

Self-Declared Benchmarks and Fund Manager Intent: Cheating or Competing?

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We examine the selection of fund self-declared benchmarks. While the incidence of style mismatched benchmarks is high at the beginning of our sample (41% of fund assets/34% of funds), it declines significantly over time. This decline is driven primarily by existing funds changing their self-declared benchmarks to correctly match their style. In examining why funds ‘correct’ their benchmarks over time, we find that investor learning, institutional investor governance, product market competition and fund company risk management all play a role. Lastly, we find that funds overseen by entrenched managers are more likely to use a mismatched benchmark.

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1. Introduction

Relative performance evaluation (RPE) is a theoretically-motivated solution to moral hazard (i.e., Lazear and Rosen (1981), Holmström (1982), Diamond and Verrecchia (1982) and Green and Stokey (1983)) that is commonplace in modern incentive contracts. Both firm executives and fund managers, for example, typically have bonus compensation that is based on performance relative to a group of peer firms, peer funds or other comparable benchmarks (i.e., Gibbons and Murphy (1990) and Ma, Tang, and Gómez (2018)). At the same time, there is a growing body of academic evidence that suggests the efficacy of this incentive tool is reduced due to the influence of the executive or manager in selecting the comparison set. In the case of CEOs, the responsibility for defining the peer group often falls upon the board's compensation committee representing underlying shareholders (i.e., Bizjak, Lemmon, Naveen (2008)), but the choice of these peers is likely influenced by CEOs, especially when relative power of the CEO is high (i.e., Dikolli, Diser, Hofmann, and Pfeiffer (2018)). In the case of fund managers, Sensoy (2009) finds that 31.2% of U.S. equity funds select incorrect benchmarks which overstate the relative performance of the fund resulting in higher flows. This evidence suggests that one cost of RPE incentivization is strategic rent-extraction by the incentivized agent.

In this paper, we explore the issue of RPE and strategic rent-extraction by revisiting the mutual fund benchmark selection setting. Unlike the single 2004 cross-section examined by Sensoy (2009), our panel data set of mutual fund benchmarks collected between 2008 and 2020, enabling us to examine both the initial selection of an style-mismatched benchmark and any changes in that benchmark over time. Consistent with the results in Sensoy (2009), we find that at the beginning of our sample, 41% of fund assets (34% of funds) have mismatched benchmarks. However, over our sample period, the percentage of mismatched assets (mismatched funds) decreases to 27% (27%).

The value-weighted trend is stronger than the equal-weighted, suggesting that large funds are switching to correct benchmarks and that investors have shifted their assets toward mutual funds that are correctly benchmarked. We find that this decrease in mismatched benchmarks is largely driven by the intensive margin (i.e., changes in benchmarks for existing funds), not the extensive margin (i.e., opening of matched funds and closing of mismatched funds). Over our sample period, almost 60% of funds with a mismatched benchmark switch to a correctly matched benchmark by the end of our sample. This decrease in mismatched benchmarks and the high rate of switching from an incorrect to a correct benchmark complements the evidence of strategic benchmark selection in Sensoy (2009), suggesting that economic forces emerging during our sample period may help to mitigate potential agency costs associated with strategic benchmark selection.

In exploring what forces may explain these trends, we first turn to a primary economic channel suggested by the principal-agent setting: improved monitoring by more sophisticated principals. In our investor setting, this improved monitoring could come about through retail investor learning and/or institutional investor oversight. In addition to this principal-agent setting, the broader literature on product market competition offers some potential economic channels. To assess whether or not funds switch their benchmarks in order to reduce competition or increase the relative desirability of their product, we look both at direct measures of competition and the impact of a switch on product characteristics which the prior literature has shown investors base their investment decision on (i.e., performance and risk). If investors make their investment decisions based on a relative comparison within a benchmark category, switching benchmarks could reduce competition and/or increase the desirability of a given product in relative terms.

The first potential channel through which principal monitoring may improve, investor learning, is simply the idea that as investors become more financially sophisticated, they are better able to

assess both the correct benchmark for the fund and the efforts of the manager to obfuscate. Shapiro (1995) argues that debiasing would eliminate obfuscation in competitive markets. In our mutual fund setting, this consumer ‘debiasing’ might occur when an investment advisor educates investors as to the nature of a competitor’s obfuscation. Once investors have learned about this obfuscation, the advisor could ‘win’ the investors’ business by offering a more efficiently priced or superior quality (judged after the obfuscation is revealed) product.

Gabaix and Laibson (2006) consider the plausibility of competitive debiasing in an active management setting. They argue against the plausibility of competitive debiasing, because two different actively managed (‘for-profit’) investment advisors would not choose in equilibrium to educate investors: “If a mutual fund company explains that stock picking is not effective and that is not effective and that fees are the primary predictable component in risk-adjusted returns, a newly educated consumer will decide to buy an index fund...” While Gabaix and Laibson’s (2006) argument may apply to actively managed advisors, we argue that two important parties may serve the role of debiasing investors. First, passive advisors such as Blackrock and Vanguard would benefit from such debiasing. As we know, both firms spend substantial amount on education. Second, third-party information providers, such as Morningstar, could provide information on the correct benchmarks of funds. Morningstar, one such third-party provider, compares fund performance to that of the average of the style-matched portfolio category, regardless of which self-declared benchmark is selected by a fund. Together, more educated investors may drive the shift in actively managed firm’s behavior away from worse benchmarks (obfuscation) towards better matched benchmarks.

Using the sample of funds that switch from a mismatched to a style-matched benchmark, we test this investor learning hypothesis. In examining investor flows before and after the switch to the style-matched benchmark, we find that not only do investors assess manager performance relative to

the correct benchmark even before the switch, but that investors appear to punish such deceptive managers with lower flows overall. We also find that investor flow sensitivity to style-matched benchmarks (irrespective of whether or not the fund discloses that benchmark) increases relative to mismatched-benchmark sensitivity, consistent with investor learning over time.

The second channel through which principal monitoring may improve, is institutional investor oversight. If more sophisticated institutional investors are investing alongside retail investors, their superior monitoring may deter the selection of mismatched benchmarks. Prior work shows that more sophisticated monitoring by institutional investors can help mitigate issues of moral hazard, benefiting retail investors in other fund products overseen by the same fund managers (e.g., Evans and Fahlenbrach (2012)). To assess the impact of this potential channel, we examine whether or not a given retail mutual fund has an institutional separate account twin. In this twin setting, the fund and the matched separate account have the same manager(s), investment strategy and highly correlated performance, but are separate pools of capital. The existence of an institutional version of the same fund allows for monitoring by the institutional investors who may be more capable of both assessing the suitability of a benchmark and influencing the choice of a correct benchmark by the manager. Analyzing our fund sample, we find that funds with an institutional twin have a higher probability of selecting a style-matched benchmark, especially when the institutional twin also has a style-matched benchmark. This result holds with fund fixed effects, suggesting that the addition of institutional twins enhances monitoring of the investment advisor for all principals in the fund.

While the RPE contract setting offers important insights into the potential economic forces at work, product market competition, has long been recognized by the economic literature as an important factor in competitive equilibria (i.e., Hotelling (1929) and Lancaster (1966)). Models of firm entry accounting for existing product characteristics (e.g., Bresnahan and Reiss (1991) and Seim

(2006)) have shown that product differentiation concerns are central both to the decision to introduce a new product and the resulting competitive equilibrium. In an asset management context, Khorana and Servaes (1999), Massa (2003), Wahal and Wang (2011) and Khorana and Servaes (2012) have shown that product differentiation plays an important role in the decision to introduce new mutual funds and in the pricing and performance strategies of existing funds.

Considering benchmark selection in this context of product differentiation², we hypothesize that increasing competition could motivate funds to choose differentiated benchmarks. If funds with the same benchmark compete for similar investors, funds may choose a market capitalization and value-growth differentiated benchmark in response to this competition.³ Examining this competition hypothesis, we find that as competition in a given benchmark category increases, as measured by the total number of funds, the number of new entrants, increase in the total value of fee waivers within the category, or the number of index fund competitors, funds with current benchmarks in the same category are more likely to switch. Similarly, in analyzing the potential competition in the corrected benchmark category, we find funds are more likely to switch if the new, corrected category is less competitive using the same proxies for competition.

In addition to the direct measures of fund competition, we also examine the product characteristics upon which the prior literature has shown investors base their investment decision (i.e., performance and risk) and how a change in benchmarks affects the relative comparison of funds within a benchmark category. Sensoy (2009) has shown, and we confirm in our sample, that fund investment decisions are sensitive to the performance of the fund relative to its benchmark. Additionally, the prior literature has shown that investors are sensitive to fund relative risk and

² See Dranove and Jin (2010) for a review of the industrial organization literature on competition and quality disclosure.

³ For example, Lewis and Sappington (1994) show that sellers may choose to disclose additional information about a product to enable improved price discrimination.

anecdotally, investment advisors use tracking error, a measure of fund relative risk, both as an overall risk control and as a determinant of fund manager compensation.⁴ If investors externally (and managers internally) care about relative performance and risk, switching the benchmark against which these two characteristics are measured may enhance the competitive position of the fund. We test this product market competition hypothesis by examining if the decision to switch to a correct benchmark relates to the performance and risk of the fund relative to both to mismatched and a matched benchmark. Our results suggest that funds time their benchmark switches and are more likely to switch to the matched benchmark when relative performance is improved and tracking error is decreased by the switch.

As a final step, to explore why some funds keep the mismatched benchmarks, we examine the impact of managerial power in benchmark selection. We find that when an external star fund manager is hired to oversee a fund with a mismatched benchmark, the probability the fund corrects its benchmark decreases. Also, the presence of an entrenched manager (as measured by the manager's tenure at the company or the percentage of the total investment advisor assets overseen by the manager) decreases the probability that the fund would switch to a style-matched benchmark.

While the vast majority of the literature on RPE focuses on CEO compensation, in examining strategic rent-extraction by incentivized agents in this paper we focus on the mutual fund setting for

⁴ For example, below is a description of the fund manager compensation scheme at Charles Schwab Investment Management (CSIM) regarding the determinants of their manager performance evaluation. "Schwab compensates each CSIM Portfolio Manager for his or her management of the funds. Each portfolio manager's compensation consists of a fixed annual ("base") salary and a discretionary bonus....The discretionary bonus is determined in accordance with the CSIM Equity and Fixed Income Portfolio Management Incentive Plan (the "Plan"), which is designed to reward consistent and superior investment performance relative to established benchmarks and/or industry peer groups....The Plan consists of two independent funding components: fund investment performance and Schwab's corporate performance. 75% of the funding is based on fund investment performance and 25% of the funding is based on Schwab's corporate performance....Investment Performance will be determined based on each fund's performance relative to one of the following criteria: industry peer group/category, established benchmark or risk adjusted performance measure....The risk adjusted performance measure utilizes annual ex-ante tracking-error guidelines, as set by the CSIM Investment Policy Committee, and then applies an information ratio adjustment to the value. An information ratio is a ratio of portfolio returns above the returns of a benchmark (usually an index) to the volatility of those returns. This ratio typically represents funds that have top third performance among peers in their category."

three reasons. First, while defining the “correct” peer group for a corporation may be difficult, standardization across fund styles and within the asset management industry makes assigning the correct peer group for a mutual fund (e.g., Morningstar investment style classifications, Lipper and Morningstar fund manager peer benchmarks, holdings characteristics, etc.) a relatively easier task. Second, while CEO peer group compensation benchmarks are disclosed in relatively opaque proxy filings, fund benchmarks are disclosed in the prospectus, on fund advertisements and websites in graphical form, making them more accessible to investors and therefore plausibly accentuating the impact of using a mismatched benchmark. Third, while the CEO’s influence on the compensation committee is indirect, fund managers and investment advisors are tasked by the SEC to directly select the benchmark against which they are compared.

The remainder of the paper proceeds as follows. Section 2 describes the data. Sections 3 through 6 comprise the results. Section 7 concludes.

2. Data

Motivated by concerns of the potential moral hazard of excess risk-taking, in 1993 the SEC started requiring mutual funds to select a “broad-based securities market index” and report graphically the performance of both the fund and benchmark’s performance to enable investor comparison. To capture each fund’s self-declared benchmark, our analysis uses snapshots of the Morningstar database collected between December 2008 and December 2020. These snapshots contain the most recent listings of self-designated prospectus benchmarks from equity mutual funds operating in the United States and the contemporaneous index characteristics. We match these snapshots to the fiscal reporting dates of our mutual fund sample to obtain the dates on which these changes to the reported benchmarks become effective. Because we use the Morningstar style box

classification to categorize both the funds and the benchmark indices, we restrict the sample to Morningstar designated US equity funds. The combined equity fund times month panel- with their benchmarks- therefore captures the aggregate, as well as individual, evolution of equity fund benchmarks in the mutual fund industry over time. All in all, we have 3,695 unique actively managed equity funds using 154 individual benchmarks conducting 806 benchmark change events across our sample. This data is supplemented with additional information on monthly characteristics including historic fund returns, Morningstar ratings, Morningstar Categories, and others from Morningstar. Table 1 reports basic summary statistics of our sample. Panel A records the timing of the 11 snapshots dating from December 2008 to December 2020. Panel B describes the respective fund-month characteristics of our final sample.

Following the comparison method in Sensoy (2009), we consider an equity fund to be mismatched if its self-designated benchmark implies an investment style that differs from the style indicated by its holdings implied Morningstar Category. Specifically, during our sample period, Morningstar Categories correspond to the 3 by 3 holdings-implied style-boxes that describe the fund and the benchmark's target stock sizes (Large Cap, Medium Cap, and Small Cap) and their investment styles (Growth, Blend, and Value). If a fund designated the S&P 500 - a Large Cap Blend index- as its prospectus benchmark but was also categorized as a Small Cap Growth oriented fund by its holdings, then it would be deemed as a mismatched equity fund. The most common benchmarks are described in Table 2 Panel A. S&P and Russell provide the largest benchmarks throughout our sample. What is striking about this table is that while the equity fund market expanded dramatically during 2008-2020 and the S&P 500 stays as the largest benchmark, both the number of funds and the fraction of assets benchmarked to it declined, from 759 to 407 and from 52.4% to 38.7%, respectively.

In the Panel B of Table 2, we describe the incidences of Mismatch of fund-time observations by their respective target size and investment style exposures. The horizontal columns categorize a fund's holdings implied size and style exposures while the vertical rows categorize the respective exposures implied by their self-designated benchmarks. We see that for every category of size and investment style, there is a certain amount of Mismatch between a fund's asset holdings and its benchmark designation. The most severe disagreement occurs in the Growth and Value exposure categories with 41.43% of *Growth* and 31.68% of Value Fund-Time observations reporting a Broad/Blend benchmarks.

3. Trend and Determinants of Mismatched Benchmarks

We begin our analysis by describing the time series trends of benchmarking accuracy across the equity funds that belong to the nine Morningstar 3*3 style boxes. Figure 1 Panel A depicts the percent of assets with mismatched benchmarks making up the sample at each snapshot. Beginning in December 2009, 41.2% of actively managed equity assets were designated with mismatched benchmarks. This estimate is similar to the 40.4% of funds that have substantially different market exposures from their self-designated benchmark measurement in Sensoy (2009) which utilized a single cross-section of active equity funds collected between 1994 to 2004. However, with the time series panel, we track the systematic changes in benchmarking accuracy by the funds operating in this market. Consistent with improvements in the relative performance evaluation, we observe a steady decrease in mismatched assets from a high of 41.2% in December 2009 to 27.7% of the sample by December 2020. Panel B and C of Figure 1 decomposes the equity fund industry wide trend into approximately extensive and intensive margins. In Panel B, we observe that the trend is more severe for funds in existence at the beginning of our sample. These funds drive the decline in our time series pattern, with

the mismatched assets declining to 27.5% as a percent of their initial values. In Panel C, we observe that new entrants typically initialize with mismatched benchmarks- seemingly more so than the intensive sample. These new entrants had a maximum Mismatched incidence rate of 41.6% at the year end of 2012. The trend, however, also became downwards in the final several years of our sample.

This trend toward improved benchmarking in the equity mutual fund market can be observed along several dimensions. The first is the dwindling usage of the S&P 500 as a broad generic benchmark by most equity mutual funds. Fewer funds use the S&P 500 as their main prospectus benchmark in 2020 than in 2008. Figure 2 displays this steady decline. The percent of assets benchmarked to the S&P 500 went from 46.9% of the market to 32.6% by the end of the sample. That is, this generic large blend index was replaced in favor of more accurate style-indices by equity mutual funds. Coinciding this change, we see that funds in 2020 used many more style and size accurate benchmark indices as their primary benchmarks. As can be observed in Table 2, at the decline of S&P 500, almost every other major style-related index increased their respect share of Total Assets by 2020.

A second dimension is the steady correction of benchmark designations by mismatched mutual funds. As shown in Figure 3, 58% of funds that were mismatched in 2008 corrected their benchmarks by switching to a style-compatible index. We show in the subsequent section that this prior mismatching of benchmarks shows up as a significant driver of changes in benchmark designations.

Lastly, we document that this effect is related to within family changes. Figure 4 records the percentage of within family assets that had correct benchmarks. We see that across Fidelity, American Funds, and T. Rowe Price, the percent of assets managed with correctly matched benchmarks steadily increased in our sample period. In summary, the trend toward more accurate benchmarks can be seen

across the equity fund industry- through the declining usage of the S&P 500, the increased accuracy of formerly mismatched equity funds, and the increase accuracy funds within individual fund families. We analyze what may drive these secular trends in the next section.

4. Flow Sensitivity

Do these benchmark changes matter? Prior literature has shown that the prospectus benchmark is a main determinant of how investor interpret a fund's past performance (Sensoy 2009). In Table 3, we replicate this result for our sample and show that the choice of a benchmark effects how investors respond to past performance. Specifically, we run a horserace by regressing measures of monthly investor flows by various performance measures that has been documented in the literature to affect investor perception. These measures include the 36-month self-declared benchmark "adjusted" returns ($Raw - Benchmark Return$), the 36-month Fama French adjusted alpha ($36 Month Alpha$), and the 3-year Morningstar Ratings ($Star Rating$). Despite all of aforementioned variables being measures of fund performance over the 3-year period, investor flows respond significantly to benchmark adjusted returns. We show that investors are more likely to deposit assets into a fund in columns (1) and (2), that these deposits are likely higher in rank magnitude in column (3) and (4), that these funds are more likely to gain market share in columns (5) and (6), and that these funds have large % increases in their net assets under management in columns (7) and (8) when a fund has performance that exceeds that of their self-designated benchmarks.

Table 4 and Table 5 look at how investors respond to *Mismatched Benchmarks* as the result of mutual funds' respective self-designations. In Table 4, we again regress measures of 12-month investor flow, but with interest in how these measures react to indicators of benchmark mismatch (*Mismatched Benchmark*) and discretionary changes to the benchmark self-designation (*Benchmark Change*). For all

four different measures of investor flow, we see that investors tend to decrease their deposits into equity funds with mismatched benchmarks- counterfactually increasing their flows into correctly benchmarked mutual funds. We interpret these coefficients as that investors have an unconditional preference for mutual funds whose benchmarks are actually consistency its holdings. *Mismatched* funds, on average, have a 2.77% lower likelihood of positive investor flows, 1.72 percentile decrease in the ranking of their dollar flows, 0.175% decrease in their respective market shares, and 0.344% decrease in their total net assets under management per month. These results indicate that *Mismatched* equity funds, during our sample period, have higher likelihood of adverse investor reaction. Interestingly, benchmark changes undertaken by a fund's management typically do not coincide with significant investor outflows- instead such changes tend to coincide with increases in a fund's share of the equity fund market: a change in a fund's benchmark is followed by an increase of its market share of 0.156% per month in the subsequent year. We examine the conditional effect of improvement to benchmarking accuracy in Table 5.

The association between investor flows and *Mismatched Benchmark* for all equity funds indicates an unconditional investor preference for funds whose benchmarks accurately reflect their respective styles. Table 5 examines the consequences of discretionary improvements to benchmark accuracy for only funds that had a previously mismatched benchmark in the 12th month prior to each panel month. In this table, we regress measurements of investor flow against *Change to Correct*, which indicates that the previously *Mismatched* fund has changed its benchmark designation to one that is consistent with the fund's contemporaneous holdings style. We observe that improving benchmarking accuracy typically results in better investor flow responses- resulting in an increased probability of positive flow (by 2.85%) and an increase in a fund's respective market share (by 0.246%) in the subsequent month. This tendency of investor flow toward previously *Mismatched* funds that have corrected their

benchmark indices, along with the average negative flow away from *Mismatched* mutual funds, indicate a real benefit to improving benchmarking accuracy for fund managers.

Table 7 records how benchmark changes affect the performance to investor flow relationship. In each case of a fund switching benchmark indices, we relate returns adjusted by both the prior benchmark and the new benchmark to monthly investor flows in the 24 months before to the 24 months after the observed change. We show that these changes in benchmark choice also affect the way that investors evaluated fund performance. Column (1) describes the horse race between the cumulative 36-month old benchmark adjusted return ($Raw - Old\ BM\ Return$) and the new benchmark adjusted returns ($Raw - New\ BM\ Return$) in determining whether investors deposited or withdrew from a fund. We observe that both benchmarks on average relate to how investors evaluated this decision. We separate the panel months into before and after the observed change in columns (2) and (5) using the *Post Switch* indicator and see that, on average, investors increased their sensitivity to the new benchmark and decreased their sensitivity to the old benchmark after the switch. Despite this, the coefficient of $Raw - New\ BM\ Return$ remained positive throughout the sample, indicating that some investors were sensitive to the new benchmark even prior to the switch. Columns (3) and (6) in conjunction with (6) and (7) decompose the regressor even further by interacting the adjusted returns with whether the new benchmark correctly correspond to the fund style and whether the old benchmark was mismatched. We see that the increase in benchmark sensitivity is primarily driven by cases where the equity fund switched to a correct benchmark from a *Mismatched* benchmark.

5. Economic Channels

5.1 Investor Learning

The flow to return sensitivity structures recorded in Table 7 indicate that investors are more sensitive to a certain type of benchmarks reported by equity funds. In column 1, the horse race between the old and new benchmark adjusted returns implies that investors were more sensitive to the new benchmarks over the old benchmark unconditionally in the whole 48 months around a benchmark changing event. One percent of the new benchmark adjusted return is followed by an increase in the probability of positive monthly flow of 58.9 basis points, whereas one percent of the old benchmark adjust returns are only followed by 43.4 basis points. This stronger correlation with new benchmarks is driven by both the months prior to and the months after the benchmark change. One percent new benchmark adjusted returns increases the probability of positive flows by 44.8 basis points (and the increase in the fund's market share by 2.87 basis points) in the 24 months before the benchmark change, and these sensitivities increase further by 26.8 basis points after the change. We interpret the base sensitivity to the new benchmark returns as that investors were partially aware of the possible benchmarks that funds were going to switch to, even prior to the switch itself.

Investor to performance relationship is linked to the correct and mismatched nature of potential benchmarks. The increase in performance sensitivities from columns (2) and (5) occurring after a benchmark change are driven primarily by the fund that switched to a *Correct Benchmark* from a *Mismatched Benchmark*. As can be observed in columns (4) and (7), a switch from a *Mismatched Benchmark* to a *Correct Benchmark* increases the sensitivity of positive flow to a one percent benchmark adjusted return by 69.2 basis points (and the fund's respective market share by 4.50 basis points), whereas the performance sensitivities do not increase significantly during other possible benchmark changes. In particular, the regression coefficient of $(\text{Raw} - \text{New BM Return}) * \text{Post Switch}$ implies that, when the benchmark changes were not accompanied by an improvement in the appropriateness of the benchmark to a fund's holding styles, a 1% increase in the new *Mismatched* benchmark adjusted returns marginally decreases the probability of positive flows by 1.98 basis points in the column (4) regression

specification, and the market share by 0.499 basis points in column (7). Switching from a correct benchmark to another correct benchmark do not significantly increase investors' sensitivity to the benchmark adjusted returns. We interpret these coefficients in the context of investor learning; investors have become less sensitive to Mismatched Benchmarks and are only rewarding flows for fund returns that are appropriately benchmarked.

If investors have learned and adjusted to inadequate benchmark disclosures by fund managers, then their decision to invest or redeem assets will likely be less dependent on misleading information sources. These investors will increase their reliance of information sources outside of a fund's disclosures and in turn be less affected by a fund's self-designated benchmark. For example, the Morningstar website discloses fund performance relative to portfolio-based Morningstar-category averages, regardless of the self-declared benchmarks. We call the adaptation of investor flows to inadequate benchmarking the Investor Learning Hypothesis. To explore this hypothesis, we investigate the investor flow sensitivity to past returns separately for equity funds with correct and mismatched benchmarks. If investors have learned to be less reliant on mismatched benchmark returns, then we would expect different sensitivities between these groups. We find evidences of this hypothesis both in the time series dimension and in the cross section of equity fund flows sensitivities.

Consistent with the learning hypothesis, we observe drastically different investor responses to past return performance for the sample of correct and mismatched equity funds. Figure 5 records the cross-sectional flow to benchmark adjusted return sensitivity coefficients of the two fund samples separately. At each month, this graph plots the regression coefficient of the future monthly investor *% Flow* to the past 36-month benchmark adjusted returns. The coefficients for the sample of correctly benchmarked equity funds are plotted in blue and that of funds with mismatched benchmark are plotted in orange. We observe that flows to both funds with correct benchmark and mismatched

benchmarks were highly sensitivity to benchmark adjusted returns at the beginning of the sample in March 2009 - 1% benchmark adjusted returns indicates between 1.50% to 2.00% increase in the monthly flows for the correct and mismatched sample. However, investor flow sensitivity to benchmark adjusted returns have trended lower over time for both sets of funds. The correctly benchmarked sample decreased their return sensitivity to about 1.27%, while the mismatched sample declined much more to 0.71% in March 2020. This larger decline for mismatched equity funds suggests that investors are learning and adjusting to the potentially misleading nature of a fund's respective prospectus benchmarks.

We explicitly test whether decreasing investor sensitivity to returns adjusted, consistent with investor learning, by *Mismatched Benchmarks* has anything to do with the secular improvement in benchmarking accuracy. Specifically, in Table 8, we construct a measure- *Flow Beta Difference*- which captures the inherently lower sensitivity of investor response to returns by *Mismatched Benchmarks*, and regress (using the probit binary response model) this variable against the indicator *Change to Correct* for the sample of previously mismatched equity funds. *Flow Beta Difference* is the incremental sensitivity of a fund's % *Flows* to a potentially well-matched benchmark over its self-designated *Mismatched* benchmark. That is, for every *Mismatched* equity fund, we assign to it a popular benchmark that is style consistent with the equity fund's holdings. We regress each fund's past 36 monthly % *Flows* against its returns adjusted this the well-matched benchmark and its self-designated benchmark. We take incremental percentage improvement in the fund flow's explanatory beta from the mismatched benchmark adjusted returns to a well-matched benchmark adjusted return as *Flow Beta Difference*.⁵ Consistent with increasing benchmarking accuracy as a managerial response to decreasing investor sensitivity to inaccurate benchmarks and increasing investor sensitivity to potentially better

⁵ Specifically $Flow\ Beta\ Difference = \max(Rolling\ 36\ month\ flow\ beta\ for\ returns\ adjusted\ by\ a\ well-matched\ benchmark / Rolling\ 36\ month\ flow\ beta\ for\ returns\ adjusted\ by\ self-designated\ benchmark - 1, 0)$.

benchmarks, we observe that this variable has significant explanatory power on *Change to Correct*. A 1% improvement in the explanatory power of an alternative benchmark on flows increases the marginal probability of a Mismatch equity fund switching to a correct benchmark by 3.67 basis points. We consider other channels that may drive this improvement in benchmarking accuracy in the following section.

5.2 Competition

We now explore market competition as another explanation for the decline of mismatched benchmarks. Even if investors do not learn about the correct benchmark of a fund, as they see the benchmark prominently displayed on the fund's webpage, prospectus, and annual reports, they may interpret it as conveying information on product positioning. For example, investors may view a fund benchmarked to the S&P 500 as a fund largely tracking the market, even if the fund's actual portfolio has a different objective. If this is the case, funds with the same benchmark (or benchmark category) compete with one another regardless of their portfolios.

Theory of industrial organization implies that companies can engage in product differentiation to soften price competition (e.g., Shaked and Sutton, 1982). Applying this framework to our setting, as competition rises among the funds with the same benchmark (or benchmark category), those funds are increasingly likely to switch to a less crowded benchmark to reduce the competitive pressure. This does not imply that funds necessarily move to matched benchmarks, because any differentiated benchmark could serve the purpose of mitigating competition. However, if we also consider the potential liability with benchmarks, the choice set is restricted, and competition can result in corrections. The reason is that while industry accepts generic benchmarks such as the S&P 500, a specific but mismatched benchmark (e.g., a large-cap fund declaring a small-cap benchmark) may raise concerns with the board of directors or the regulators. Together, we predict that a fund is more likely

to switch benchmarks when the category of its current benchmark is subject to higher competition and explore whether the benchmark switches are more likely to be corrections.

In the sample of equity funds in the Morningstar 3-by-3 style boxes during 2009-2020, we construct three different measures of competition. To start, while our sample contains actively managed funds, they are subject to the competition from index funds that track the same indices (Cremers, Ferreira, Matos, Starks 2016; Sun 2021). We measure the competitive pressure from passive funds using the number of index funds in a benchmark category and the market share of index funds in that benchmark category. The competition from index funds reflects the commoditization of the category and can result from the low performance of actively managed funds, as well as the loss of investor interest in actively managed funds benchmarked to that category. We thus expect that index fund competition pushes funds to switch away their benchmarks. Next, moving to competition within actively managed funds, we rely on the most used measure of price competition – the practice by funds to voluntarily waive part of their gross expense ratio (Christoffersen 2001). We focus on the aggregate use of fee waivers at the category level and focus on the recent changes in the fee waiver levels.

The above competition measures are constructed at the benchmark category level following the Morningstar classifications of benchmarks (similar 3-by-3 boxes), so that funds with benchmarks in the same category are considered as competing with one another. Measuring competition at the benchmark category level instead of at the benchmark index level avoids underestimating competition for unpopular benchmark indices that are only used by one or a few funds but are similar to the more widely used indices. Since the competition measures tend to be persistent over time and the fee waivers data is only available at the annual frequency, we calculate them at the yearly frequency and reduce the panel to the yearly level by retaining the observations in December.

Table 8 presents the relationship between competition and funds' benchmark choices estimated with a Probit model. Importantly, since product differentiation may also entail a switch of portfolio strategy that accompanies the benchmark switch, we exclude all funds whose Morningstar category changes in each period. This restriction drops about 5% of the observations used for the regressions. We include style-box-by-year fixed effects in the regressions, thus comparing funds with the same style of portfolios at the same in time but with different self-declared benchmark categories. Columns 1-3 examine whether higher competition in the category of the fund's current benchmark predicts that the fund switches benchmark in the following year, conditional on other fund characteristics. We keep funds with both matched and mismatched benchmarks in columns 1-3, because competition could affect both groups: the currently matched funds could switch to another matched benchmark or a mismatched benchmark under competitive pressure. In columns 4-6, we restrict to the subsample of mismatched funds and focus on benchmark correction as the outcome variable. We cluster the standard errors at the benchmark category level because that is the level of variation in the competition measures.

The "competition" variable in Table 8 includes different measures as indicated by the column headers. Columns 1 and 4 use the natural logarithm of the number of index funds in a style box. Since larger categories tend to have more index funds, we control for category size. Columns 2 and 5 use the market share of index funds expressed as the fraction of the assets in a holdings-based style box that is in passive strategies, including both index mutual funds and exchange-traded funds. Columns 3 and 6 examine the change in the fee waiver size from year $t-3$ to t as a proxy for a recent rise in price competition. For the levels of the fee waivers aggregated to the benchmark category level, we first calculate fee_waiver_i where the aggregate fee waiver is the fraction of total revenues that are voluntarily waived

by funds $\left(\frac{\sum_{i \in j} WaivedExpenseRatio_{it} \times TNA_{it}}{\sum_{i \in j} GrossExpenseRatio_{it} \times TNA_{it}}\right)$ where i stands for a fund and j indicates a benchmark category, and then take the difference from year $t-3$ to t .

The results in columns 1-3 suggest that consistent with our hypothesis, higher competitive pressure from index funds or more intense price competition in year t is positively associated with benchmark switches in year $t+1$. To better interpret the Probit coefficients, we report the marginal effects of the main regressors scaled by one standard deviation of each competition variable. The marginal effects are similar: One standard deviation higher competition is associated with between 2% and 8% higher likelihood of switching benchmark in the next period, and all effects are significant at the 0.05 level at least. Thus, the results are consistent with funds switching benchmarks as a response to competition pressure.

We then ask whether the competition channel contributes to benchmark correction in addition to differentiation. In columns 4-6, we restrict the sample to the subset of funds with mismatched benchmarks in year t . With the fixed effects explained above, the analysis compares funds with mismatched benchmarks in the same portfolio category but facing different levels of competition due to their self-declared benchmarks. Out of these funds, we are interested in whether a rising level of competition in a fund's declared benchmark category predicts that the fund is more likely to correct its benchmark, compared with its peers with mismatched benchmarks. We see that the results of columns 1-2 carry through to columns 4-5, suggesting that the competition from index funds tends to push actively managed funds to switch to matched benchmarks. In column 6, however, we see that the effect of fee waivers drop out completely. Taken together, the results suggest that price competition among actively managed funds as measured by fee waivers can lead to funds to switch benchmarks, not necessarily to the matched ones, but the competition from index funds is a strong predictor for benchmark corrections.

5.3 Governance

The literature has shown that mismatched benchmarks arise out of agency settings with unsophisticated principals. However, if the fund serving unsophisticated investors is simultaneously monitored by sophisticated institutional investors, we should expect a reduction in agency problems. Evans and Falenbrach (2012) shows that managers often offer both retail and institutional versions of the same portfolio, which are run by the same portfolio managers using the same investment strategy, and that consistent with monitoring, the presence of an institutional twin improves the governance at the retail fund, as shown by greater managerial effort and lower fees. Based on that insight, we hypothesize that the presence of institutional twins reduces the likelihood of having mismatched benchmarks.

To construct measures on the availability, quality, and size of the institutional twins, we employ datasets from Morningstar on retail funds, institutional funds—mutual funds with only institutional share classes—and separately managed accounts offered primarily to institutional entities. Following Evans and Falenbrach (2012), we match both separate accounts and institutional funds to the retail mutual funds, requiring the same investment advisor, at least one common portfolio manager, the same Morningstar category classification, and a monthly gross return correlation of at least 0.95. In the rest of this section, we will call both types of twins (separate accounts and institutional funds) the “institutional twins” without distinguishing them. We work with a yearly panel and employ the inception dates of the twins to determine the years in which a retail fund has twin(s) or gets a twin added, and which fund of the twin (retail or institutional) was introduced earlier.

While it is reasonable to assume that institutional investors on average are more sophisticated than retail investors, some institutional investors may not be, or may not monitor effectively.

Therefore, we further measure whether the institutional twins themselves have matched benchmarks. The self-declared benchmarks of the institutional twins are available in the time series; therefore, we have time variation in the quality of those benchmarks. The benchmarks of separate accounts, however, are only available with one snapshot in 2018. We therefore extrapolate the benchmark of the separate accounts – if a separate account has a matched benchmark in 2018, we assume that it is matched for all observations, and vice versa.

Table 9 reports the results of our tests of the governance hypothesis. We estimate in the full sample of equity funds a Probit model of the determinants for having mismatched benchmarks. All regressions include category-by-year fixed effects, thus the comparison is between funds in the same portfolio category that have or do not have twins. Standard errors are clustered by fund in this table, since both the dependent variable and the independent variable are persistent within the fund. In columns 1 (2), the main regressor of interest is an indicator for whether the mutual fund has an institutional twin (an institutional twin with a matched benchmark) in year t , same as the timing of the dependent variable. The sample size shrinks by about one half in Column 2 because the data on the benchmark quality of the institutional twins are missing for a large fraction of funds. The marginal effects suggest that in the cross section, funds with institutional twins are 6% less likely to have mismatched benchmarks, and that those whose twins have correct benchmarks are 16% less likely to be mismatched. These results support the governance hypothesis, and in particular suggest that sophisticated institutional investors (those having matched benchmarks themselves) can more effectively discipline the retail fund in the pair.

While columns 1-2 are cross-sectional, columns 3-4 include fund fixed effects, thus exploiting only time-series changes when a twin is added. All funds that never have a change in the dependent variable are dropped by the Probit model, thus the number of observations is lower. While cross-

sectional variations in the availability of twins may be correlated with omitted variables such as fund-family level marketing and distribution strategy, adding fund fixed effects helps us tighten up identification by focusing on the same funds before and after an institutional twin is added. Columns 3 and 4 suggest, interestingly, that only the additions of twins with correct benchmarks have a disciplinary effect. The marginal effect in column 4 is similar in magnitude to that in column 2. Lastly, in column 5, we restrict the sample to funds whose twins are added later than the retail fund's inception (instead of twin first), continue to include fund fixed effects, and obtain a similar effect around the creations of twins for these funds.

5.4 Risk Management

The last hypothesis we examine for why benchmarks become more matched overtime is motivated by the idea that investors, funds, and fund families often view the volatility in benchmark-adjusted returns, i.e., the tracking error, as one measure of riskiness of investment products. This incentive is further reinforced by the practice at many fund companies that link fund manager compensation to the tracking errors of their funds. Therefore, to reduce the perceived riskiness of the funds, fund managers have an incentive to switch to more correctly matched benchmarks. Based on the risk management hypothesis, we expect that funds are more likely to switch to correct benchmarks when switching to correct can reduce the tracking error by more.

We test the risk management hypothesis in Table 10. The dependent variable is an indicator that equals one if a fund switches to a matched benchmark from year t to $t+1$. We calculate the tracking errors of each fund around their old self-declared benchmarks as the standard deviation in the monthly benchmark-adjusted returns during a 36-month period up to the December of year t . For all funds, we also calculate the counterfactual tracking errors had they switched to the largest

benchmark in the matched benchmark category and take the difference in the two tracking errors (the counterfactual, correct benchmark minus the current self-declared benchmark). The difference should be exactly zero for funds that are currently benchmarked to the largest benchmark in their matched category, and close to zero for other funds with matched benchmarks. For the funds with mismatched benchmarks, we expect the difference to be negative, i.e., the funds can reduce their tracking errors by switching to the matched benchmarks. Following the result from Sensoy (2009) that funds seek to look better with their choice of benchmarks, we also include the 36-month benchmark-adjusted returns under the old benchmark, together with the difference in benchmark-adjusted performance had the fund switched to the matched benchmark. Again, the difference should be (close to) zero for the funds that currently have matched benchmarks.

Table 10 estimates the relationship between tracking errors, relative performance, and the decision by funds to switch to matched benchmarks. The dependent variable is an indicator equal to one if a fund switches to a benchmark that matches its portfolio in year $t+1$, and zero otherwise. We include the portfolio-based Morningstar style box by time fixed effects in all regressions, to estimate whether the regressors of interest can predict switching to correct among peers with similar portfolios in the same year. In columns 1-3, we include the full sample (please note that even funds with matched benchmarks may further reduce their tracking errors by switching), and in columns 4-6, we use only the mismatched sample. Further, we cluster the standard errors by fund to allow for the persistence in the independent variables.

Column 1 of Table 10 focuses on the relative tracking error analysis and shows that when the potential reduction in tracking errors is one standard deviation higher in magnitude, funds are 0.8% more likely to switch to matched benchmarks. In column 2, we turn to examine the role of the relative performance. Confirming Sensoy (2009), when the improvement in the benchmark-adjusted

performance is one standard deviation higher, funds are 0.5% more likely to switch to correct benchmarks. In column 3, we put both determinants in one regression, and the estimated marginal effects stay the same for both. In columns 4-6, we focus on the funds with currently mismatched benchmarks in year t . Unsurprisingly, the results are stronger in this subsample. Overall, this section uncovers the incentive of funds and fund families to reduce tracking error, in addition to the desire to increase relative performance, is a separate determinant for the choice of the self-declared benchmark. The results suggest that fund families may want to trade off considerations over relative performance and tracking errors. More generally, in an agency setting, the agent has an incentive to maximize relative performance to start, over time, the volatility in the relative performance may lead risk-averse agents to switch back to the most matched benchmark.

6. Managerial Entrenchment

Given that such corrections in benchmarking are advantageous from the perspective of investors flows, corporate governance, as well as alleviating potential liabilities to the fund family, why haven't all equity funds corrected their mismatched benchmarks? We document that managerial entrenchment may delay benchmark corrections in the equity fund industry. Table 11 relates measures of managerial entrenchment and power to potential benchmark mismatches. *Manager Tenure Length* is the (average) number of observed months that the fund's manager(s) had spent at the fund family. *% Family Managed* is the (average) percent of a fund family's asset under management in equity funds managed by the fund's manager(s). We show that these measures are all positively related to the likelihood of a fund reporting a Mismatched Benchmark. In our most general specification in column (5), one additional year worked at a fund family by the fund manager increases the probability of *Benchmark Mismatch* by 0.747%, and a 1% increase in the Manager's share of family assets increases the

probability of a Benchmark Mismatch by 0.125%. These coefficients represent economically important magnitudes. The probability of a *Mismatched Benchmark* is roughly 32.44% in our general sample. The standard deviations of *Manager Tenure Length* and *% Family Managed* are 5.89 years and 36.95% respectively. Therefore, single standard deviations of *Manager Tenure Length* and *% Family Managed* increases the likelihood of benchmark mismatch by 13.5% and 14.2% from their unconditional means respectively. These results are suggestive of managerial entrenchment being significant barriers toward industry wide adoption of style consistent benchmarks.

7. Conclusion

In 1993, the SEC began requiring mutual funds to select and disclose a “broad-based securities market index” to mitigate concerns about the potential moral hazard of excess risk-taking. In that disclosure, the SEC explains that “The choice of an appropriate benchmark is important in evaluating performance because it is important to compare apples to apples.” They also indicate that investors should be wary of funds that select style mismatched benchmarks, suggesting they “should question why that benchmark was used.”

While this focus on correct risk-adjustment and the SEC’s recognition of the potential for relative performance evaluation (RPE) to mitigate moral hazard is to be commended, there were at least three aspects of the SEC’s regulatory approach to this issue that fell short. First, the regulatory guidance uses the S&P 500 as an example of an appropriate benchmark which may have led to the overuse of this often style-mismatched benchmark. At the beginning of our sample, over 50% of fund assets were benchmarked to the S&P 500 and it constituted the most commonly used style-mismatched benchmark. Second, the SEC’s guidance on what constitutes an “Appropriate Index” focuses entirely on the independence of the index provider and the treatment of expenses and fails

to provide direction about how the benchmark's investment style should relate to that of the fund. Third, the SEC directs the fund itself, not an independent third party, to select the appropriate benchmark.

Given these three shortcomings, the evidence of Sensoy (2009) that style-mismatched benchmarks are frequently selected by funds is not surprising. The prior literature suggests that one potential cost of using RPE in incentive contracts is strategic rent-extraction by the incentivized agent and these three shortcomings enable this form of obfuscation.

In this paper, however, we find that forces outside the explicit incentive contract have power to effectively 'monitor' the manager, decreasing the incidence of mismatched benchmarks and the associated moral hazard. Specifically, investor learning, institutional investor governance and product market competition are associated with decreases in mismatched benchmarks, consistent with the underlying economics. These important results suggest new mechanisms external to the incentive contract that academics, practitioners and regulators should consider in their analysis of and suggested solutions to address moral hazard. At the same time, we find that in spite of these forces, funds with entrenched managers are still more likely to employ a mismatched benchmark.

References

- Barber, Brad M, Xing Huang, and Terrance Odean, 2016, Which factors matter to investors? evidence from mutual fund flows, *Review of Financial Studies* 29, 2600-2642.
- Ben-David, Itzhak, Jiacui Li, Andrea Rossi, and Yang Song, 2018, What do mutual fund investors really care about?, Working Paper .
- Berk, Jonathan B, and Jules H van Binsbergen, 2016, Assessing asset pricing models using revealed preference, *Journal of Financial Economics* 119, 1-23.
- Bresnahan, Timothy F., and Peter C. Reiss, 1991, Entry and competition in concentrated markets, *Journal of Political Economy* 99, 977-1009.
- Carlin, Bruce Ian, and Gustavo Manso, 2011, Obfuscation, learning, and the evolution of investor sophistication, *Review of Financial Studies* 24, 754-785.
- Chakraborty, Indraneel, Alok Kumar, Tobias Muhlhofer, and Ravi Sastry, 2018, Does limited investor attention explain mutual fund flows? evidence from sector funds, University of Miami Working Paper .
- Chevalier, Judith, and Glenn Ellison, 1997, Risk Taking by Mutual Funds as a Response to Incentives, *Journal of Political Economy* 105, 1167-1200.
- Christoffersen, Susan E. K. “Why Do Money Fund Managers Voluntarily Waive Their Fees?” *The Journal of Finance* 56, no. 3 (2001): 1117-1140.
- Cremers, Martijn, Miguel A. Ferreira, Pedro Matos, and Laura Starks. “Indexing and Active Fund Management: International Evidence.” *Journal of Financial Economics* 120, no. 3 (2016): 539-560.

Del Guercio, Diane, and Paula A Tkac, 2008, Star power: The effect of monrningstar ratings on mutual fund flow, *Journal of Financial and Quantitative Analysis* 43, 907-936.

Dranove, David, and Ginger Zhe Jin, 2010, Quality disclosure and certification: Theory and practice, *Journal of Economic Literature* 48, 935-63.

Ellison, Glenn, and Alexander Wolitzky, 2012, A search cost model of obfuscation, *The RAND Journal of Economics* 43, 417-441.

Evans, Richard B, and Rudiger Fahlenbrach, 2012, Institutional investors and mutual fund governance: Evidence from retail-institutional fund twins, *The Review of Financial Studies* 25, 3530-3571.

Fama, Eugene F, and Kenneth R French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of financial economics* 33, 3-56.

Green, Jerry R., and Nancy L. Stokey, 1983, A comparison of tournaments and contracts, *Journal of Political Economy* 91, no. 3: 349-364.

Hastings, Justine S, and Jeffrey M Weinstein, 2008, Information, school choice, and academic achievement: Evidence from two experiments, *The Quarterly journal of economics* 123, 1373-1414.

Hortacsu, Ali, and Chad Syverson, 2004, Product differentiation, search costs, and competition in the mutual fund industry: A case study of s&p 500 index funds, *The Quarterly Journal of Economics* 119, 403-456.

Hotelling, Harold, 1929, A new approach to consumer theory, *Economic Journal* 39, 41-57.

Ippolito, Pauline M, and Alan D Mathios, 1990, The regulation of science-based claims in advertising, *Journal of Consumer Policy* 13, 413-445.

Khorana, Ajay, and Henri Servaes, 1999, The determinants of mutual fund starts, *The Review of Financial Studies* 12, 1043-1074.

Khorana, Ajay, and Henri Servaes, 2012, What drives market share in the mutual fund industry?, *Review of Finance* 16, 81-113.

Lancaster, Kelvin J., 1966, A new approach to consumer theory, *Journal of Political Economy* 74, 132-157.

Lazear, Edward P., and Sherwin Rosen, 1981, Rank-order tournaments as optimum labor contracts, *Journal of political Economy* 89, no. 5: 841-864.

Lewis, Tracy R, and David EM Sappington, 1994, Supplying information to facilitate price discrimination, *International Economic Review* 309-327.

Massa, Massimo, 2003, How do families affect fund performance? when performancemaximization is not the only game in town, *Journal of Financial Economics* 67, 249-304.

Nagel, Stefan, 2013, Empirical cross-sectional asset pricing, *Annu. Rev. Financ. Econ.* 5, 167-199.

Reuter, Jonathan, and Eric Zitzewitz, 2015, How much does size erode mutual fund performance? a regression discontinuity approach, Working Paper .

Seim, Katja, 2006, An empirical model of firm entry with endogenous product-type choices, *Rand Journal of Economics* 37, 619-640.

Sensoy, Berk A, 2009, Performance evaluation and self-designated benchmark indexes in the mutual fund industry, *Journal of Financial Economics* 92, 25-39.

Shaked, Avner, and John Sutton, 1982, Relaxing price competition through product differentiation, *The Review of Economic Studies* 3-13.

Sharpe, William F, 1998, Morningstar's risk-adjusted ratings, *Financial Analysts Journal* 21-33.

Sirri, Erik R, and Peter Tufano, 1998, Costly Search and Mutual Fund Flows, *Journal of Finance* 53, 1589-1622.

Sun, Yang, 2021, Index Fund Entry and Financial Product Market Competition, *Management Science* 67, 500-523.

Wahal, Sunil, and Albert (Yan) Wang, 2011, Competition among mutual funds, *Journal of Financial Economics* 99, 40-59.

Panel A.

Snapshot Date	Snapshot Date
December 31, 2008	November 24, 2015
December 31, 2009	October 13, 2017
March 5, 2010	August 27, 2018
September 17, 2012	September 4, 2019
September 11, 2013	December 7, 2020
June 5, 2014	

Panel B.

	Full Sample			
	N	Mean	Median	SD
Benchmark Mismatch	317,167	0.322	0	0.467
Benchmark Change	300,026	0.0327	0	0.178
Large	317,167	0.545	1	0.498
Small	317,167	0.249	0	0.432
Growth	317,167	0.396	0	0.489
Value	317,167	0.260	0	0.439
Size (\$ million)	317,167	1,824	247	11,590
Family Size (\$ million)	317,167	68,690	10,170	212,100
Age (year)	311,289	15.81	13.50	13.32
Percent Flow (%)	313,655	-0.866%	-0.516%	0.127%
Change in Market Share (%)	313,866	0.106%	-0.228%	4.16%
FF Alpha 36m (%)	274,169	-8.35%	-8.37%	10.6%
Star Rating	317,167	1.990	2.003	1.656
Net Expense Ratio (%)	305,167	1.186%	1.182%	0.617%

Table 1. Summary Statistics. Panel A describes the timing of the snapshots of benchmarks of active equity mutual funds in our sample. The benchmarks reported at these snapshots are then matched to the funds' respective prospectus reporting dates for the timing of their exact release. Panel B describes the summary statistics of each fund-month observations of these equity funds. Our sample consists of equity mutual funds between December 2008 and December 2020. *Mismatched Benchmark* indicates whether the mutual fund's self-designated benchmark has a style that is different from its Morningstar designated holding style. *Benchmark Change* indicates a change in the self-designated fund benchmark from 12 months prior. *Large*, *Small*, *Growth*, and *Value* are indicators of the size and investment style as indicated by the Morningstar equity style box. *Size* is the dollar assets under management by the mutual fund. *Family Size* is the dollar assets under management in the equity fund sector by the family of the mutual fund. *Percent Flow (%)* is the monthly net dollar flow into the mutual fund divided by its beginning fund size. *Change in Market Share (%)* is the one-month percentage change in the market share of a mutual fund in total the equity fund sector. *FF Alpha 36m (%)* is the cumulative Fama-French adjusted fund return from the prior 36 months. *Net Expense Ratio (%)* is the average net expense ratio of the equity fund.

Panel A.

Rank	Benchmark Name	Assets Dec 2008 (\$ Billion)	Fraction of Total Assets Dec 2008	No. Funds
1	S&P 500	960.0	52.4%	759
2	Russell 1000 Value	161.6	8.8%	187
3	Russell 2000	122.0	6.7%	214
4	Russell 1000 Growth	118.3	6.5%	197
5	Russell Mid Cap Value	51.9	2.8%	73
6	Russell 3000 Growth	48.3	2.6%	40
7	Russell 2000 Value	45.3	2.5%	118
8	Russell Mid Cap Growth	45.1	2.5%	115
9	Russell 3000	39.9	2.2%	60
10	S&P Mid Cap 400	36.5	2.0%	48

Rank	Benchmark Name	Assets Dec 2020 (\$ Billion)	Fraction of Total Assets Dec 2020	No. funds
1	S&P 500	2,019.4	38.7%	407
2	Russell 1000 Growth	724.4	13.9%	147
3	Russell 1000 Value	508.2	9.7%	171
4	Russell Mid Cap Growth	255.1	4.9%	80
5	Russell 2000 Growth	197.2	3.8%	108
6	Russell 2000	194.2	3.7%	150
7	Russell 1000	174.5	3.3%	62
8	Russell 3000	165.8	3.2%	59
9	Russell 3000 Growth	154.6	3.0%	37
10	Russell Mid Cap Value	139.7	2.7%	72

Panel B.

		Size Target Indicated by Holdings					
		Large		Mid		Small	
BM Size Target	Large/Broad	167,752	99.57%	15,871	24.54%	3,083	3.97%
	Mid	509	0.30%	46,044	71.18%	2,959	3.81%
	Small	218	0.13%	2,772	4.29%	71,633	92.22%
	Total	168,479		64,687		77,675	

		Style Indicated by Holdings					
		Blend		Growth		Value	
BM Style	Broad/Blend	90,831	85.74%	51,430	41.43%	25,589	31.68%
	Growth	634	0.60%	72,008	58.01%	105	0.13%
	Value	14,468	13.66%	686	0.55%	55,090	68.19%
	Total	105,933		124,124		80,784	

Table 2. Panel A. The largest ten benchmarks by assets at the beginning (December 2008) and the end (December 2020) of our sample. Panel B. Fund Month Observations Mismatched by Size Target and Styles.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Positive Flow _{t+1}		Percentile Flow Rank _{t+1}		% Change in Market Share _{t+1}		% Flow _{t+1}	
Raw – Benchmark Return _t	0.362*** (0.0369)	0.437*** (0.0546)	0.195*** (0.0250)	0.282*** (0.0441)	0.0332*** (0.00261)	0.0362*** (0.00339)	0.0929*** (0.0109)	0.103*** (0.0136)
36 Month Alpha _t	0.783*** (0.0473)	0.671*** (0.0585)	0.496*** (0.0345)	0.434*** (0.0443)	0.0538*** (0.00308)	0.0490*** (0.00368)	0.108*** (0.0105)	0.102*** (0.0124)
Star Rating _t	0.0645*** (0.00394)	0.0728*** (0.00393)	0.0284*** (0.00289)	0.0498*** (0.00275)	0.00307*** (0.000240)	0.00366*** (0.000250)	-0.00261*** (0.000616)	-0.00162** (0.000654)
Log Fund Size _t		-0.00419* (0.00243)		-0.0371*** (0.00183)		-0.000860*** (0.000134)		-0.00235*** (0.000448)
Log Family Size _t		-0.00669*** (0.00159)		-0.00489*** (0.000982)		0.000237*** (9.18e-05)		0.000405 (0.000279)
Expense Ratio _t		0.00428 (0.00859)		0.00103 (0.00485)		0.000834* (0.000475)		0.00286* (0.00150)
Log Age _t		-0.110*** (0.00553)		-0.0523*** (0.00372)		-0.00271*** (0.000297)		-0.00679*** (0.000813)
Share Load Fees _t		-0.0119 (0.00914)		-0.0205*** (0.00636)		-0.000726 (0.000504)		-0.00533*** (0.00156)
Date X MS Box FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	269,503	264,634	269,503	264,634	269,647	264,746	266,900	262,048
Adjusted R-squared	0.109	0.152	0.071	0.199	0.097	0.196	0.052	0.067

Table 3. Determinants of Monthly Fund Flow. This table regresses measures of investor flow into equity funds on its past 36-month net returns adjusted by their respective self-designated benchmarks. *Raw – Benchmark Return* is the difference between the cumulative 36 month net return from the fund and its self-designated benchmark. *Positive Flow* indicates that investors had deposited dollar into the fund in net in the next month. *Percentile Flow* is the percentile ranking (1 being the top percentile and 0 being the bottom percentile of all equity funds) of the net dollars flow from investors into the mutual fund during the next month. *Change in Market Share* is the percent change in the share of the fund over the total equity mutual fund market. *% Flow* is the dollar flow as the percent of a fund’s total net assets into the fund in the next month. Only monthly observations with greater than negative 50% *% Flow* and less than 200% *% Flow* are kept for the regression. The standard errors, reported in parenthesis, are clustered at the fund level. *, **, *** indicates statistical significance at the 90%, 95%, and 99% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Positive Flow _{t+1}		Percentile Flow Rank _{t+1}		% Change in Market Share _{t+1}		% Flow _{t+1}	
Mismatched Benchmark _t	-0.0125*	-0.0277***	0.00423	-0.0172***	-0.00162***	-0.00175***	-0.00236**	-0.00344***
	(0.00756)	(0.00728)	(0.00599)	(0.00510)	(0.000398)	(0.000403)	(0.00109)	(0.00112)
Benchmark Change _t	0.00814	0.00873	0.0173**	0.0108	0.00160**	0.00156**	-8.48e-05	-0.000458
	(0.0104)	(0.0101)	(0.00729)	(0.00675)	(0.000717)	(0.000713)	(0.00196)	(0.00195)
36 Month Alpha _t	1.592***	1.498***	0.916***	0.985***	0.105***	0.104***	0.188***	0.191***
	(0.0418)	(0.0388)	(0.0333)	(0.0293)	(0.00287)	(0.00289)	(0.00784)	(0.00766)
Log Fund Size _t		0.00457*		-0.0314***		-0.000358***		-0.00207***
		(0.00246)		(0.00186)		(0.000133)		(0.000439)
Log Family Size _t		-0.00662***		-0.00486***		0.000273***		0.000635**
		(0.00166)		(0.00101)		(9.51e-05)		(0.000273)
Expense Ratio _t		0.000434		-0.00167		0.000597		0.00284**
		(0.00981)		(0.00563)		(0.000445)		(0.00130)
Log Age _t		-0.107***		-0.0499***		-0.00242***		-0.00605***
		(0.00573)		(0.00381)		(0.000314)		(0.000820)
Share Load Fees _t		-0.0236**		-0.0286***		-0.00135***		-0.00531***
		(0.00958)		(0.00663)		(0.000512)		(0.00156)
Date X MS Box FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	267,155	262,821	267,155	262,821	267,268	262,933	264,586	260,268
Adjusted R-squared	0.102	0.127	0.076	0.171	0.179	0.182	0.049	0.055

Table 4. Mismatched Benchmarks and Investor Flows. This table regresses measures of investor flow into equity funds on whether equity fund's benchmark designations are mismatched. The sample consists of the monthly observations of equity mutual funds between December 2008 and December 2020. *Mismatched Benchmark* indicates that the equity fund's Morningstar holdings style differs from the style categorization of its self-designated benchmark. *Benchmark Change* indicates that the equity fund's current benchmark differs from its reported benchmark from 12 months prior. *Positive Flow* indicates that investors had deposited dollar into the fund in net in the next month. *Percentile Flow* is the percentile ranking (1 being the top percentile and 0 being the bottom percentile of all equity funds) of the net dollars flow from investors into the mutual fund during the next month. *Change in Market Share* is the percent change in the share of the fund over the total equity mutual fund market. *% Flow* is the dollar flow as the percent of a fund's total net assets into the fund in the next month. Only monthly observations with greater than negative 50% *% Flow* and less than 200% *% Flow* are kept for the regression. *Benchmark Change* indicates a change in the self-designated fund benchmark from 12 months prior. *36 Month Alpha* is the Fama French 3-factor adjusted fund return from the past 36 months. The standard errors, reported in parenthesis, are clustered at the fund level. *, **, *** indicates statistical significance at the 90%, 95%, and 99% level respectively.

	(1)	(2)	(3)	(4)
	Positive Flow _{t+1}	Percentile Flow Rank _{t+1}	% Change in Market Share _{t+1}	% Flow _{t+1}
Change to Correct _t	0.0285** (0.0124)	0.0105 (0.00796)	0.00246*** (0.000886)	0.00245 (0.00251)
36 Month Alpha _t	1.368*** (0.0545)	0.871*** (0.0406)	0.0944*** (0.00415)	0.155*** (0.00897)
Log Fund Size _t	0.00461 (0.00388)	-0.0322*** (0.00280)	-0.000333 (0.000236)	-0.00145** (0.000617)
Log Family Size _t	-0.00883*** (0.00267)	-0.00712*** (0.00162)	0.000163 (0.000166)	0.000370 (0.000421)
Expense Ratio _t	0.00579 (0.0167)	0.00160 (0.00743)	0.000490 (0.000774)	0.00253 (0.00211)
Log Age _t	-0.115*** (0.00902)	-0.0465*** (0.00575)	-0.00298*** (0.000498)	-0.00720*** (0.00125)
Share Load Fees _t	-0.0210 (0.0152)	-0.0188* (0.0103)	-0.00222** (0.000909)	-0.00663*** (0.00231)
Date X Mbox FE	Yes	Yes	Yes	Yes
Observations	87,905	87,905	87,949	87,260
Adjusted R-squared	0.147	0.212	0.175	0.068

Table 5. Benchmark Changes and Investor Flows. This table regresses measures of investor flow into equity funds on changes to an equity fund's benchmark designations for only previously mismatched equity funds. The sample consists of monthly observations of equity mutual funds between December 2008 and December 2020. To be part of the sample, a fund must be *Mismatched* 12 months prior to the panel date. *Change to Correct* indicates that the previously *Mismatched* fund has changed its benchmark designation to be consistent with its contemporaneous holdings style. *Positive Flow* indicates that investors have deposited dollars into the fund in net during the next month. *Percentile Flow* is the percentile ranking (1 being the top percentile and 0 being the bottom percentile of all equity funds) of next month's net dollars flow from investors into the mutual fund. *Change in Market Share* is the percent change in the share of the fund over the total equity mutual fund market. *% Flow* is the dollar flow as the percent of a fund's total net assets into the fund in the next month. Only monthly observations with greater than negative 50% *% Flow* and less than 200% *% Flow* are kept for the regression. *Benchmark Change* indicates a change in the self-designated fund benchmark from 12 months prior. *36 Month Alpha* is the Fama French 3-factor adjusted fund return from the past 36 months. The standard errors, reported in parenthesis, are clustered at the fund level. *, **, *** indicates statistical significance at the 90%, 95%, and 99% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Positive Flow				% Change in Market Share			Percentile Flow Rank	% Flow
Raw– Old BM Return	0.434*** (0.0844)	0.583*** (0.101)	0.581*** (0.101)	0.580*** (0.101)	0.0404*** (0.00611)	0.0402*** (0.00611)	0.0401*** (0.00611)	0.365*** (0.0805)	0.0740*** (0.0167)
Raw– New BM Return	0.589*** (0.0913)	0.448*** (0.109)	0.449*** (0.109)	0.449*** (0.109)	0.0287*** (0.00686)	0.0287*** (0.00686)	0.0288*** (0.00686)	0.189** (0.0871)	0.0492*** (0.0186)
(Raw– Old BM Return) * Post Switch		-0.274** (0.108)	-0.0920 (0.150)	-0.0889 (0.150)	-0.0110 (0.00685)	1.23e-05 (0.0103)	7.92e-05 (0.0103)	-0.186 (0.118)	-0.0144 (0.0280)
(Raw– New BM Return) * Post Switch		0.268** (0.124)	-0.0239 (0.166)	-0.0263 (0.166)	0.0115 (0.00818)	-0.00490 (0.0120)	-0.00499 (0.0120)	-0.0591 (0.126)	0.00964 (0.0332)
(Raw– Old BM Return) * Post Switch * Correct New BM			-0.277 (0.186)	0.303 (0.279)		-0.0166 (0.0119)	0.00478 (0.0161)	0.296 (0.209)	0.107 (0.0663)
(Raw– New BM Return) * Post Switch * Correct New BM			0.504** (0.213)	0.0198 (0.296)		0.0280* (0.0148)	0.00146 (0.0179)	0.137 (0.217)	-0.0299 (0.0623)
(Raw– Old BM Return) * Post Switch * Correct New BM * Mismatched Old BM				-0.806*** (0.275)			-0.0304** (0.0150)	-0.375* (0.212)	-0.127* (0.0660)
(Raw– Old BM Return) * Post Switch * Correct New BM * Mismatched Old BM				0.692** (0.298)			0.0405** (0.0177)	0.279 (0.231)	0.117* (0.0623)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,373	33,373	33,345	33,345	33,371	33,343	33,343	33,340	33,100
Adjusted R-squared	0.087	0.087	0.088	0.090	0.112	0.112	0.113	0.045	0.072

Table 6. Investor flow on fund performances adjusted by new and old benchmarks. The panel consists of monthly observations of equity funds around the -24 to 24 months of their benchmark switches occurring between December 2008 and December 2020. *Positive Flow* indicates that investors had deposited dollar into the fund in net during the month. *Percentile Flow* is the percentile ranking (1 being the top percentile and 0 being the bottom percentile of all equity funds) of the net monthly dollars flow from investors into the mutual fund. *Raw* and *BM* returns are the cumulative net returns of the mutual fund and the designated benchmark in the prior 36 months. *Post Switch* indicates that the observation occurred after the change in benchmark designation. *Correct New BM* indicates that the new self-designated benchmark has a style that corresponds to the style indicated by the mutual fund's holdings. *Mismatched Old BM* indicates that the fund has a Morningstar style that is different from the style of its old self-designated Benchmark. The standard errors, reported in parenthesis, are clustered at the fund level. *, **, *** indicates statistical significance at the 90%, 95%, and 99% level respectively.

	(1)	(2)	(3)
	Change to Correct _{t+1}		
Flow Beta Difference _t	0.0292*** (0.0107)	0.0319*** (0.0111)	0.0318*** (0.0112)
36 Month Alpha _t	-0.503* (0.272)	-0.475* (0.278)	-0.401 (0.302)
Log Fund Size _t			-0.0785*** (0.0212)
Log Family Size _t			0.0791*** (0.0142)
Expense Ratio _t			0.0383 (0.0578)
Log Age _t			0.0516 (0.0519)
Share Load Fees _t			0.223*** (0.0736)
Date FE	Yes	No	No
Date X Mbox FE	No	Yes	Yes
Observations	73,600	64,892	64,484
Pseudo R-squared	0.0422	0.0667	0.0884

Table 7. Investor flow sensitivity and changing to correct benchmarks. This table conducts probit regression on whether the fund corrects its benchmark designation on investor flow betas measured over the past 36 months for the panel of previously Mismatched equity funds. The sample consists of monthly observations of equity mutual funds between December 2008 and December 2020. *Flow Beta Difference* is the incremental sensitivity of a fund's % *Flows* to a well-matched benchmark over its self-designated Mismatched benchmark. *Change to Correct* indicates that the previously Mismatched fund will change its benchmark designation to be consistent with its contemporaneous holdings style. The standard errors, reported in parenthesis, are clustered at the fund level. *, **, *** indicates statistical significance at the 90%, 95%, and 99% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Change BM, t+1			Change to matched BM, t+1		
	Full sample			Mismatched subsample		
Competition measure	# Index	Index shr.	Fee waiver	# Index	Index shr.	Fee waiver
Competition, t	0.260*** (0.048)	1.886*** (0.300)	11.260** (4.505)	0.298*** (0.089)	1.900*** (0.435)	-4.355 (9.506)
[Marginal effects of one SD change in main independent variable]	0.023*** (0.004)	0.016*** (0.003)	0.084** (0.034)	0.033*** (0.010)	0.020*** (0.005)	-0.041 (0.090)
Category size, t	-0.025 (0.045)	0.070** (0.033)	0.196*** (0.030)	-0.079 (0.076)	0.117*** (0.045)	0.160*** (0.058)
ln(Fund size), t	-0.046*** (0.016)	-0.042*** (0.016)	-0.033* (0.019)	-0.077*** (0.027)	-0.077*** (0.027)	-0.035 (0.030)
ln (Fund family size), t	0.011 (0.013)	0.005 (0.013)	-0.008 (0.014)	0.084*** (0.017)	0.081*** (0.016)	0.047*** (0.014)
ln (Fund age), t	0.041 (0.034)	0.041 (0.033)	0.032 (0.039)	0.043 (0.038)	0.048 (0.038)	0.049 (0.051)
Net expense ratio, t	0.004 (0.063)	-0.023 (0.061)	-0.063 (0.086)	-0.036 (0.088)	-0.058 (0.087)	-0.154 (0.113)
Load fund share, t	0.195*** (0.068)	0.190*** (0.068)	0.255*** (0.082)	0.308*** (0.110)	0.322*** (0.109)	0.455*** (0.116)
Net flow 12m, t	-0.610 (0.399)	-0.590 (0.402)	-0.880** (0.446)	-0.575 (0.881)	-0.575 (0.883)	-0.822 (0.964)
Three-factor alpha 36m, t	-0.798*** (0.262)	-0.805*** (0.260)	-0.931*** (0.334)	-0.988** (0.414)	-0.984** (0.415)	-1.429*** (0.463)
MS category-by-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,308	16,385	12,404	4,728	4,728	3,631
Pseudo R-squared	0.0852	0.0855	0.0813	0.119	0.122	0.139

Table 8. Probit estimates on competition at the benchmark-category level and benchmark switches. Observations are at the fund-by-year level. $Change\ BM_{t+1}$ ($Change\ to\ correct\ BM_{t+1}$) equals one if a fund switches its benchmark (switches to a benchmark that matches its portfolio) in year t+1, and zero otherwise. Measures of competition are at the benchmark-category level and include the natural logarithm of the number of index funds (columns 1, 4), the market share of index funds (columns 2, 5), and the change in the fee waiver size representing the difference between t-3 and t in the value-weighted fractions of aggregate gross fund expenses that are reduced through fee waivers (columns 3, 6). Marginal effects of the competition measures are reported after the main regression coefficients and are scaled by the standard deviation of the competition measure. All regressions include time-by-portfolio category fixed effects. Standard errors are clustered by benchmark category and reported in the parentheses.

	(1)	(2)	(3)	(4)	(5)
	Mismatched BM, t				
	Full sample				Addition sample
Has inst. twins, t	-0.193*** (0.052)		-0.040 (0.255)		
Has twins with correct BM, t		-0.538*** (0.072)		-0.776** (0.365)	-0.845* (0.483)
[Marginal effects]	-0.061*** (0.016)	-0.160*** (0.020)	-0.008 (0.054)	-0.155** (0.073)	-0.154* (0.089)
ln(Fund size), t	0.069*** (0.018)	0.025 (0.025)	-0.062 (0.083)	-0.055 (0.110)	-0.225 (0.170)
ln (Fund family size), t	-0.102*** (0.012)	-0.073*** (0.019)	-0.153* (0.089)	-0.345*** (0.127)	-0.311* (0.180)
ln (Fund age), t	-0.112*** (0.042)	-0.181*** (0.059)	-0.224 (0.374)	-0.352 (0.472)	-2.709*** (1.041)
Net expense ratio, t	0.226*** (0.078)	0.104 (0.122)	0.531 (0.354)	1.363*** (0.481)	0.310 (0.788)
Load fund share, t	-0.149** (0.071)	-0.042 (0.096)	0.606* (0.364)	0.752* (0.449)	0.637 (0.601)
Net flow 12m, t	-0.037 (0.298)	-0.025 (0.370)	0.954 (0.881)	1.660 (1.230)	-0.269 (1.854)
Three-factor alpha 36m, t	0.188 (0.226)	0.121 (0.353)	-0.141 (0.510)	-0.565 (0.733)	0.296 (1.061)
MS category-by-time FE	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	Yes	Yes	Yes
Observations	20,498	11,941	6,507	4,066	2,022
Pseudo R-squared	0.122	0.109	0.466	0.487	0.536

Table 9. Probit estimates on governance by institutional investors and the likelihood of mismatched benchmarks. Observations are at the fund-by-year level. *Mismatched BM_t* indicates whether the mutual fund's self-designated benchmark has a classification that is different from its Morningstar designated holding classification. *Has inst. twins* indicates that a fund has a separate account or institutional fund twin ("institutional twin"), and *Has twins with correct BM* indicates that a fund has an institutional twin which has a matched benchmark. Marginal effects of the main regressors are reported. All regressions include time-by-portfolio category fixed effects. Columns 3-5 include fund fixed effects. Column 5 includes only retail funds whose inception dates are before those of the twins. Standard errors are clustered by fund and reported in the parentheses.

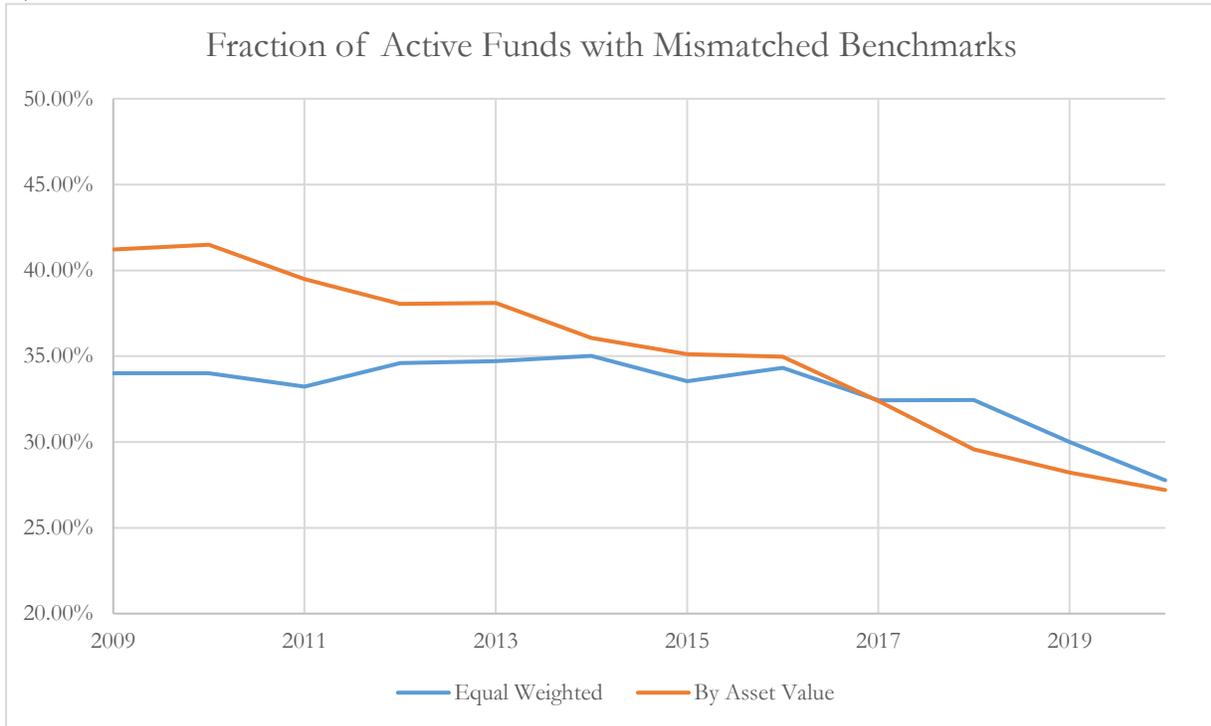
	(1)	(2)	(3)	(4)	(5)	(6)
	Change to correct, t+1					
	Full sample			Mismatch sample		
36m tracking error old, t	4.060 (3.609)		3.206 (3.951)	-18.048*** (5.800)		-19.199*** (5.919)
36m diff tracking error (correct-old), t	-60.379*** (10.041)		-65.788*** (10.941)	-69.054*** (11.031)		-72.618*** (11.104)
[Marginal effects of one standard deviation change in variable]	-0.008*** (0.001)		-0.009*** (0.002)	-0.028*** (0.005)		-0.030*** (0.005)
36m BM adj. return old, t		-0.235 (0.282)	-0.307 (0.278)		-0.022 (0.355)	-0.070 (0.384)
36m diff BM adj. return (correct-old), t		1.662*** (0.414)	1.880*** (0.476)		0.769 (0.473)	1.324*** (0.505)
[Marginal effects of one standard deviation change in variable]		0.005*** (0.002)	0.007*** (0.002)		0.008 (0.005)	0.014*** (0.005)
ln (Size), t	-0.045*** (0.017)	-0.035** (0.017)	-0.047*** (0.017)	-0.079*** (0.023)	-0.074*** (0.023)	-0.083*** (0.023)
ln (Fund family size), t	0.017 (0.011)	0.013 (0.011)	0.020* (0.011)	0.070*** (0.017)	0.071*** (0.017)	0.070*** (0.017)
Load fund share, t	0.209*** (0.062)	0.207*** (0.060)	0.213*** (0.062)	0.260*** (0.089)	0.297*** (0.086)	0.270*** (0.089)
ln (Age), t	0.020 (0.035)	0.018 (0.035)	0.020 (0.036)	0.025 (0.054)	0.052 (0.053)	0.026 (0.054)
Net expense ratio, t	-0.121 (0.079)	-0.088 (0.077)	-0.124 (0.080)	0.031 (0.121)	-0.053 (0.112)	0.027 (0.121)
12m net flow, t	-1.037** (0.477)	-1.068** (0.482)	-1.116** (0.494)	-0.938 (0.771)	-1.036 (0.776)	-1.271 (0.796)
MS category-by-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,965	15,955	15,955	4,802	4,802	4,802
Pseudo R-squared	0.0779	0.0632	0.0858	0.117	0.0911	0.121

Table 10. Probit regression on tracking errors and benchmark switches. *Change to correct* BM_{t+1} equals one if a fund switches to a benchmark that matches its portfolio in year t+1, and zero otherwise. *36m Tracking error old* is the 36 months tracking error between the monthly returns of the fund and its self-declared benchmark in year t. *36m Diff tracking error (correct-old)* is calculated as the difference between the holdings implied benchmark tracking error and the old benchmark tracking error. *36m BM adj. return old* is the 36-months benchmark adjusted raw return of the fund. *36m diff BM adj. return (correct-old)* is the difference between the holdings implied benchmark adjusted returns and the old benchmark adjusted returns. Marginal effects are reported after the main regression coefficients. All regressions include time-by-portfolio category fixed effects. Columns 4-6 restrict to a subsample of funds with mismatched benchmarks at year t. Standard errors are clustered by fund and reported in the parentheses.

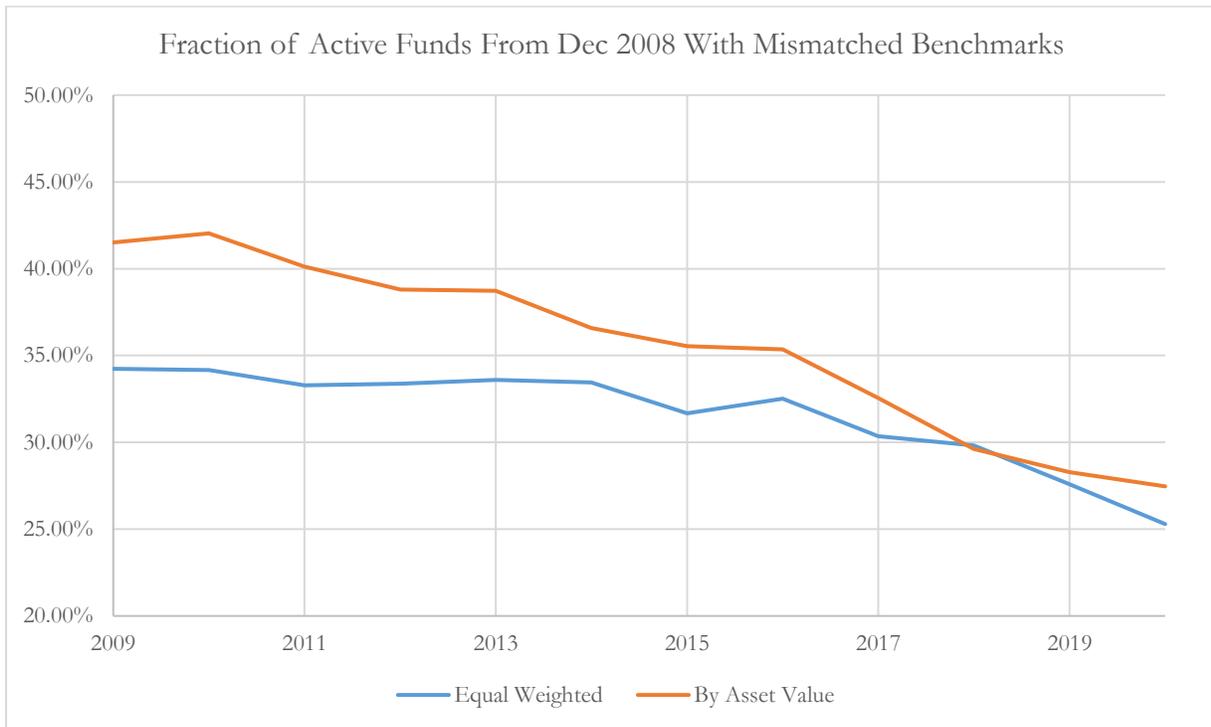
	(3)	(4)	(5)	(6)	(10)
	Mismatched Benchmark _t				
Manager Tenure Length _t	0.00860*** (0.00119)	0.00864*** (0.00123)			0.00747*** (0.00128)
% Family Managed _t			0.252*** (0.0206)	0.161*** (0.0302)	0.125*** (0.0306)
36 Month Alpha _t	0.0115 (0.0713)	0.0434 (0.0708)	0.0332 (0.0685)	0.0544 (0.0705)	0.0481 (0.0705)
Log Fund Size _t		0.0189*** (0.00528)		0.0121** (0.00549)	0.0122** (0.00545)
Log Family Size _t		-0.0340*** (0.00352)		-0.0172*** (0.00476)	-0.0201*** (0.00473)
Expense Ratio _t		0.0339** (0.0163)		0.0393** (0.0171)	0.0356** (0.0163)
Log Age _t		-0.0423*** (0.0123)		-0.0173 (0.0122)	-0.0353*** (0.0124)
Share Load Fees _t		-0.0278 (0.0210)		-0.0199 (0.0216)	-0.0130 (0.0213)
Date X MS Box FE	Yes	Yes	Yes	Yes	Yes
Observations	270,166	266,033	270,166	266,033	266,033
Adjusted R-squared	0.099	0.137	0.127	0.133	0.141

Table 11. Regression of contemporaneous measures of managerial power on the indicator of a mismatched benchmarks. The panel consist of the snapshots of equity mutual funds between December 2008 and December 2020. *Mismatched Benchmark* indicates whether the mutual fund's self-designated benchmark has a style that is different from its Morningstar designated holding style. *Manager Tenure Length* is the (average) number of observed years that the fund's manager(s) had spent at the fund family. *% Family Managed* is the (average) percent of a fund family's asset under management in equity funds managed by the fund's manager(s). The standard errors, reported in parenthesis, are clustered at the fund level. *, **, *** indicates statistical significance at the 90%, 95%, and 99% level respectively.

A)



B)



C)

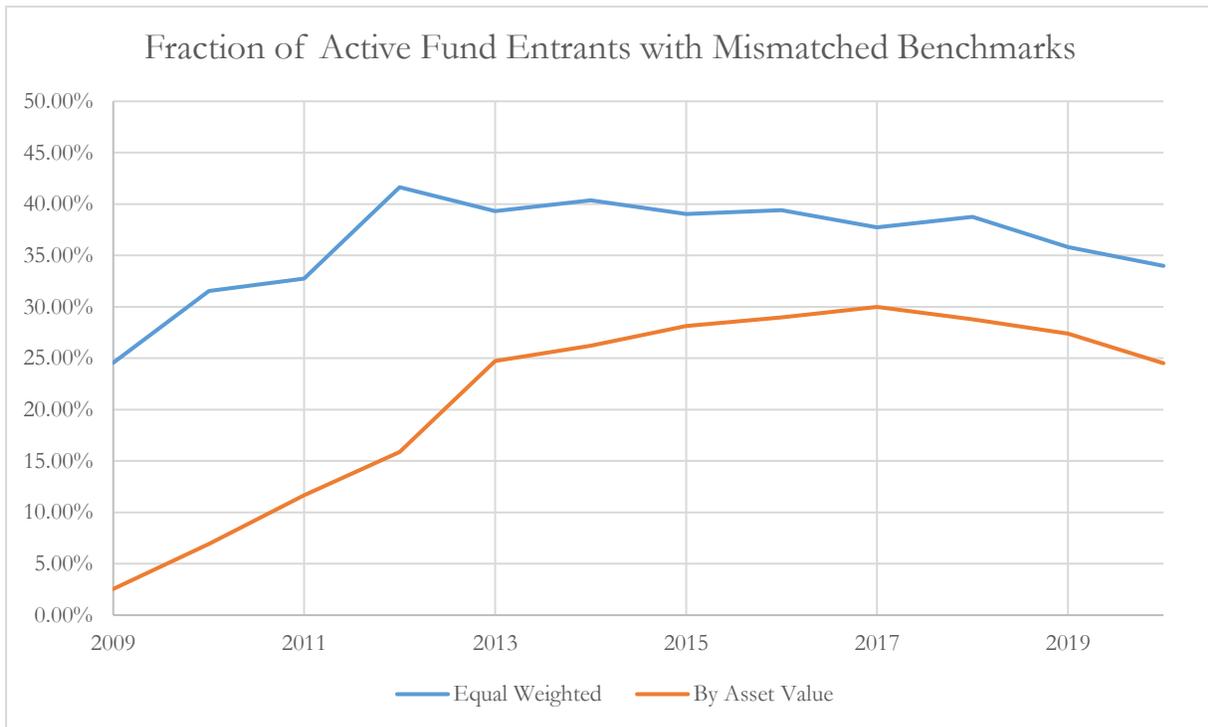


Figure 1. A) Fraction of Active Funds with Mismatched Benchmarks. This figure shows the percent of total active equity assets under management in funds with mismatched benchmarks at the year-end over time. B) Intensive Margin. Fraction of Active Funds existing in December 2008 with Mismatched Benchmarks. This figure shows the percent of total active equity assets under management in funds with mismatched benchmarks over time for only funds in existence on December 2008. C) Extensive Margin. Fraction of Active Funds that entered the equity fund market post 2008 with Mismatched Benchmarks. This figure shows the percent of total active equity assets under management in funds with mismatched benchmarks over time for funds entering the equity fund market after December 2008.

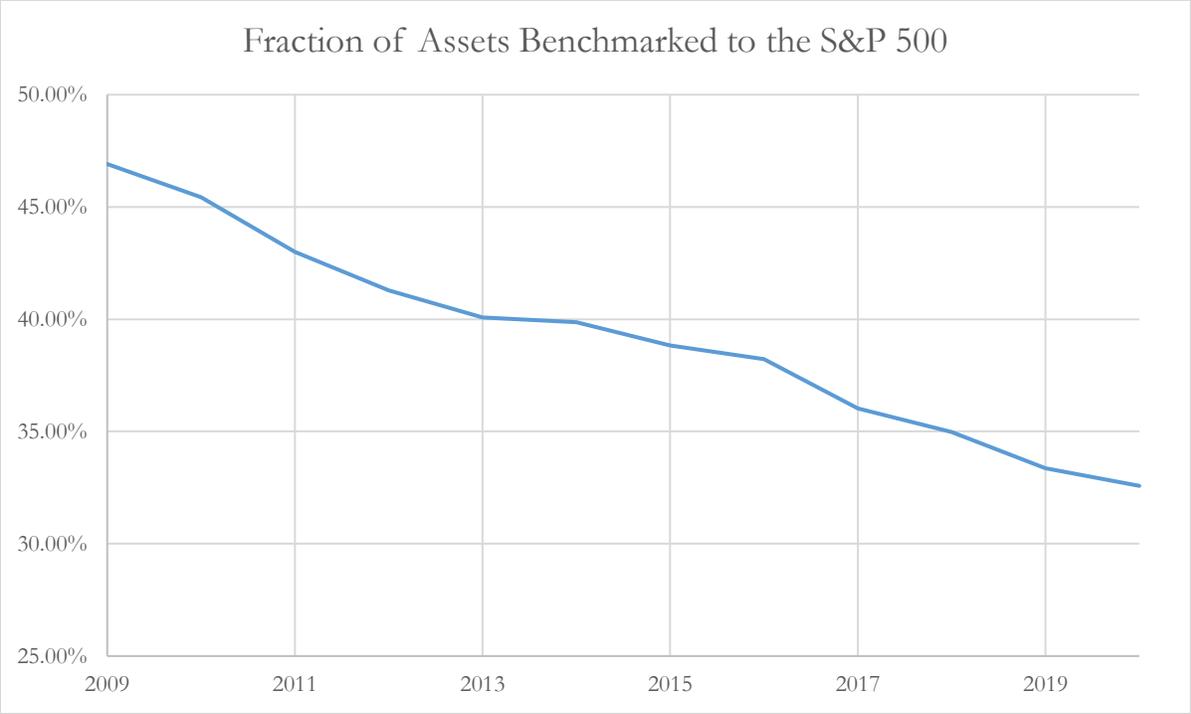


Figure 2. Fraction of Active Funds Benchmarked to the S&P 500. This figure shows the percent of total active equity assets under management in funds with S&P 500 as their prospectus benchmark over time. The sample is between December 2008 and December 2020.

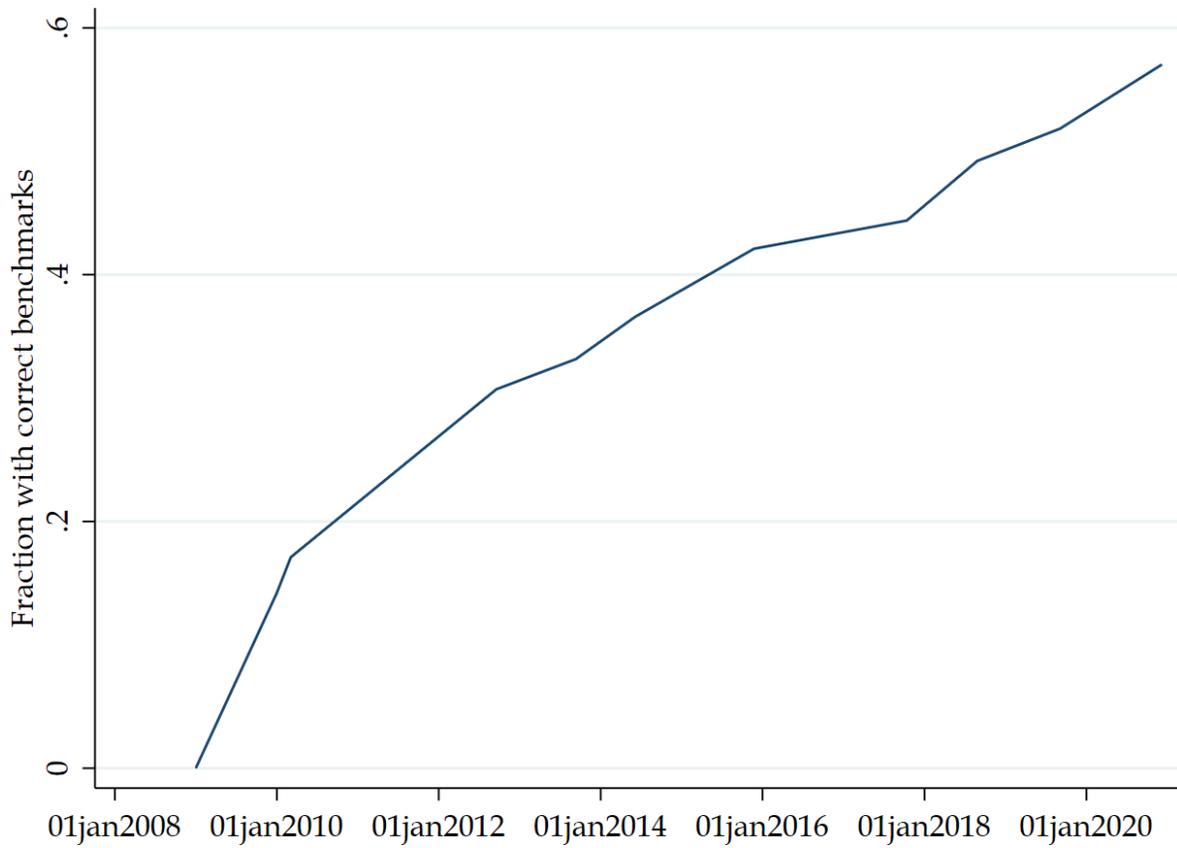


Figure 3. The Mismatched Funds from 2008 overtime. This figure shows the percent of funds with mismatched benchmarks at December 2008 with correct benchmarks over time. The sample is between December 2008 and December 2020.

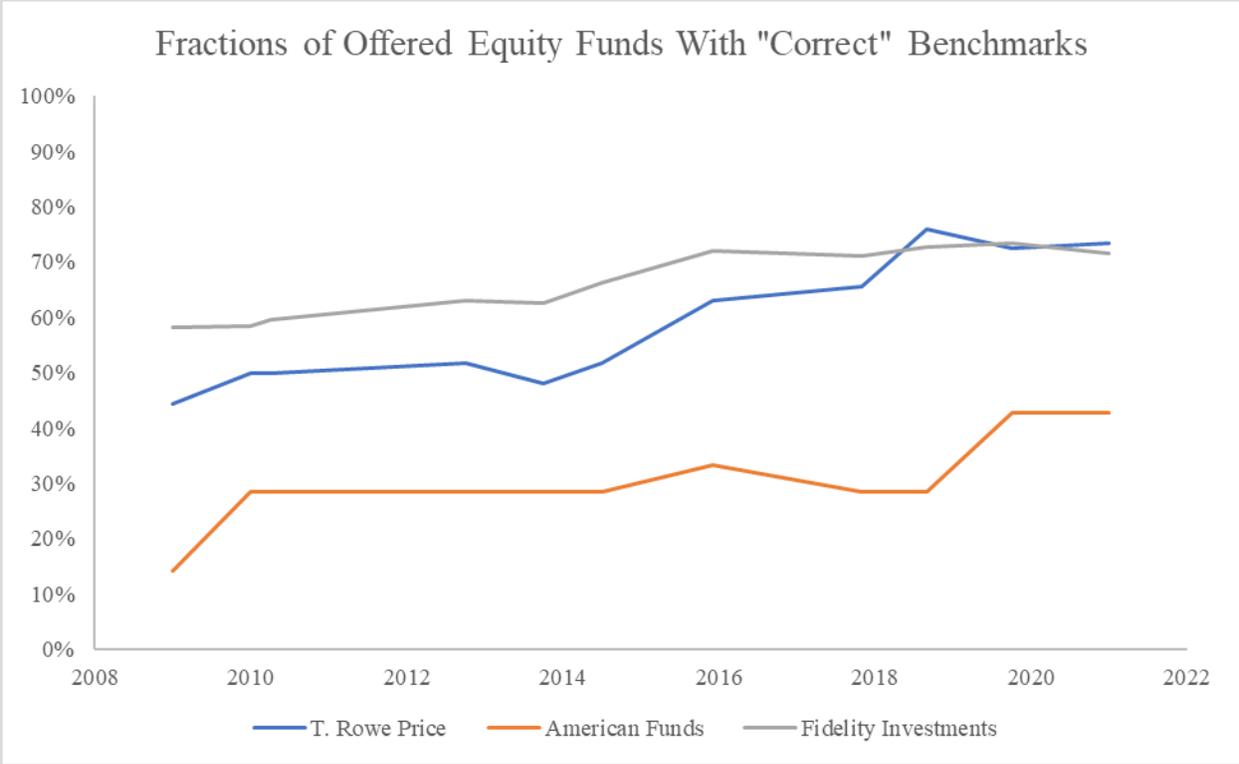


Figure 4. Fraction of Offered Active Equity Funds with Mismatched Benchmarks Within Fund Families. This figure shows the percent of total active equity assets under management in funds with mismatched benchmarks within certain Large Fund Families over time. The blue, orange, and grey lines show the fraction of funds with mismatched benchmarks offered by T. Rowe Price, American Funds, and Fidelity respectively. The sample is between December 2008 and December 2020.

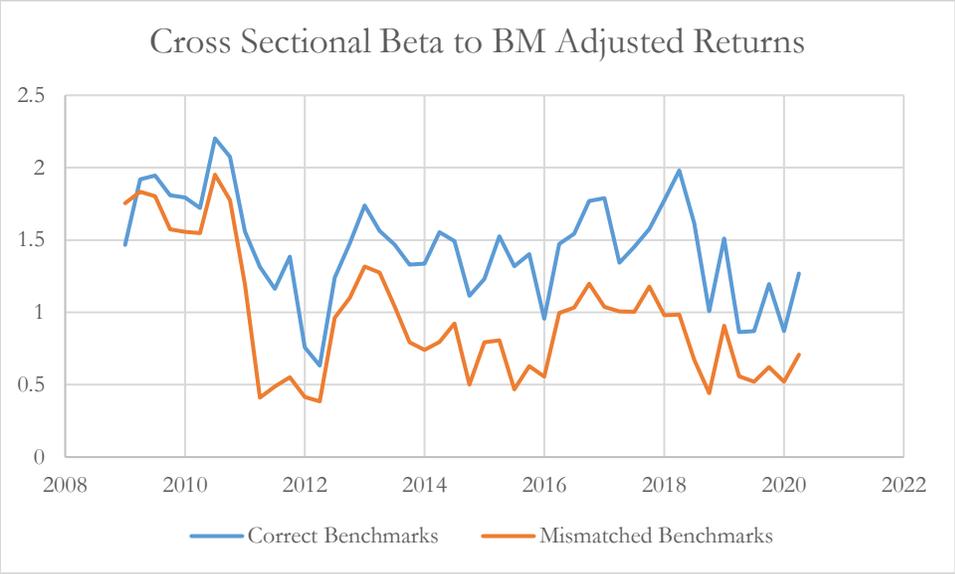


Figure 5. The 12-Month Investor Flow to Performance Sensitivity of Correctly Benchmarked and Mismatched Benchmarked Equity Funds. This figure shows the OLS regression coefficients of % Flows to equity funds against 36-Month self-designated benchmark adjusted returns for funds with correct benchmarks (blue) mismatched benchmarks (orange) between December 2008 and December 2020.