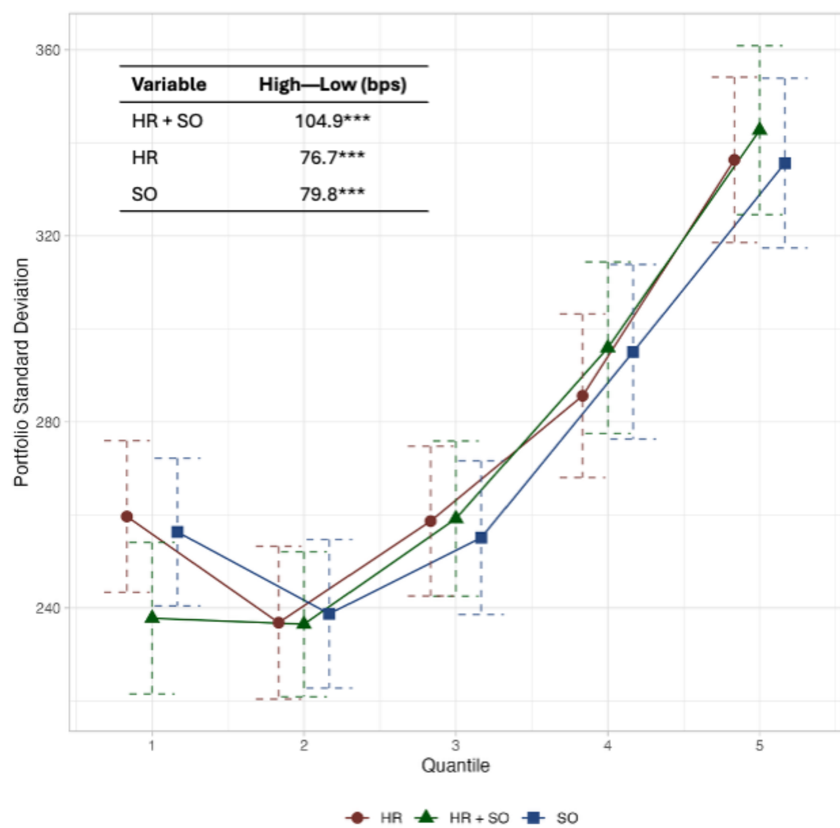


Table 7: Fund Volatility

This table reports the estimates from regressions of Benchmark-Adjusted Return Volatility at quarter t on strategy measures and other fund characteristics at quarter $t-1$. All specifications include Morningstar Category and calendar quarter fixed effects. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. *t-statistics* are based on two-way clustered standard errors at fund and year-quarter levels and are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

	Dep. Variable$_t$: Benchmark-Adjusted Volatility (bps)					
Variable$_{t-1}$	1	2	3	4	5	6
HR + SO	3.088***					
	(9.589)					
$\mathbb{1}$(HR+SO = 0)		−4.091***				
		(−2.790)				
HR			2.807***			
			(6.323)			
SO				3.748***		
				(8.691)		
HR–SO					−0.264	
					(−0.956)	
BA						−0.236
						(−1.475)
ADJUSTED_RETURNS	0.007**	0.009**	0.007**	0.009***	0.009**	0.009**
	(2.446)	(2.433)	(2.137)	(2.832)	(2.428)	(2.412)
SIZE	1.518*	1.659*	1.703**	1.428*	1.638*	1.640*
	(1.872)	(1.947)	(2.035)	(1.734)	(1.919)	(1.922)
FAMILY_SIZE	−5.881***	−5.576***	−5.789***	−5.773***	−5.672***	−5.672***
	(−6.582)	(−6.182)	(−6.385)	(−6.389)	(−6.158)	(−6.155)
EXPENSE_RATIO	0.238***	0.272***	0.258***	0.249***	0.271***	0.271***
	(6.476)	(7.110)	(6.863)	(6.712)	(7.102)	(7.106)
TURNOVER	0.075***	0.094***	0.084***	0.084***	0.094***	0.093***
	(3.156)	(3.554)	(3.341)	(3.357)	(3.545)	(3.534)
INSTITUTIONAL	−7.806	−8.653	−8.41	−8.084	−8.76	−8.757
	(−1.312)	(−1.424)	(−1.403)	(−1.348)	(−1.447)	(−1.447)
FLOW	0.046	0.036	0.042	0.041	0.037	0.037
	(1.398)	(1.048)	(1.248)	(1.231)	(1.074)	(1.071)
FUND_AGE	−0.689	−0.988	−1.017	−0.578	−0.948	−0.941
	(−0.150)	(−0.213)	(−0.220)	(−0.125)	(−0.204)	(−0.203)
EXPERIENCE	6.559***	6.660***	6.621***	6.585***	6.654***	6.639***
	(2.947)	(2.939)	(2.945)	(2.935)	(2.928)	(2.922)
STOCKS_HELD	−0.058***	−0.048***	−0.053***	−0.054***	−0.049***	−0.049***
	(−5.307)	(−4.578)	(−4.949)	(−5.015)	(−4.600)	(−4.610)
STYLE_PREMIUM_1	0.674	0.331	0.425	0.607	0.328	0.321
	(0.585)	(0.300)	(0.372)	(0.550)	(0.297)	(0.292)
STYLE_PREMIUM_2	1.847	1.615	1.761	1.708	1.613	1.602
	(1.100)	(0.976)	(1.051)	(1.030)	(0.977)	(0.970)
STYLE_PREMIUM_3	0.972	0.714	0.890	0.777	0.689	0.676
	(1.115)	(0.795)	(1.016)	(0.875)	(0.769)	(0.753)
Observations	62,473	62,473	62,473	62,473	62,473	62,473
R-Squared	0.128	0.122	0.125	0.126	0.122	0.122
Fixed Effects:	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date

Table 8: Fund Flows

This table reports the estimates from regressions of Quarterly Fund Flows at quarter t on strategy measures and other fund characteristics at quarter $t-1$. We define FLOW in each quarter as the net flow into the fund divided by the lagged size of the fund. All specifications include Morningstar Category and calendar quarter fixed effects. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. *t-statistics* are based on two-way clustered standard errors at fund and year-quarter levels and are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

	Dep. Variable$_t$: Quarterly Fund Flows (%)							
Variable$_{t-1}$	1	2	3	4	5	6	7	8
HR + SO	0.025**							
	(2.614)							
$\mathbb{1}$(HR+SO = 0)		−0.041*						
		(−1.720)						
HR			0.114**		0.124***			
			(2.350)		(2.848)			
SO				−0.125***	−0.149***			
				(−3.021)	(−3.494)			
HR–SO						0.128***		0.104***
						(3.643)		(3.569)
BA							0.074***	0.061***
							(2.712)	(2.658)
ADJ_RETURNS$_{[t-1]}$	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(10.611)	(10.510)	(10.574)	(10.542)	(10.616)	(10.499)	(10.486)	(10.491)
ADJ_RETURNS$_{[t-4,t-2]}$	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(2.293)	(2.291)	(2.289)	(2.295)	(2.295)	(2.290)	(2.289)	(2.290)
ADJ_RETURNS$_{[t-12,t-5]}$	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(5.710)	(5.584)	(5.579)	(5.772)	(5.775)	(5.628)	(5.625)	(5.645)
SIZE	−0.145*	−0.146*	−0.146*	−0.143*	−0.144*	−0.145*	−0.146*	−0.145*
	(−1.747)	(−1.761)	(−1.765)	(−1.732)	(−1.736)	(−1.754)	(−1.761)	(−1.754)
FAMILY_SIZE	0.022	0.020	0.021	0.021	0.022	0.019	0.019	0.019
	(0.531)	(0.479)	(0.491)	(0.504)	(0.530)	(0.457)	(0.462)	(0.458)
EXPENSE_RATIO	−0.009***	−0.010***	−0.009***	−0.009***	−0.009***	−0.010***	−0.010***	−0.010***
	(−4.736)	(−4.945)	(−4.893)	(−4.754)	(−4.715)	(−4.930)	(−4.934)	(−4.927)
TURNOVER	−0.004***	−0.005***	−0.005***	−0.004***	−0.004***	−0.005***	−0.005***	−0.005***
	(−4.222)	(−4.531)	(−4.366)	(−4.355)	(−4.218)	(−4.521)	(−4.524)	(−4.522)
INSTITUTIONAL	−0.803***	−0.786***	−0.793***	−0.798***	−0.803***	−0.787***	−0.786***	−0.786***
	(−4.119)	(−4.047)	(−4.067)	(−4.111)	(−4.122)	(−4.049)	(−4.047)	(−4.048)
FLOW	0.153***	0.153***	0.153***	0.153***	0.153***	0.153***	0.153***	0.153***
	(8.046)	(8.056)	(8.052)	(8.050)	(8.046)	(8.057)	(8.057)	(8.055)
FUND_AGE	−0.816***	−0.817***	−0.815***	−0.819***	−0.817***	−0.818***	−0.818***	−0.818***
	(−5.382)	(−5.392)	(−5.372)	(−5.407)	(−5.388)	(−5.395)	(−5.394)	(−5.395)
EXPERIENCE	0.029	0.023	0.025	0.027	0.029	0.023	0.023	0.023
	(0.277)	(0.222)	(0.246)	(0.256)	(0.276)	(0.220)	(0.221)	(0.220)
STOCKS_HELD	0.004*	0.004*	0.003	0.004*	0.004*	0.004*	0.004*	0.004*
	(1.686)	(1.693)	(1.517)	(1.867)	(1.686)	(1.686)	(1.747)	(1.724)
STYLE_PREMIUM_1	0.001	0.004	0.003	−0.001	−0.001	0.003	0.004	0.003
	(0.003)	(0.046)	(0.041)	(−0.008)	(−0.009)	(0.036)	(0.043)	(0.036)
STYLE_PREMIUM_2	−0.084	−0.083	−0.083	−0.084	−0.084	−0.083	−0.082	−0.083
	(−1.524)	(−1.498)	(−1.506)	(−1.520)	(−1.527)	(−1.499)	(−1.489)	(−1.495)
STYLE_PREMIUM_3	0.002	0.005	0.004	0.004	0.003	0.005	0.005	0.005
	(0.040)	(0.087)	(0.063)	(0.064)	(0.044)	(0.090)	(0.092)	(0.092)
Observations	62,623	62,623	62,623	62,623	62,623	62,623	62,623	62,623
R-Squared	0.073	0.072	0.072	0.072	0.073	0.072	0.072	0.072
Fixed Effects:	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date

Table 9: Fund Flows, Mentions of Holdings, and Contributions

This table reports the estimates from regressions of Quarterly Fund Flows at quarter t on strategy measures and other fund characteristics at quarter $t-1$. We define FLOW in each quarter as the net flow into the fund divided by the lagged size of the fund. MENTIONED_HR is an indicator variable taking value of one if the fund mentions at least one homerun holding in its managerial discussion of performance in its N-CRS form and zero otherwise in the current year. MENTIONED_SO is an indicator variable taking value of one if the fund mentions at least one strikeout holding in its managerial discussion of performance in its N-CRS form and zero otherwise. HIGH–CONTRIBUTION_HR is an indicator variable taking value of one if the contribution of the fund's HRs to its performance is above the median and zero otherwise. Similarly, HIGH–CONTRIBUTION_SO is an indicator variable taking value of one if the contribution of the fund's SOs to its performance is above the median and zero otherwise. All specifications include Morningstar Category and calendar quarter fixed effects. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. Columns 1 - 3 have a smaller sample size because they use the Mentions data that begin in 2003. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

	Dep. Variable$_t$: Quarterly Fund Flows (%)				
Variable$_{t-1}$	1	2	3	4	5
HR	0.075***		0.064***	0.056**	
	(2.933)		(2.796)	(2.311)	
MENTIONED_HR	0.704***		0.623***		
	(3.898)		(3.358)		
HR × MENTIONED_HR	0.078***		0.084***		
	(3.064)		(3.398)		
SO		−0.085***	−0.082***		−0.071**
		(−3.517)	(−3.432)		(−2.981)
MENTIONED_SO		−0.647***	−0.582***		
		(−3.351)	(−2.955)		
SO × MENTIONED_SO		−0.102****	−0.102***		
		(−4.880)	(−4.842)		
HIGH–CONTRIBUTION_HR				1.423***	
				(2.894)	
HR × HIGH–CONTRIBUTION_HR				0.102***	
				(3.604)	
HIGH–CONTRIBUTION_SO					−1.616***
					(−3.081)
SO × HIGH–CONTRIBUTION_SO					−0.121***
					(−4.056)
ADJ._RETURNS$_{[t-1]}$	0.005***	0.005***	0.005***	0.004***	0.004***
	(9.383)	(9.295)	(9.429)	(10.597)	(10.567)
ADJ._RETURNS$_{[t-4,t-2]}$	0.001*	0.001*	0.001*	0.001**	0.001**
	(1.742)	(1.747)	(1.744)	(2.288)	(2.294)
ADJ._RETURNS$_{[t-12,t-5]}$	0.001***	0.001***	0.001***	0.001***	0.001***
	(8.192)	(8.328)	(8.329)	(5.576)	(5.764)
SIZE	−0.122	−0.119	−0.122	−0.146*	−0.145*
	(−1.375)	(−1.354)	(−1.383)	(−1.762)	(−1.758)
FAMILY_SIZE	−0.045	−0.026	−0.033	0.018	0.018
	(−1.050)	(−0.610)	(−0.758)	(0.437)	(0.436)
EXPENSE_RATIO	−0.012***	−0.012***	−0.012***	−0.009***	−0.009***
	(−5.487)	(−5.567)	(−5.386)	(−4.887)	(−4.742)
TURNOVER	−0.004***	−0.004***	−0.004***	−0.005***	−0.004***
	(−3.228)	(−3.228)	(−3.059)	(−4.380)	(−4.388)
INSTITUTIONAL	−0.763***	−0.796***	−0.766***	−0.795***	−0.796***
	(−3.655)	(−3.805)	(−3.673)	(−4.086)	(−4.106)
FLOW	0.146***	0.147***	0.144***	0.153***	0.153***
	(6.986)	(7.059)	(6.882)	(8.052)	(8.055)
FUND_AGE	−0.803***	−0.830***	−0.815***	−0.814***	−0.817***
	(−4.625)	(−4.806)	(−4.704)	(−5.369)	(−5.385)
EXPERIENCE	0.004	0.001	0.012	0.026	0.021
	(0.032)	(0.010)	(0.100)	(0.252)	(0.203)
STOCKS_HELD	0.001	0.001	0.001	0.001	0.001
	(1.215)	(1.074)	(1.357)	(0.349)	(0.324)
STYLE_PREMIUM_1	−0.111	−0.123	−0.114	0.001	−0.001
	(−0.886)	(−0.983)	(−0.926)	(0.007)	(−0.017)
STYLE_PREMIUM_2	−0.139*	−0.138	−0.138	−0.083	−0.083
	(−1.674)	(−1.645)	(−1.642)	(−1.503)	(−1.503)
STYLE_PREMIUM_3	0.025	0.023	0.024	0.004	0.001
	(0.313)	(0.289)	(0.305)	(0.072)	(0.011)
Observations	36,912	36,912	36,912	62,623	62,623
R-Squared	0.071	0.071	0.072	0.072	0.073
Fixed Effects:	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date

Figure 4: Distribution of Fund Expense Ratio

This figure shows the distribution of Expense Ratios within portfolios of funds with the highest and lowest HR+SO. In each quarter, funds are sorted and funds in the 20^{th} and 80^{th} *percentile* are assigned to the *Low HR+SO* and *High HR+SO* portfolios, respectively. Expense Ratios in the following quarter for each of these funds are presented in the figure. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

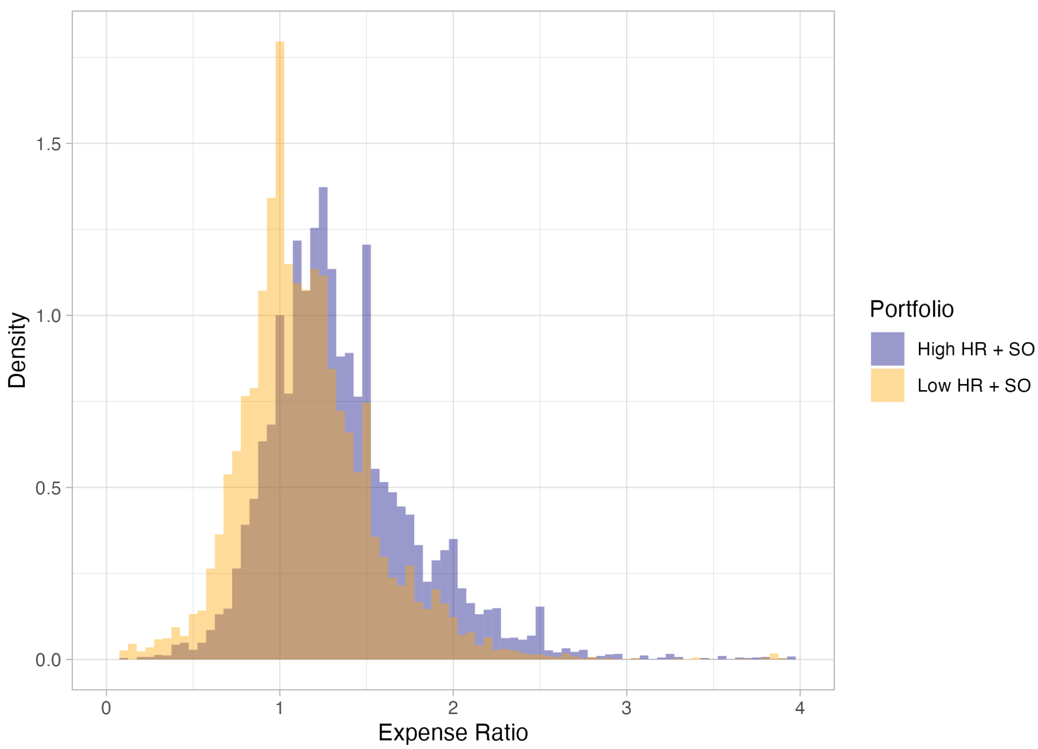


Table 10: Fund Expense Ratios

This table reports the estimates from regressions of Annual Expense Ratios at quarter t on strategy measures and other fund characteristics at quarter $t-1$. All specifications include Morningstar Category and calendar quarter fixed effects. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. *t-statistics* are based on two-way clustered standard errors at fund and year-quarter levels and are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

	Dep. Variable$_t$: Annual Expense Ratio (bps)						
Variable$_{t-1}$	1	2	3	4	5	6	7
HR+SO	0.503***						
	(5.399)						
$\mathbb{1}$(HR+SO = 0)		−1.909***					
		(−4.611)					
HR			0.410***				
			(4.018)				
SO				0.675***			
				(5.676)			
HR–SO					−0.089		−0.082
					(−1.347)		(−1.438)
BA						−0.026	0.002
						(−0.841)	(0.049)
ADJUSTED_RETURNS	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***	−0.003***
	(−3.641)	(−3.094)	(−3.379)	(−3.295)	(−3.030)	(−3.054)	(−3.029)
SIZE	−3.855***	−3.859***	−3.844***	−3.879***	−3.866***	−3.861***	−3.866***
	(−7.899)	(−7.863)	(−7.843)	(−7.936)	(−7.871)	(−7.864)	(−7.871)
FAMILY_SIZE	−2.775***	−2.765***	−2.767***	−2.762***	−2.753***	−2.755***	−2.753***
	(−6.810)	(−6.788)	(−6.778)	(−6.776)	(−6.739)	(−6.743)	(−6.739)
TURNOVER	0.032***	0.035***	0.034***	0.033***	0.035***	0.035***	0.035***
	(4.161)	(4.370)	(4.269)	(4.270)	(4.376)	(4.367)	(4.377)
INSTITUTIONAL	−24.566***	−24.871***	−24.757***	−24.634***	−24.851***	−24.858***	−24.851***
	(−14.835)	(−14.882)	(−14.851)	(−14.847)	(−14.875)	(−14.872)	(−14.875)
FLOW	0.009	0.008	0.008	0.009	0.008	0.008	0.008
	(1.456)	(1.312)	(1.355)	(1.421)	(1.305)	(1.301)	(1.305)
FUND_AGE	−5.012***	−5.087***	−5.080***	−5.000***	−5.077***	−5.085***	−5.077***
	(−3.646)	(−3.689)	(−3.683)	(−3.641)	(−3.684)	(−3.687)	(−3.684)
EXPERIENCE	1.828**	1.867**	1.850**	1.844**	1.869**	1.868**	1.870**
	(2.016)	(2.041)	(2.030)	(2.028)	(2.043)	(2.042)	(2.043)
STOCKS_HELD	−0.022***	−0.021***	−0.021***	−0.022***	−0.021***	−0.021***	−0.021***
	(−8.521)	(−8.222)	(−8.341)	(−8.458)	(−8.235)	(−8.233)	(−8.230)
STYLE_PREMIUM_1	0.064	0.001	0.019	0.056	0.006	0.003	0.006
	(0.250)	(0.002)	(0.075)	(0.226)	(0.022)	(0.012)	(0.022)
STYLE_PREMIUM_2	−0.132	−0.170	−0.152	−0.150	−0.172	−0.173	−0.172
	(−0.626)	(−0.795)	(−0.708)	(−0.714)	(−0.806)	(−0.808)	(−0.808)
STYLE_PREMIUM_3	0.155	0.109	0.135	0.129	0.107	0.108	0.107
	(0.814)	(0.576)	(0.708)	(0.683)	(0.563)	(0.566)	(0.564)
Observations	70,962	70,962	70,962	70,962	70,962	70,962	70,962
R-Squared	0.336	0.332	0.333	0.335	0.332	0.332	0.332
Fixed Effects:	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date

Table 11: Fund Expense Ratios and Mentions of Holdings

This table reports the estimates from regressions of Annual Expense Ratios at quarter t on strategy measures and other fund characteristics at quarter $t-1$. MENTIONED_HR is an indicator variable taking value of one if the fund mentions at least one homerun holding in its managerial discussion of performance in its N-CRS form and zero otherwise in the current year. MENTIONED_SO is an indicator variable taking value of one if the fund mentions at least one strikeout holding in its managerial discussion of performance in its N-CRS form and zero otherwise. All specifications include Morningstar Category and calendar quarter fixed effects. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. *t-statistics* are based on two-way clustered standard errors at fund and year-quarter levels and are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

	Dep. Variable$_t$: Annual Expense Ratio (bps)		
Variable$_{t-1}$	1	2	3
HR	0.351***		0.358***
	(3.904)		(3.870)
MENTIONED_HR	4.689***		4.807***
	(5.153)		(5.347)
HR × MENTIONED_HR	0.142*		0.137*
	(1.934)		(1.904)
SO		0.657***	0.619***
		(3.967)	(4.085)
MENTIONED_SO		4.124***	4.213***
		(5.020)	(5.215)
SO × MENTIONED_SO		0.114*	0.103*
		(1.880)	(1.815)
ADJ._RETURNS$_{[t-1]}$	−0.004***	−0.004***	−0.004***
	(−3.304)	(−3.249)	(−3.534)
ADJ._RETURNS$_{[t-4,t-2]}$	−0.001	−0.001	−0.001
	(−1.253)	(−1.277)	(−1.275)
ADJ._RETURNS$_{[t-12,t-5]}$	−0.002***	−0.002***	−0.002***
	(−5.038)	(−5.099)	(−5.144)
SIZE	−3.801***	−3.842***	−3.810***
	(−6.772)	(−6.859)	(−6.796)
FAMILY_SIZE	−3.007***	−3.037***	−3.016***
	(−7.044)	(−7.130)	(−7.094)
TURNOVER	0.046***	0.045***	0.043***
	(4.475)	(4.369)	(4.161)
INSTITUTIONAL	−21.748***	−21.572***	−21.576***
	(−13.040)	(−12.891)	(−13.020)
FLOW	0.015***	0.012**	0.017***
	(2.700)	(2.229)	(3.001)
FUND_AGE	−5.000***	−4.891***	−4.950***
	(−2.949)	(−2.892)	(−2.929)
EXPERIENCE	1.165	1.184	1.121
	(1.108)	(1.126)	(1.072)
STOCKS_HELD	−0.041***	−0.041***	−0.042***
	(−6.187)	(−6.143)	(−6.341)
STYLE_PREMIUM_1	0.029	0.133	0.086
	(0.121)	(0.527)	(0.355)
STYLE_PREMIUM_2	−0.03	−0.046	−0.024
	(−0.093)	(−0.151)	(−0.079)
STYLE_PREMIUM_3	−0.008	−0.022	−0.01
	(−0.037)	(−0.098)	(−0.047)
Observations	41,885	41,885	41,885
R-Squared	0.344	0.344	0.346
Fixed Effects:	Category & Date	Category & Date	Category & Date

Table 12: Passive Funds - Predictive Regressions of Strategies on Fund Characteristics

This table reports the estimates from regressions of HR+SO and $\mathbb{1}(\text{HR+SO} = 0)$ at quarter t on fund characteristics at quarter $t-1$. The sample includes passively managed diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outline in Section A. Each unit of observations is at fund-quarter level and all independent variables are lagged. *t-statistics* are based on two-way clustered standard errors at fund and year-quarter levels and are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

	HR+SO_t			$\mathbb{1}(\text{HR+SO} = 0)_t$		
Variable_{t-1}	1	2	3	4	5	6
SIZE	−0.253	0.09	−0.116	−0.112	−0.256	−0.221
	(−1.572)	(0.951)	(−0.799)	(−0.686)	(−1.205)	(−1.392)
FAMILY_SIZE	0.025	−0.099	0.198*	−0.410*	−0.34	0.008
	(0.188)	(−1.167)	(1.692)	(−1.701)	(−1.519)	(0.104)
EXPENSE_RATIO	1.159*	0.118	0.803	0.032	0.421	−0.987*
	(1.967)	(0.297)	(0.934)	(0.019)	(0.240)	(−1.707)
TURNOVER	0.003**	0.001	0.001	−0.004	−0.003	−0.001
	(2.015)	(1.128)	(0.967)	(−1.612)	(−1.349)	(−1.082)
INSTITUTIONAL	0.911*	−0.010	0.047	−1.028	−0.813	0.371
	(1.684)	(−0.033)	(0.179)	(−1.175)	(−0.975)	(1.204)
FLOW	−0.001	−0.003	−0.003	0.006	0.007*	0.006
	(−0.124)	(−1.375)	(−1.054)	(1.533)	(1.672)	(1.639)
FUND_AGE	0.248	−0.053	−0.703	0.243	0.053	0.463
	(0.674)	(−0.197)	(−1.508)	(0.328)	(0.071)	(1.390)
EXPERIENCE	0.065	−0.154	0.074	0.175	0.363	0.105
	(0.294)	(−1.224)	(0.539)	(0.378)	(0.739)	(1.262)
STOCKS_HELD	0.006***	0.004***	0.001*	−0.002**	−0.002**	−0.001
	(9.504)	(7.828)	(1.792)	(−2.255)	(−2.102)	(−0.773)
INTERCEPT	8.562**			14.235*		
	(2.409)			(1.718)		
Observations	5,276	5,276	5,276	5,276	5,276	5,276
R-Squared	0.31	0.588	0.708	0.021	0.028	0.407
Fixed Effects:	–	Category	Fund	–	Category	Fund

Table 13: Passive Funds - Returns, Volatility, Flows, and Expense Ratios

This table reports the estimates from regressions of Benchmark-Adjusted Returns, Volatility, Quarterly Flows, and Annual Expense Ratios on quarter t on strategy measures and other fund characteristics at quarter $t-1$. All specifications include Morningstar Category and calendar quarter fixed effects. The sample includes passively managed diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outline in Section A. Each unit of observations is at fund-quarter level and all independent variables are lagged. *t-statistics* are based on two-way clustered standard errors at fund and year-quarter levels and are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

Dep. Variable$_t$:	Net Returns (bps)		Volatility (bps)		Flow (%)		Expense Ratio (bps)	
Variable$_{t-1}$	1	2	3	4	5	6	7	8
HR+SO	−1.037		3.296		0.126		0.413	
	(−0.557)		(1.373)		(1.070)		(0.720)	
$\mathbb{1}$(HR+SO = 0)		−0.345		0.487		0.011		0.026
		(−0.649)		(1.244)		(0.291)		(0.144)
ADJUSTED_RETURNS	−0.023	−0.025	0.005	0.009	0.001	0.001	−1.744***	−1.693***
	(−0.403)	(−0.436)	(0.318)	(0.499)	(0.268)	(0.392)	(−4.387)	(−4.244)
SIZE	−2.22	−2.406	−0.367	0.21	−4.116***	−4.075***	−10.085***	−10.040***
	(−1.105)	(−1.191)	(−0.223)	(0.123)	(−5.920)	(−5.908)	(−6.134)	(−6.090)
FAMILY_SIZE	1.778	1.643	−1.325	−1.229	1.372***	1.368***	−1.318	−1.319
	(1.333)	(1.229)	(−0.884)	(−0.790)	(3.193)	(3.107)	(−0.985)	(−0.983)
EXPENSE_RATIO	−0.316***	−0.318***	0.173**	0.181**	−0.080***	−0.079***		
	(−4.066)	(−4.121)	(2.352)	(2.439)	(−4.786)	(−4.645)		
TURNOVER	−0.007	−0.008	−0.011	−0.010	0.011***	0.012***	0.085***	0.085***
	(−0.327)	(−0.389)	(−0.934)	(−0.829)	(3.349)	(3.361)	(5.729)	(5.690)
INSTITUTIONAL	3.977	3.477	−9.337**	−8.210*	−0.435	−0.392	−15.038***	−14.984***
	(0.844)	(0.728)	(−2.093)	(−1.763)	(−0.345)	(−0.307)	(−3.533)	(−3.532)
FLOW	−0.055	−0.055	0.052	0.051	−0.121***	−0.120***	0.031	0.032
	(−0.763)	(−0.774)	(1.110)	(1.067)	(−5.496)	(−5.503)	(1.552)	(1.572)
FUND_AGE	9.396	8.910	−4.353	−3.506	0.254	0.343	8.226*	8.354*
	(1.560)	(1.491)	(−0.853)	(−0.693)	(0.151)	(0.202)	(1.830)	(1.871)
EXPERIENCE	−2.203	−2.003	1.063	0.382	−1.192	−1.245	0.701	0.633
	(−0.610)	(−0.562)	(0.486)	(0.176)	(−1.112)	(−1.156)	(0.267)	(0.242)
STOCKS_HELD	0.005	0.002	−0.014***	−0.006*	0.001	0.002*	−0.006**	−0.005**
	(0.849)	(0.486)	(−2.982)	(−1.711)	(1.102)	(1.926)	(−2.326)	(−2.058)
Observations	6,076	6,076	5,246	5,246	6,088	6,088	6,088	6,088
R-Squared	0.072	0.072	0.392	0.379	0.165	0.165	0.595	0.595
Fixed Effects:	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date

Online Appendix A:

Additional Tables And Figures

Table A.1: Definition of Variables

This table provides the detailed definition of variables used in the study. For more details about the variable construction, refer to Section A

Variable	Definitions
Quarterly Gross Returns (%)	Quarterly gross returns reported by Morningstar/CRSP
Quarterly Net Returns (%)	Quarterly Net returns reported by Morningstar/CRSP
Benchmark-Adjusted Net Returns (%)	Quarterly Net returns in excess of the quarterly returns of the benchmark index reported by Morningstar
four-Factor Alpha (%)	Quarterly net returns in excess of a Carhart (1997) four-factor model that is estimated using the previous 36 quarterly returns.
Benchmark-Adjusted Returns Volatility (%)	The standard deviation of the fund's monthly net return in excess of the benchmark index reported by Morningstar over the previous 12 months.
HR+SO (%)	Equal to the number of stocks held by the fund at the beginning of the quarter that are identified as homerun or strikeout stocks during the quarter, scaled by total number of stocks held by the fund at the beginning of the quarter.*
HR (%)	Equal to the number of stocks held by the fund at the beginning of the quarter that are identified as homerun stocks during the quarter, scaled by total number of stocks held by the fund at the beginning of the quarter.*
SO (%)	Equal to the number of stocks held by the fund at the beginning of the quarter that are identified as strikeout stocks during the quarter, scaled by total number of stocks held by the fund at the beginning of the quarter. *
HR–SO (%)	The difference between homeruns and Strikeouts in a given quarter.*
BA (%)	Equal to the number of stocks held by the fund at the beginning of the quarter that are identified as hits during the quarter, scaled by total number of stocks held by the fund at the beginning of the quarter.*
Mentioned HR	A Dummy variable taking value of one if the fund mentions at least one homerun holding in the managerial discussion of performance section of its N-CSR form in that year.
Mentioned SO	A Dummy variable taking value of one if the fund mentions at least one strikeout holding in the managerial discussion of performance section of its N-CSR form in that year.
Fund size ($ Million)	The sum of assets under management of share classes of the fund in $ millions.
Family Size ($ Million)	The sum of assets under management of active US equity funds offered by the fund family in $ millions.
Fund Flow (%)	The change in the value of the fund's assets above and beyond the effect of its returns scaled by the previous assets size.
Expense Ratio (%)	The annual expense ratio reported by Morningstar.
Turnover Ratio (%)	The annual turnover ratio reported by Morningstar.
Fund Age (Years)	The number of years passed since the inception of the first share class of the fund.
Number of Stocks Held	The number unique stocks the fund holds in its portfolio.
Retail Focus	A Dummy variable taking value of one if the fund's biggest share class is retail.
Institutional	A Dummy variable taking value of one if the fund's biggest share class is institutional.
Manager Experience (Years)	The average experience of all managers managing the fund. Experience for each manager is defined as the number of years passed since the manager appeared as a manager in the data for the first time since 1972.
Style Premiums 1-3	The quarterly returns of the three long-short factor strategies for which a fund carries the greatest factor exposure during the preceding one year, which can differ by fund.
*	A stock is identified as a homerun or a strikeout if its portfolio-adjusted quarterly return is above the 90^{th} or below the 10^{th} *percentile* of the distribution, respectively. Portfolio adjustment is performed using FF25 Portfolios based on book-to-market and market capitalization. A stock is a hit if its return exceeds it's corresponding FF25 portfolio return in the quarter.

Table A.2: Transition Matrix

This table reports transition matrices across sorted portfolios based on HR (Panel A), SO (Panel B), HR+SO (Panel C), HR–SO (Panel D), BA (Panel E), and benchmark-adjusted net returns (Panel F). At quarter t, funds are sorted into 5 portfolios ($Portfolio_t$). Then, funds are followed for one and four quarters, and sorted again into 5 new portfolios ($Portfolio_{t+1}$ and $Portfolio_{t+4}$). $Cell_{i,j}$ represents the percentage of funds in portfolio i at quarter t that transitions to portfolio j in $t+1$ or $t+4$. DNR represents the percentage of funds that do not report in quarter $t+1$ or $t+4$. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

$Portfolio_t$	$Portfolio_{t+1}$						$Portfolio_{t+4}$					
Panel A: HR												
	Low	2	3	4	High	DNR	Low	2	3	4	High	DNR
Low	32%	18%	14%	9%	6%	20%	30%	19%	14%	10%	7%	21%
2	19%	23%	18%	12%	7%	20%	20%	23%	18%	13%	7%	20%
3	13%	19%	20%	17%	11%	20%	14%	18%	19%	17%	11%	20%
4	9%	13%	17%	22%	19%	20%	10%	13%	17%	21%	19%	20%
High	7%	7%	11%	20%	36%	20%	7%	7%	12%	19%	35%	20%
Panel B: SO												
	Low	2	3	4	High	DNR	Low	2	3	4	High	DNR
Low	35%	18%	14%	9%	5%	20%	33%	17%	14%	10%	6%	20%
2	18%	26%	20%	11%	5%	20%	18%	25%	19%	12%	6%	20%
3	14%	18%	21%	17%	9%	20%	15%	19%	20%	17%	10%	20%
4	9%	12%	17%	23%	20%	20%	10%	12%	17%	22%	19%	20%
High	5%	5%	9%	20%	41%	20%	6%	6%	10%	19%	38%	21%
Panel C: HR+SO												
	Low	2	3	4	High	DNR	Low	2	3	4	High	DNR
Low	37%	23%	12%	6%	2%	20%	35%	22%	14%	6%	2%	20%
2	23%	25%	19%	10%	3%	20%	23%	25%	19%	10%	4%	20%
3	13%	19%	24%	18%	6%	20%	13%	19%	22%	18%	7%	20%
4	5%	10%	18%	28%	19%	20%	7%	10%	18%	26%	19%	19%
High	2%	3%	7%	19%	49%	20%	2%	4%	8%	20%	46%	21%
Panel D: HR–SO												
	Low	2	3	4	High	DNR	Low	2	3	4	High	DNR
Low	20%	15%	13%	14%	18%	20%	18%	15%	13%	15%	18%	21%
2	15%	18%	18%	16%	14%	20%	15%	17%	18%	17%	14%	20%
3	13%	18%	18%	18%	13%	20%	14%	18%	18%	16%	13%	20%
4	14%	17%	17%	17%	14%	20%	14%	18%	17%	17%	14%	20%
High	18%	14%	14%	15%	20%	20%	19%	14%	14%	15%	19%	19%
Panel E: BA												
	Low	2	3	4	High	DNR	Low	2	3	4	High	DNR
Low	19%	15%	14%	15%	18%	20%	17%	15%	14%	15%	18%	21%
2	15%	17%	17%	16%	15%	20%	15%	17%	17%	17%	15%	20%
3	14%	17%	18%	17%	14%	20%	14%	17%	18%	17%	14%	21%
4	15%	17%	17%	17%	15%	20%	15%	17%	17%	17%	15%	19%
High	18%	15%	14%	15%	19%	20%	19%	15%	14%	15%	18%	19%
Panel F: Benchmark-adjusted Net Returns												
	Low	2	3	4	High	DNR	Low	2	3	4	High	DNR
Low	23%	18%	16%	16%	20%	7%	21%	17%	15%	16%	19%	12%
2	17%	21%	21%	19%	16%	5%	17%	19%	19%	19%	16%	10%
3	16%	20%	22%	21%	15%	6%	15%	20%	20%	19%	15%	10%
4	17%	20%	21%	21%	17%	6%	16%	19%	20%	19%	17%	9%
High	20%	16%	15%	17%	24%	7%	21%	16%	16%	17%	21%	9%

Table A.3: Alternative Strategy Measures - Likelihood of Mentioning HR and SO Holdings

This table reports the estimates from regressions of MENTIONED at quarter t on alternative strategy measures and other fund characteristics at quarter $t-1$. MENTIONED is an indicator variable taking value of one if the fund mentions at least one homerun or strikeout holding in its managerial discussion of performance in its N-CRS form and zero otherwise. *HR_VW* and *SO_VW* are value-weighted measures of HR and SO using holdings as weight. *HR_RW* and *SO_RW* are value-weighted measures of HR and SO using returns as weight. *HR_Top20* and *SO_Top20* are equal-weighted measures of HR and SO using only the 20 largest holdings. All specifications include Morningstar Category and calendar quarter fixed effects. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. *t-statistics* are based on two-way clustered standard errors at fund and year-quarter levels and are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

	Dep. Variable$_t$: MENTIONED					
	1	2	3	4	5	6
HR_VW	0.981***					
	(7.094)					
SO_VW		0.867***				
		(5.441)				
HR_RW			1.178***			
			(6.157)			
SO_RW				1.039***		
				(5.943)		
HR_Top20					1.426***	
					(6.958)	
SO_Top20						1.344***
						(4.664)
ADJ._RETURNS	0.008***	0.005***	0.008***	0.005***	0.008***	0.005***
	(7.589)	(5.036)	(7.683)	(5.110)	(7.656)	(4.924)
SIZE	−0.174	−0.092	−0.183	−0.105	−0.184	−0.095
	(−0.384)	(−0.216)	(−0.403)	(−0.244)	(−0.405)	(−0.222)
FAMILY_SIZE	2.421***	3.103***	2.388***	3.093***	2.454***	3.119***
	(7.176)	(10.063)	(7.091)	(10.040)	(7.270)	(10.054)
EXPENSE_RATIO	−0.028	0.009	−0.027	0.007	−0.023	0.015
	(−1.517)	(0.585)	(−1.484)	(0.480)	(−1.270)	(0.980)
TURNOVER	−0.002	0.013*	−0.001	0.012*	0	0.015**
	(−0.281)	(1.882)	(−0.227)	(1.839)	(−0.062)	(2.077)
INSTITUTIONAL	−4.442***	−3.651**	−4.479***	−3.662**	−4.308***	−3.513**
	(−2.980)	(−2.460)	(−3.000)	(−2.468)	(−2.885)	(−2.362)
FLOW	0.013	−0.029	0.014	−0.029	0.013	−0.030*
	(1.131)	(−1.635)	(1.215)	(−1.641)	(1.133)	(−1.687)
FUND_AGE	−2.694**	−1.759*	−2.730**	−1.778*	−2.757**	−1.808*
	(−2.307)	(−1.735)	(−2.338)	(−1.688)	(−2.355)	(−1.677)
EXPERIENCE	−0.082	0.549	−0.121	0.55	−0.087	0.508
	(−0.096)	(0.740)	(−0.142)	(0.741)	(−0.102)	(0.682)
STOCKS_HELD	−0.005	−0.003	−0.005	−0.004	−0.004	−0.001
	(−1.264)	(−0.729)	(−1.510)	(−1.119)	(−1.098)	(−0.380)
Observations	58,769	58,769	58,769	58,769	58,769	58,769
R-Squared	0.094	0.090	0.094	0.091	0.093	0.088
Fixed Effects:	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date

Figure A.1: Swinging For the Fences by Fund Age

This figure shows average HR+SO, HR, SO, and HR–SO for funds of different ages in the sample. Fund-quarter observations are first grouped by fund age. Average HR+SO, HR, SO, and HR–SO are reported for each age group. Fund Age is limited to 20 years because the number of funds drops to insufficient levels for statistical inference. The shaded area represents 95% confidence interval. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

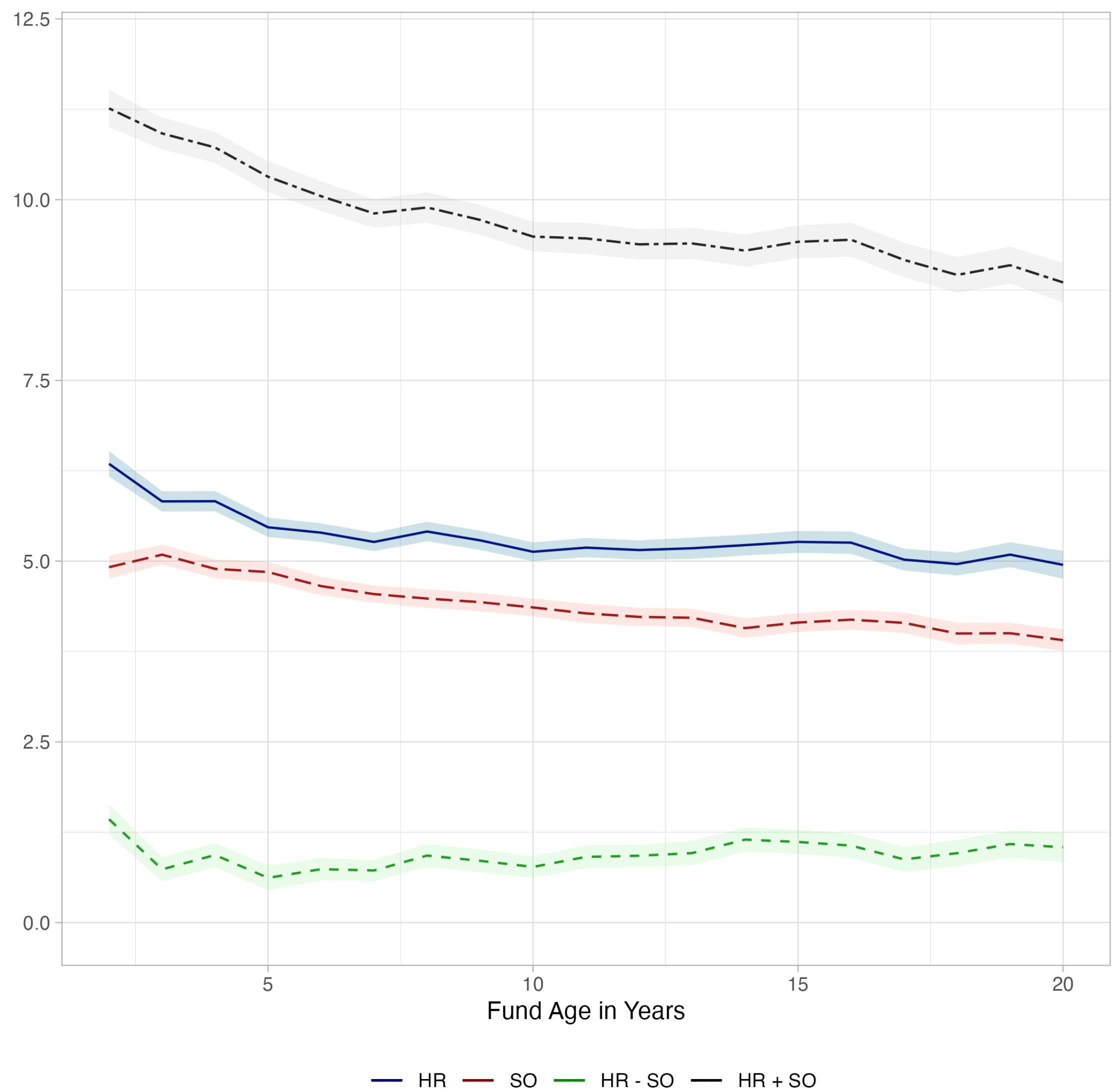


Table A.4: Regressions of Strategies on Momentum Factor Loadings

This table reports the estimates from regressions of HR+SO, $\mathbb{1}(\text{HR+SO} = 0)$, HR, SO, HR–SO, and BA at quarter t on the fund's estimated loading on the momentum factor at quarter $t-1$ while controlling for other fund characteristics. We measure the fund's loading on the momentum factor in each quarter by estimating a Carhart (1997) factor model during the previous 36 quarters. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. *t-statistics* are based on two-way clustered standard errors at fund and year-quarter levels and are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

	HR+SO_t	$\mathbb{1}(\text{HR+SO=0})_t$	HR_t	SO_t	HR–SO_t	BA_t
Variable_{t-1}	1	2	3	4	5	6
MOM Factor Loading	0.001	−0.002	−0.001	0.001	−0.002	−0.005
	(−0.072)	(−0.184)	(−0.152)	(0.097)	(−0.191)	(−0.786)
Observations	55,241	55,241	55,241	55,241	55,241	55,241
R-Squared	0.369	0.072	0.236	0.254	0.009	0.006
Control Variables:	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects:	Category	Category	Category	Category	Category	Category

Table A.5: Alternative Analysis of Fund Returns

This table reports the estimates from alternative regression specifications of Benchmark-Adjusted Net Returns at quarter t on strategy measures and other fund characteristics at quarter $t-1$. Columns 1 - 6 uses ADJUSTED_RETURNS as the dependent variable and include fund and calendar quarter fixed effects. Columns 7 - 12 use Carhart (1997) four-factor α as the dependent variable and include Morningstar Category and calendar quarter fixed effects. Control Variables are included in the specifications but are not reported for brevity. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. *t-statistics* are based on two-way clustered standard errors at fund and year-quarter levels and are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

	Dep. Variable$_t$: Benchmark-Adjusted Net Returns (bps)						Dep. Variable$_t$: Four-factor α (bps)					
Variable$_{t-1}$	1	2	3	4	5	6	7	8	9	10	11	12
HR + SO	−0.454						−0.672					
	(−0.479)						(−0.989)					
$\mathbb{1}$(HR+SO = 0)		−0.088						0.085				
		(−1.094)						(1.061)				
HR			0.165						1.27			
			(0.109)						(1.110)			
SO				−0.723						−2.417$*$		
				(−0.643)						(−1.806)		
HR—SO					0.215						0.437	
					(0.217)						(0.477)	
BA						−0.356						−0.493
						(−0.496)						(−0.815)
ADJ._RETURNS	−0.003	−0.003	−0.003	−0.003	−0.003	−0.003						
	(−0.079)	(−0.086)	(−0.082)	(−0.082)	(−0.085)	(−0.087)						
FOUR-FACTOR α							0.033	0.033	0.033	0.032	0.033	0.033
							(1.286)	(1.297)	(1.308)	(1.263)	(1.289)	(1.308)
Observations	69,829	69,829	69,829	69,829	69,829	69,829	63,498	63,498	63,498	63,498	63,498	63,498
R-Squared	0.094	0.094	0.094	0.094	0.094	0.094	0.094	0.094	0.094	0.094	0.094	0.094
Control Variables:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects:	Fund & Date	Fund & Date	Fund & Date	Fund & Date	Fund & Date	Fund & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date

Table A.6: Alternative Strategy Measures - Returns, Volatility, Flows, and Expense Ratios

This table reports the estimates from regressions of Returns, Volatilities, Flows, and Fees at quarter t on alternative strategy measures and other fund characteristics at quarter $t-1$.*HR_VW* and *SO_VW* are value-weighted measures of HR and SO using holdings as weight. *HR_RW* and *SO_RW* are value-weighted measures of HR and SO using returns as weight. *HR_Top20* and *SO_Top20* are equal-weighted measures of HR and SO using only the 20 largest holdings. All specifications include Morningstar Category and calendar quarter fixed effects. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. *t-statistics* are based on two-way clustered standard errors at fund and year-quarter levels and are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

Panel A: Value-Weighted Measures

Dep var:	Returns			Volatility			Flow			Fees		
	1	2	3	4	5	6	7	8	9	10	11	12
HR+SO_VW	0.988			2.972***			0.019*			0.516***		
	(0.874)			(9.655)			(1.819)			(2.862)		
HR_VW		2.217			2.845***			0.118**			0.502***	
		(1.528)			(7.136)			(2.381)			(3.139)	
SO_VW			−0.937			3.207***			−0.152***			0.609***
			(−0.665)			(7.569)			(−2.977)			(3.455)
Observations	69,829	69,829	69,829	62,473	62,473	62,473	61,739	61,739	61,739	70,962	70,962	70,962
R-Squared	0.049	0.051	0.049	0.127	0.124	0.124	0.135	0.135	0.135	0.976	0.976	0.976
fixed effects:	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category	Category	Category

Panel B: Return-Weighted Measures

Dep var:	Returns			Volatility			Flow			Fees		
	1	2	3	4	5	6	7	8	9	10	11	12
HR+SO_RW	0.773			2.399***			0.021*			0.514***		
	(0.701)			(8.796)			(1.785)			(3.781)		
HR_RW		0.957			2.208***			0.101**			0.516***	
		(0.786)			(7.478)			(2.166)			(4.079)	
SO_RW			0.001			4.773***			−0.135**			0.645***
			(0.001)			(7.095)			(−2.373)			(3.535)
Observations	69,829	69,829	69,829	62,473	62,473	62,473	61,739	61,739	61,739	70,962	70,962	70,962
R-Squared	0.049	0.049	0.049	0.126	0.125	0.124	0.135	0.135	0.135	0.976	0.976	0.976
fixed effects:	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category	Category	Category

Panel C: Top20 Holdings Measures

Dep var:	Returns			Volatility			Flow			Fees		
	1	2	3	4	5	6	7	8	9	10	11	12
HR+SO_Top20	0.853			1.815***			0.041**			0.579***		
	(1.359)			(10.012)			(1.994)			(3.698)		
HR_Top20		1.293			1.469***			0.126***			0.604***	
		(1.488)			(6.383)			(3.394)			(4.646)	
SO_Top20			−0.184			2.147***			−0.141***			0.617***
			(−0.227)			(8.393)			(−3.289)			(4.070)
Observations	69,829	69,829	69,829	62,473	62,473	62,473	61,739	61,739	61,739	70,962	70,962	70,962
R-Squared	0.049	0.050	0.049	0.125	0.123	0.123	0.135	0.135	0.135	0.976	0.976	0.976
fixed effects:	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category	Category	Category

Table A.7: Benchmark-Adjusted Gross Returns

This table reports the estimates from regressions of Benchmark-Adjusted Gross Returns at quarter t on strategy measures and other fund characteristics at quarter $t-1$. All specifications include Morningstar Category and calendar quarter fixed effects. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. *t-statistics* are based on two-way clustered standard errors at fund and year-quarter levels and are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

	Dep. Variable$_t$: Benchmark-Adjusted Gross Returns (bps)					
Variable$_{t-1}$	1	2	3	4	5	6
HR + SO	0.134					
	(0.119)					
$\mathbb{1}$(HR+SO = 0)		−0.155				
		(−1.612)				
HR			1.107			
			(0.691)			
SO				−0.99		
				(−0.717)		
HR–SO					1.122	
					(1.136)	
BA						0.136
						(0.187)
ADJUSTED_RETURNS	0.027	0.026	0.026	0.027	0.026	0.027
	(0.784)	(0.780)	(0.773)	(0.787)	(0.774)	(0.787)
SIZE	−5.309***	−5.304***	−5.278***	−5.262***	−5.227***	−5.299***
	(−4.603)	(−4.600)	(−4.564)	(−4.570)	(−4.527)	(−4.572)
FAMILY_SIZE	3.401***	3.235***	3.355***	3.445***	3.392***	3.410***
	(4.005)	(3.842)	(3.879)	(3.972)	(3.836)	(3.844)
EXPENSE_RATIO	−0.01	−0.009	−0.013	−0.002	−0.006	−0.008
	(−0.189)	(−0.159)	(−0.242)	(−0.046)	(−0.115)	(−0.144)
TURNOVER	−0.029	−0.031	−0.032	−0.026	−0.029	−0.029
	(−0.908)	(−0.938)	(−0.991)	(−0.802)	(−0.898)	(−0.873)
INSTITUTIONAL	−3.842	−4.095	−3.75	−4.027	−3.917	−3.878
	(−1.161)	(−1.245)	(−1.142)	(−1.211)	(−1.187)	(−1.173)
FLOW	0.089	0.09	0.09	0.087	0.089	0.089
	(1.114)	(1.135)	(1.132)	(1.098)	(1.118)	(1.115)
FUND_AGE	−0.772	−0.761	−0.793	−0.853	−0.876	−0.794
	(−0.303)	(−0.299)	(−0.313)	(−0.333)	(−0.344)	(−0.310)
EXPERIENCE	−1.443	−1.461	−1.467	−1.4	−1.429	−1.427
	(−0.692)	(−0.703)	(−0.709)	(−0.670)	(−0.690)	(−0.685)
STOCKS_HELD	0.011	0.01	0.01	0.013*	0.012	0.012
	(1.471)	(1.445)	(1.311)	(1.811)	(1.585)	(1.615)
STYLE_PREMIUM_1	0.227	0.189	0.237	0.137	0.15	0.205
	(0.086)	(0.071)	(0.090)	(0.052)	(0.056)	(0.077)
STYLE_PREMIUM_2	2.951	2.955	2.981	2.925	2.96	2.953
	(1.013)	(1.016)	(1.026)	(1.004)	(1.020)	(1.016)
STYLE_PREMIUM_3	−3.172	−3.197	−3.123	−3.198	−3.141	−3.168
	(−1.347)	(−1.342)	(−1.335)	(−1.339)	(−1.326)	(−1.340)
Observations	69,844	69,844	69,844	69,844	69,844	69,844
R-Squared	0.048	0.048	0.048	0.048	0.048	0.048
Fixed Effects:	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date

Figure A.2: Cross–Sectional Volatility of Four-Factor α

This figure shows cross-sectional Four-Factor α Volatility within portfolios sorted on HR+SO, HR, and SO. In each quarter, funds are sorted into 5 portfolios. For each portfolio, standard deviation of the Carhart (1997) four-factor α distribution is calculated. Then, the time series average of the cross-sectional standard deviations are reported in the Figure. Error bars report 95% confidence intervals. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

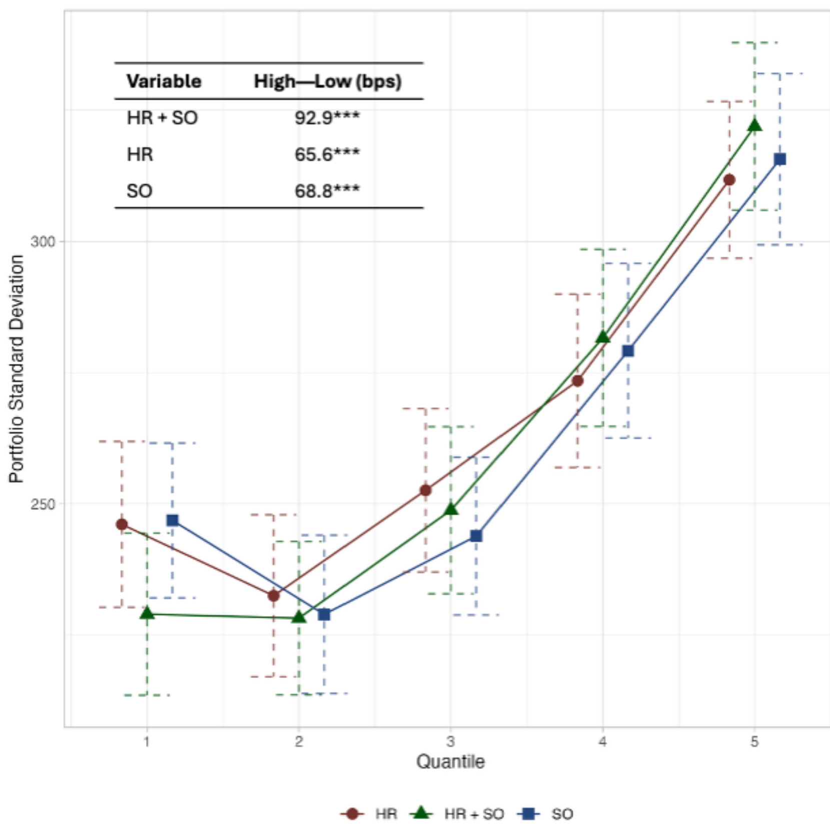


Table A.8: Alternative Analysis of Fund Volatility

This table reports the estimates from alternative regression specifications of Volatility at quarter t on strategy measures and other fund characteristics at quarter $t-1$. Columns 1 - 6 uses volatility of Benchmark-Adjusted Returns as the dependent variable and include fund and calendar quarter fixed effects. Columns 7 - 12 use volatility of Carhart (1997) four-factor α as the dependent variable and include Morningstar Category and calendar quarter fixed effects. Control Variables are included in the specifications but are not reported for brevity. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. *t-statistics* are based on two-way clustered standard errors at fund and year-quarter levels and are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

	Dep. Variable$_t$: Benchmark-Adjusted Volatility (bps)						Dep. Variable$_t$: Four-factor Volatility (bps)					
Variable$_{t-1}$	1	2	3	4	5	6	7	8	9	10	11	12
HR + SO	1.457***						2.984***					
	(3.243)						(6.573)					
$\mathbb{1}$(HR+SO = 0)		−2.016***						−3.992***				
		(−3.471)						(−3.672)				
HR			1.061***						2.766***			
			(2.879)						(6.749)			
SO				1.642***						3.710***		
				(6.381)						(8.852)		
HR–SO					−0.141						−0.217	
					(−0.728)						(−0.832)	
BA						−0.139						−0.188
						(−1.228)						(−1.065)
ADJUSTED_RETURNS	0.007*	0.007**	0.008**	0.007**	0.008**	0.008**						
	(1.839)	(2.041)	(2.104)	(2.130)	(2.051)	(2.031)						
FOUR–FACTOR α							0.004*	0.004*	0.005*	0.005**	0.005**	0.004**
							(1.881)	(1.796)	(1.770)	(1.982)	(2.078)	(2.191)
Observations	62,473	62,473	62,473	62,473	62,473	62,473	61,264	61,264	61,264	61,264	61,264	61,264
R-Squared	0.257	0.256	0.256	0.256	0.256	0.256	0.11	0.105	0.107	0.108	0.105	0.105
Control Variables:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects:	Fund & Date	Fund & Date	Fund & Date	Fund & Date	Fund & Date	Fund & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date

Table A.9: Fund Flow Ranks

This table reports the estimates from regressions of Fund Flow Rank at quarter t on strategy measures and other fund characteristics at quarter $t-1$. All specifications include Morningstar Category and calendar quarter fixed effects. Control Variables are included in the specifications but are not reported for brevity. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. *t-statistics* are based on two-way clustered standard errors at fund and year-quarter levels and are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

	Dep. Variable$_t$: Quarterly Flow Rank							
Variable$_{t-1}$	1	2	3	4	5	6	7	8
HR+SO	0.126**							
	(1.809)							
$\mathbb{1}$(HR+SO = 0)		−0.605***						
		(−2.949)						
HR			0.144***		0.137***			
			(2.786)		(2.758)			
SO				−0.179***	−0.166***			
				(−2.825)	(−2.787)			
HR–SO						0.138***		0.138***
						(3.019)		(3.132)
BA							0.099***	0.101***
							(3.383)	(3.033)
ADJUSTED_RETURNS	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***
	(10.383)	(10.291)	(10.349)	(10.293)	(10.371)	(10.255)	(10.252)	(10.252)
ADJUSTED_RETURNS$_4$	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**
	(1.993)	(1.994)	(1.992)	(1.996)	(1.995)	(1.995)	(1.994)	(1.995)
ADJUSTED_RETURNS$_{12}$	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(7.225)	(7.094)	(7.107)	(7.247)	(7.263)	(7.115)	(7.109)	(7.120)
SIZE	−2.790***	−2.793***	−2.794***	−2.787***	−2.787***	−2.791***	−2.793***	−2.791***
	(−7.235)	(−7.241)	(−7.245)	(−7.225)	(−7.227)	(−7.236)	(−7.243)	(−7.237)
FAMILY_SIZE	0.159	0.159	0.156	0.157	0.159	0.153	0.154	0.153
	(1.148)	(1.152)	(1.117)	(1.132)	(1.146)	(1.096)	(1.100)	(1.096)
Expense	−0.035***	−0.036***	−0.036***	−0.035***	−0.035***	−0.036***	−0.036***	−0.036***
	(−6.539)	(−6.701)	(−6.654)	(−6.553)	(−6.522)	(−6.681)	(−6.687)	(−6.680)
TURNOVER	−0.013***	−0.014***	−0.014***	−0.013***	−0.013***	−0.014***	−0.014***	−0.014***
	(−4.827)	(−5.063)	(−4.934)	(−4.964)	(−4.827)	(−5.078)	(−5.082)	(−5.080)
INSTITUTIONAL	−0.228	−0.193	−0.208	−0.225	−0.231	−0.201	−0.2	−0.201
	(−0.510)	(−0.432)	(−0.463)	(−0.503)	(−0.515)	(−0.449)	(−0.447)	(−0.449)
FLOW	0.237***	0.237***	0.237***	0.237***	0.237***	0.238***	0.238***	0.238***
	(15.756)	(15.763)	(15.760)	(15.772)	(15.762)	(15.777)	(15.770)	(15.771)
FUND_AGE	−2.487***	−2.484***	−2.483***	−2.494***	−2.492***	−2.488***	−2.485***	−2.488***
	(−5.429)	(−5.422)	(−5.418)	(−5.445)	(−5.440)	(−5.432)	(−5.422)	(−5.431)
EXPERIENCE	0.983***	0.973***	0.976***	0.979***	0.982***	0.970***	0.972***	0.970***
	(3.333)	(3.303)	(3.311)	(3.318)	(3.332)	(3.292)	(3.294)	(3.292)
STOCKS_HELD	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(2.891)	(2.765)	(2.786)	(2.866)	(2.896)	(2.744)	(2.752)	(2.746)
STYLE_PREMIUM_1	0.073	0.082	0.08	0.072	0.071	0.079	0.081	0.079
	(0.388)	(0.437)	(0.425)	(0.380)	(0.375)	(0.423)	(0.430)	(0.423)
STYLE_PREMIUM_2	−0.166	−0.162	−0.162	−0.165	−0.166	−0.161	−0.161	−0.161
	(−0.874)	(−0.851)	(−0.855)	(−0.866)	(−0.873)	(−0.845)	(−0.843)	(−0.845)
STYLE_PREMIUM_3	0.02	0.027	0.023	0.023	0.021	0.027	0.027	0.027
	(0.139)	(0.190)	(0.165)	(0.162)	(0.147)	(0.191)	(0.187)	(0.190)
Observations	61,739	61,739	61,739	61,739	61,739	61,739	61,739	61,739
R-squared	0.110	0.109	0.111	0.110	0.110	0.110	0.109	0.111
Fixed Effects:	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date	Category & Date

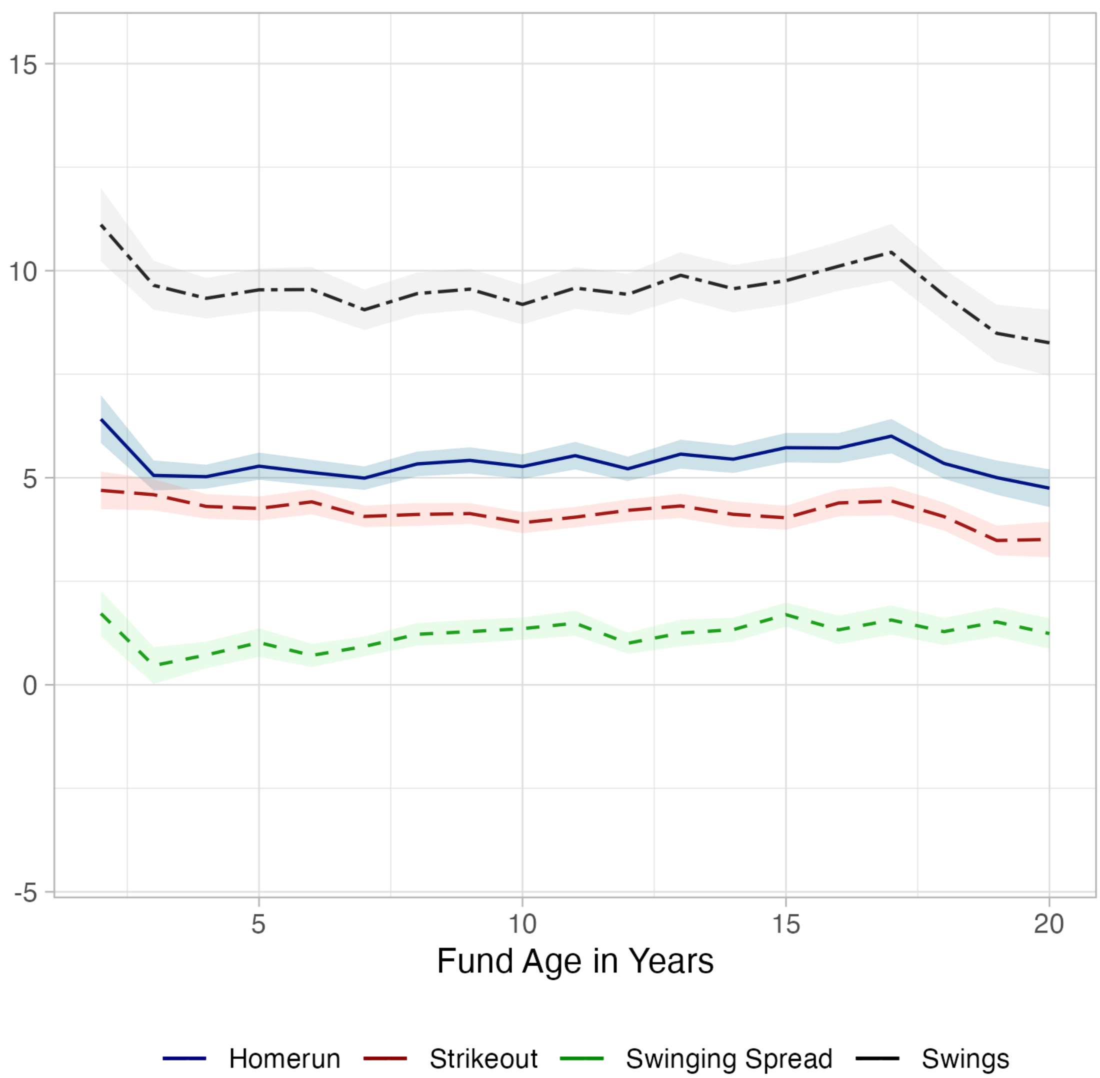
Table A.10: Fund Flows - the Role of Retail Investor Focus

This table reports the estimates from regressions of Quarterly Fund Flows at quarter t on strategy measures and other fund characteristics at quarter $t-1$. We define fund flow in each quarter as the net flow into the fund divided by the lagged size of the fund. Retail is an indicator variable taking value of one if the fund's primary focus is retail investors and zero otherwise in the current year. All specifications include Morningstar Category and calendar quarter fixed effects. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

	Dep. Variable$_t$: Quarterly Fund Flows (%)			
Variable$_{t-1}$	1	2	3	4
HR + SO	−0.002			
	(−1.253)			
(HR + SO) × Retail Fund	0.038**			
	(2.130)			
HR		0.072*		0.074**
		(1.820)		(2.265)
HR × Retail Fund		0.064**		0.059**
		(2.406)		(2.465)
SO			−0.087**	−0.093**
			(−2.469)	(−2.515)
SO × RETAIL_FUND			−0.057**	−0.062**
			(−2.448)	(−2.550)
RETAINL_FUND	0.362***	0.391***	0.366***	0.363***
	(5.050)	(5.138)	(5.188)	(5.088)
ADJ._RETURNS$_{[t-1]}$	0.005***	0.005***	0.005***	0.005***
	(7.880)	(7.824)	(7.808)	(7.848)
ADJ._RETURNS$_{[t-4,t-2]}$	0.002**	0.002**	0.002**	0.002**
	(2.031)	(2.029)	(2.034)	(2.032)
ADJ._RETURNS$_{[t-12,t-5]}$	0.001***	0.001***	0.001***	0.001***
	(7.168)	(7.082)	(7.254)	(7.246)
SIZE	−0.169**	−0.169**	−0.168**	−0.168**
	(−2.219)	(−2.208)	(−2.212)	(−2.213)
FAMILY_SIZE	0.023	0.025	0.021	0.023
	(0.514)	(0.474)	(0.499)	(0.511)
EXPENSE_RATIO	−0.023***	−0.024***	−0.023***	−0.023***
	(−5.066)	(−5.151)	(−5.048)	(−5.042)
TURNOVER	−0.006***	−0.007***	−0.006***	−0.006***
	(−2.673)	(−2.861)	(−2.701)	(−2.658)
FLOW	0.135***	0.135***	0.135***	0.135***
	(4.545)	(4.523)	(4.558)	(4.557)
FUND_AGE	−0.708***	−0.701***	−0.704***	−0.707***
	(−5.153)	(−5.130)	(−5.142)	(−5.149)
EXPERIENCE	0.024	0.025	0.027	0.021
	(0.210)	(0.213)	(0.218)	(0.202)
STOCKS_HELD	0.001	0.001	0.001	0.001
	(1.557)	(1.351)	(1.515)	(1.565)
STYLE_PREMIUM_1	0.014	0.021	0.011	0.011
	(0.103)	(0.149)	(0.077)	(0.080)
STYLE_PREMIUM_2	−0.092	−0.088	−0.092	−0.092
	(−0.683)	(−0.658)	(−0.686)	(−0.684)
STYLE_PREMIUM_3	−0.193	−0.188	−0.19	−0.191
	(−1.136)	(−1.110)	(−1.119)	(−1.123)
Observations	61,739	61,739	61,739	61,739
R-Squared	0.131	0.130	0.130	0.134
Fixed Effects:	Category & Date	Category & Date	Category & Date	Category & Date

Figure A.3: Passive Funds - Swinging for the Fences by Fund Age

This figure shows average HR+SO, HR, SO, and HR–SO for funds of different ages in the sample. Fund-quarter observations are first grouped by fund age. Average HR+SO, HR, SO, and HR–SO are reported for each group. Fund Age is limited to 20 years because the number of funds drops to insufficient levels for statistical inference. The shaded area represents 95% confidence interval. The sample includes passively managed diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outline in Section A. Each unit of observations is at fund-quarter level and all independent variables are lagged. All variables are defined in Section A as well as Table A.1 of Online Appendix A.



Online Appendix B:

Swinging for the Fences and other Factor Exposures

Although we show in Section D that swinging for the fences as a strategy is inherently different from active share, industry concentration, and momentum, the existing literature has documented a myriad of other factors that deliver abnormal returns. In this section, we investigate whether swinging for the fences as an investment strategy is an artifact of simple exposure to a certain factor already documented in the literature.

McLean and Pontiff (2016) review 97 predictors of future returns in an examination of their out-of-sample predictive power. However, Harvey et al. (2016) and Feng et al. (2020) argue that most of these new factors are redundant relative to the existing factors and only a few have statistically significant explanatory power beyond the hundreds of factors proposed in the past. Nonetheless, mutual funds may choose to actively load their portfolios on these factors in hopes of generating abnormal returns. In the absence of accounting for them, swinging for the fences may appear as a deliberate stock picking strategy while it is the result of exposure to one or more of the existing factors. To address this concern, we start from a comprehensive list of existing factors from The Open Asset Pricing Project[31] and provide two sets of analysis at the stock as well as mutual fund level.

Our fist analysis is at the stock level. We estimate each homerun stock's exposure to all 211 factors using 250 daily returns preceding the homerun quarter. For each

[31] Chen and Zimmermann (2022) provide data and code that reproduces 211 factors that finance research has shown to provide cross-sectional stock return predictability. The code, data, and description of the factors are publicly available at https://www.openassetpricing.com.

homerun stock, we record five factors with the highest exposures. Then, we calculate for each of the 212 factors the share of homerun stocks that have high exposure to the factor (i.e., the factor is among the top five factors the homerun has the highest exposure to). We report the ten most prevalent factors in Panel A of Table B.1.

If becoming a homerun stock is the result of significant exposure to a certain factor, we expect to see that factor to be among the five highest–exposure factors for a large portion of homerun stocks. Contrary to this expectation, the results show that the most prevalent factor, *Forecast Earnings per Share (FEPS)* studied by Cen, Hilary, and Wei (2013), is relevant for only 8.8% of homerun stocks. In general, the 10 most prevalent factors reported in Table B.1, on average, are relevant for only 6.7% of homerun stocks. The tenth most prevalent factor, Haugen and Baker (1996)'s *Volume to Equity Ratio*, is relevant for only 5.9% of homerun stocks. We report in Table B.1 with strikeouts. This lack of prevalence for one or more factors suggests that becoming a homerun or a strikeout is not the result of exposure to existing factors.

In our second analysis, we repeat the same procedure at the fund level to examine whether certain factor(s) are relevant to all or most funds that swing for the fences. Specifically, we estimate the same 212 factor exposures using 250 daily returns preceding the quarter in which we measure the SF strategy measures. Then, we record the five most relevant factors for each fund-quarter observation as those with the highest estimated exposures. In each quarter, we sort funds into five quintiles based on HR. For each relevant factor, we compute the share of funds in each quintile the factor is relevant (i.e., the factor is among the fund's top five factors with the highest exposure).[32] Finally, we report these

[32]When we compute factor prevalence for each quintile in quarter t, we use factors' exposures (relevance)

shares for the ten most prevalent factors in Panel B of Table B.1. There are two important takeaways.

Similar to the stock-level evidence, we find that even the most prevalent factor, Ali, Hwang, and Trombley (2003)'s *Idiosyncratic Return Volatility*, is relevant for only 24% of funds in the High–HR quintile. In other words, three out of four funds that most aggressively swing for the fences do not have high exposures to Ali et al. (2003)'s *Idiosyncratic Return Volatility*. Overall, the 10 most prevalent factors, on average, are relevant for only 15.7% of funds. More importantly, if swinging for the fences is the result of funds chasing certain factor(s), then these factors should emerge as prevalent for a large portion of High–HR quintile while not being prevalent at all for funds in the Low–HR quintile. In contrast to this expectation, the share of funds with high exposure to each of the ten factors is fairly similar across all quintiles. For example, 22% of funds in the Low–HR quintile have high exposure to Ali et al. (2003)'s *Idiosyncratic Return Volatility*, only 2% lower than the High-HR quintile. This suggests that while all funds are exposed to certain factors, this exposure is not related to their tendency to swing for the fences.

Our analysis, both at the stock and fund levels, suggests that swinging for the fences, a strategy that picks stocks with the potential to deliver extreme returns (i.e., homeruns), is different from existing active management strategies and existing factors found to predict future returns.

from quarter $t-1$. Also, we combine the middle quintiles into one for brevity.

Table B.1: Homeruns and other Forms of Extreme Returns

This table reports the factors that homerun stocks as well as Funds with more homeruns have exposure to. Panel A shows factor exposures at the stock level. In each quarter, we estimate each stock's exposure to 212 factors from previous literature using the preceding 250 trading days and keep five factors with the highest exposure. Then, we calculate the share of homeruns for which a factor is among the top five factors and report the shares for the ten most prevalent factors. At quarter t, a stock is defined as a *homerun* if its quarterly portfolio-adjusted returns is above the 90^{th} percentile of its peers. At the same quarter, a stock is identified as a *Strikeout* if its quarterly portfolio-adjusted returns is below the 10^{th} percentile of its peers. Panel B reports factor exposures at the fund level. In each quarter, we estimate each fund's exposure to 212 factors from previous literature using the preceding 250 trading days and keep five factors with the highest exposure. Then, we sort the sample of funds into quintiles according to their HR and calculate the share of funds in each quintile for which a factor is among the top five factors. We report the share of funds for the ten most prevalent factors for High HR, Low HR and the rest of quintiles. The sample includes active diversified equity mutual funds with a 3×3 Morningstar category from 1993 to 2020 that meet the inclusion criteria outlined in Section A. All variables are defined in Section A as well as Table A.1 of Online Appendix A.

Panel A: Factor Exposures at the Stock Level			
Rank	Factor Name	% Homeruns	% Strikeouts
1	Forecast Earnings per Share (FEPS)	8.8	9.6
2	Amihud Illiquidity	7.3	5.9
3	Frazzini-Pedersen Beta	6.7	6.8
4	Long-term EPS forecast	6.6	6.0
5	Firm Age	6.5	6.5
6	IVOL (AHT)	6.3	7.0
7	MB	6.3	5.6
8	Tail Risk Beta	6.3	5.1
9	Long-term EPS Forecast	6.0	5.9
10	Volume to Equity	5.9	6.0

Panel B: Factor Exposures at the Fund Level Across HR Quintiles				
		High HR	2,3, and 4	Low HR
Rank	Factor Name	% Funds	% Funds	% Funds
1	IVOL (AHT)	24.8	22.3	21.3
2	Tail Risk Beta	20.3	20.4	19.0
3	Long-term EPS forecast	19.9	18.9	20.8
4	Realized Volatility	17.7	15.7	16.9
5	IVOL (3 Factor)	17.5	15.1	14.8
7	Frazzini-Pedersen Beta	16.7	14.3	14.5
6	Volume to Equity	16.1	15.2	14.9
8	Market-to-Book	15.2	13.8	12.7
9	Asset-to-Market	15.1	18.2	12.3
10	Short Interest	14.7	15.6	11.7

Online Appendix C:

Examples of N-CSR Filings

Form N-CSR filing (Certified Shareholder Report) is required for all registered management investment companies, including mutual funds, as part of the SEC's rule making following the Sarbanes-Oxley Act of 2002. While these filings include detailed information about a fund's performance, holdings, and expenses, we are particularly interested in the Management Discussion of Fund Performance, where fund managers explain in narrative form the key factors that influenced performance.

The key factors that managers attribute to performance in the managerial discussion vary wildly. Some mangers limit their discussion to industry trends and/or macroeconomic conditions as key factors. James Advantage Funds is an example of such disclosure practice. This fund primarily attributes its performance to industry–level portfolio allocations and trends. Figure C.1 shows a screenshot of its annual N-CSR filing in 2017. The management highlights the fact that "*The Fund was underweight in the Finance, Industrial, and Technology sectors*" as the key factor that contributed to the poor performance of the Small Cap Fund relative to its designated benchmark, Russell 3000. The discussion of performance for its Micro Cap and Mid Cap funds follow the similar pattern.

In contrast, some managers will mention specific holdings that were notable contributors or detractors to fund performance. Marisco Investment Fund is an example of management highlighting specific holdings in its N-CSR filings. Figure C.2 shows a screenshot of its annual N-CSR filing in 2018. Marisco's fund manager, Tom Marisco, highlights Netflix, Amazon, and Adobe Systems as three holdings that contributed to the funds performance. Moreover, management explicitly mentions these stocks' returns, which creates a salient effect for every investor that reads this report. The manager also highlights Celgene Corporation, Alibaba Group Holding, and Applied Materials, Inc. as three holdings that held the fund's performance back in comparison to its benchmark.

For each N-CSR filing, we detect the discussion of performance section for each fund under the management of the registered advisor. Then, we identify whether the fund managers discuss their homerun and strikeout holdings as key contributors and detractors to performance and define two indicator variables: MENTIONED_HR and MENTIONED_SO, which take values of 1 if the fund mentions at least one homerun as a contributor and at least one strikeout as a detractor in that year, respectively, and zero otherwise. In our sample, Figure C.1 leads us to code MENTIONED_HR and MENTIONED_SO as zeros for James Advantage Small Cap, Mid Cap, and Micro Cap funds for 2017. Conversely, Figure C.2 leads us to code MENTIONED_HR and MENTIONED_SO as ones in 2018 for Marisco Investment Growth Fund.

Figure C.1: James Advantage Funds 2017 N-CSR Filing

This figure shows management discussion of fund performance in page 2 of an N-CSR filing in 2017 filed by James Advantage Funds. The N-CSR filing is publicly available on SEC's EDGAR database.

Shareholder Letter | James Advantage Funds

June 30, 2017 (Unaudited)

Investment Philosophy

The Fund's adviser does its own research using quantitative databases and statistical expertise and other elements to help measure risk levels and the potential impact on future stock and bond price movements. The adviser employs a proprietary investment approach to select equity securities for the Funds it believes are undervalued and more likely to appreciate. The adviser focuses on characteristics such as being overlooked by Wall Street, management commitment, value and neglect. The adviser also assesses a number of fundamental factors such as earnings, earnings trends, price earnings multiples, return on assets, other financial statement data as well as its own proprietary calculations. The adviser evaluates over 8,000 companies of all capitalization ranges. For the James Micro Cap, the James Small Cap and the James Mid Cap Fund, the adviser refines its approach by using a capitalization screen and evaluates thousands of companies within the appropriate capitalization range. For all Funds, the adviser normally will sell a security when the investment no longer meets the adviser's investment criteria. The adviser's Investment Committee has a great deal of investment experience, exceeding over 200 years in total with James. We believe our combination of quantitative modeling and hands-on management makes us unique and supports the James Advantage Funds.

Fund Performance

Three key issues have been driving the markets in the last year.

- The stock and bond markets have had to adapt to a rising Fed Funds rate. The Federal Reserve (Fed) has started to tighten and is now even looking to reduce holdings on their balance sheet. Much of the stock advance in the last 9 years has come because of the support of the Federal Reserve.
- The market has digested the Presidential election and rallied strongly based on the hope of lower regulations and lower taxes. Hope may eventually run dry, but it has sustained the market since the election.
- Our economy, while underwhelming, has been stronger than most of the world and this strength attracts investors into the U.S. markets.

The James Balanced: Golden Rainbow Fund Retail Class shares rose 3.92% over the twelve months ended June 30, 2017. Its blended secondary benchmark, a composite index comprised of the Russell 2000® Index, the S&P 500® Index and the Barclays Capital U.S. Intermediate Government/Credit Bond Index, rose by 10.21%. The Fund trailed this benchmark as our type of investing lagged growth stocks over the year. As mentioned previously, many stocks are in their own bear market and the Fund was not immune. Our holdings in Finance and Technology stocks advanced, but did not keep up with those in the benchmark and we were underweighted in what we viewed as expensive technology stocks. In addition, bond prices fell during the period. Previous winning industries, like Airlines and Refiners, slipped when oil prices bounced back.

The James Small Cap Fund rose 11.36% over the fiscal year versus a rise of 24.60% for the Russell 2000® Index, its benchmark. The Fund was underweight in the Finance, Industrial, and Technology sectors, which contributed to the underperformance compared to the benchmark.

The James Mid Cap Fund rose 10.50% over the year while its benchmark, the S&P 400® MidCap Value Index, rose 18.47%. The Fund's positions in Finance, Industrial and Utility stocks lagged, which were underweighted to those in the benchmark.

The James Micro Cap Fund rose 14.90% while its benchmark, the Russell Microcap® Index, rose 27.61% over the fiscal year. This Fund focuses on companies with market capitalizations at the time of purchase no larger than the stocks in the Russell Microcap® Index, including exchange traded funds that invest primarily in such securities. The Fund's over weighted holdings in Utilities and Industrial stocks held performance down while holdings in Finance stocks were a big boost.

The James Long-Short Fund rose 10.32%, while its benchmark, the S&P 500® Index, rose 17.90%. The Long-Short Fund can be leveraged up to 130%, but does not have to be leveraged, nor is it required to have any short positions at all. This Fund attempts to take advantage of volatile markets where it can capitalize on market swings, both up and down. The Fund's prospectus advises shareholders and potential shareholders not to expect a tight correlation to the S&P 500®Index. The Fund lagged its benchmark because many of the stocks sold short were growth stocks, which outperformed the mostly value stocks held in long positions. Compared to the benchmark, the Fund was underweight positions in the Technology and Finance sectors. The Fund did not use any bond investments during the year.

Finally, the James Aggressive Allocation Fund rose 6.54% while its blended secondary benchmark, 65% Russell 3000® and 35% Barclays U.S. Aggregate Government/Credit Bond Index, rose 11.60%. The Fund seeks to provide total return through a combination of growth and income. Preservation of capital in declining markets is a secondary objective. It is expected the Fund will usually run higher equity levels than the James Balanced: Golden Rainbow Fund and in this period it outperformed the James Balanced: Golden Rainbow Fund as a result.

Please see the following charts for longer term comparisons for all our Funds.

2 www.jamesfunds.com

Figure C.2: Marisco Investment Funds 2018 N-CSR Filing

This figure shows management discussion of fund performance in page 2 of an N-CSR filing in 2018 filed by Marisco Investment Funds. The N-CSR filing is publicly available on SEC's EDGAR database.

GROWTH FUND

INVESTMENT REVIEW BY TOM MARSICO (UNAUDITED)

The Marsico Growth Fund posted a total return of +23.10% for the one-year fiscal period ended September 30, 2018. The Fund substantially outperformed the S&P 500 Index, the Fund's benchmark index, which had a total return of +17.91% over the same time period. Please see the Fund's Overview for more detailed information about the Fund's longer-term performance for various time periods ended September 30, 2018.

The performance data for the Fund quoted here represent past performance, and past performance is not a guarantee of future results. Investment return and principal value of an investment will fluctuate so that an investor's shares, when redeemed, may be worth more or less than their original cost. Current performance may be lower or higher than the performance information quoted. To obtain performance information current to the most recent month-end, please call 888-860-8686 or visit marsicofunds.com.[(1)]

This review highlights Fund performance over a one-year fiscal period. Shareholders should keep in mind that the Fund is intended for long-term investors who hold their shares for substantially longer periods of time. You should also keep in mind that our current views and beliefs regarding all investments discussed in this report are subject to change at any time. References to specific securities, industries, and sectors discussed in this report are not recommendations to buy or sell such securities or related investments, and the Fund may not necessarily hold these securities or investments today. Please see the accompanying Schedule of Investments for the percentage of the Fund's portfolio represented by the securities mentioned in this report as of the end of the reporting period.

The Fund is subject to broad risks associated with investing in equity securities markets generally, including the risks that the securities and markets in which it invests may experience volatility and instability, that domestic and global economies and markets may undergo periods of cyclical change and decline, that investors may at times avoid investments in equity securities, and that investments may not perform as anticipated. Please see the Prospectus for more information.

The Fund is not managed to track the benchmark index, and may hold a substantially overweight or underweight position in a sector, industry, or security compared to its weight in the benchmark. The Fund may be subject to risks associated with a particular sector or other area in which it is overweight, including the risk that the stocks of companies within one area could simultaneously decline in price because of an event that affects the entire area. For informational purposes, the discussion below may compare the benchmark weight or performance of a sector or industry to the investment approach of the Fund.

The Growth Fund's outperformance during the one-year period ended September 30, 2018, as compared to the S&P 500 Index, was primarily attributable to certain Fund holdings in the Consumer Discretionary and the Information Technology sectors.

Stock prices of two Consumer Discretionary companies held by the Fund performed very strongly during the reporting period. Streaming content provider Netflix, Inc. returned +106% and was a large positive contributor during the period. The company has continued to penetrate the growing market for streaming content and, in our opinion, is adopting the right strategy in building content as rapidly as possible. Over the past year, Netflix has begun increasing subscription prices as well, hence improving already high operating margins. The current management team, headed by Reed Hastings and Ted Sarandos, has been extremely successful in securing great talent and high-quality content, and we believe it has the right strategy for continued success.

Online e-commerce platform Amazon.com, Inc. was also a strong positive contributor during the period, returning +108%. Amazon continues to benefit from consumers' growing preference to shop online, and has been adding new features to its Prime membership offering, leading to substantial growth. Advertising and cloud computing remain large opportunities for the company.

Several of the Fund's Information Technology holdings also rose substantially during the period, including computer software company Adobe Systems, Inc. (+81%), which was a top positive contributor. Adobe has executed well recently, and has witnessed a positive inflection in new subscribers to its software, which we believe reflects a trend of increasing corporate budgets allocated to improving business software.

GROWTH FUND

From a portfolio positioning standpoint, JPMorgan Chase & Co. (+12%) ("JPM") was added to the Growth Fund during the period to modestly alter exposure to the Financials sector with a high-quality bank that we expect should continue to compound its earnings. It represents a blue-chip company that appears to offer significant growth potential over the medium to long-term period. First, JPM is an earnings growth and capital return story among large financials, as it continues to take market share across its business units and is starting to level off on its regulatory spending, thereby allowing for more profit to be returned to shareholders. We expect EPS (earnings-per-share) growth in double digits over the next several years. Second, JPM is highly rate-sensitive in benefiting from the spread between short-term interest it pays to depositors and higher long-term interest rates it receives from loan borrowers. While the Federal Reserve raised short-term interest rates several times in 2018, long-term rates also generally rose, and JPM is positioned to be a natural beneficiary. Finally, JPM has a high corporate tax rate, and is a strong beneficiary of tax reforms which have lowered that rate for 2018.

From a sector allocation perspective, the Fund's performance was boosted by having a substantial overweight exposure to the Information Technology sector – the strongest-performing sector of the S&P 500 Index during the period – as compared to its benchmark index. When put in historical context, we don't believe valuations for the Information Technology sector are unreasonably stretched at these levels, especially when considered through the lens of future earnings growth rates, and a pullback in the sector that occurred after the reporting period. We also continue to believe in the management teams and long-term business models of many of these innovative companies. In addition, Fund performance was aided by an underweight allocation to the weak-performing Consumer Staples sector.

Several positions in the Health Care sector didn't perform as we anticipated, hindered performance and were sold during the period. Celgene Corporation (-33% prior to being sold) was one such position. Celgene halted a drug trial on one product and struggled with another lead product for psoriatic arthritis, which caused us to sell the position.

Additionally, certain positions in the Information Technology sector such as Alibaba Group Holding Ltd. Spon. ADR (-5%) and Applied Materials, Inc. ("AMAT")(-23% prior to being sold) were weak during the period and held back Fund performance when compared to its benchmark. We maintained our position in Alibaba because, in our view, the fundamentals of Alibaba remain as strong as ever with impressive top-line growth and operating margin profile. Likewise, the company operates one of the strongest business models and possesses a powerful competitive moat. However, the stock was impacted during the period as it felt the impact of the developing trade war between the US and China.

We sold AMAT, which provides machines used in the production of memory chips, because deteriorating industry fundamentals for the major global producers of memory chips have caused them to defer spending on new machines from AMAT. While we believe the reduced spending cycle will be relatively short in duration compared to prior down-cycles in memory chip spending because of the increased consolidation of the industry, it is difficult to know how much worse the spending environment could get before it improves. Long-term, there will be substantially more memory chips needed for applications from servers to phones to autos, but shorter-term it appears there is more supply than demand.

From a sector allocation perspective, the Fund was held back slightly relative to its benchmark index by having a 4% average cash weight during the period. The Fund occasionally may hold more cash than usual as a temporary defensive measure, or as a strategic measure enabling it to take rapid advantage of opportunities to buy stocks at favorable prices.

During the reporting period, the Fund reduced its exposure to the Health Care and Real Estate sectors. The Fund increased its allocations to the Information Technology, Consumer Discretionary, and Industrials sectors. There were no significant changes to the Fund's allocations to the Materials, Financials and Consumer Staples sectors.

Fiscal Period-End Investment Posture

As of September 30, 2018, the Fund's largest sector allocations included Information Technology, Consumer Discretionary and Health Care. As of that date, the Fund had no exposure to the Energy, Telecommunication Services or Utilities sectors.

Sincerely,

THOMAS F. MARSICO
PORTFOLIO MANAGER