Three Essays on Style Drift in Mutual Funds

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Abstract

This thesis seeks to enhance our collective understanding of style drift in mutual funds. The first essay of this thesis provides a critical review of the current literature on the topic of style drift and presents newer ways of viewing the concept. In particular, it provides a detailed analysis of the U.S. mutual funds industry and proposes a conceptual framework to present a fuller picture of the phenomenon. This framework introduces the concept of style enhancement and presents a newer way of viewing style drift. The proposed framework offers insights beyond the traditional notion that classifies all types of deviations under one broad phenomenon of "style drift."

This thesis then, in Essay Two, attempts to identify a threshold level of deviation beyond which a fund is likely to be classified as misclassified. This essay provides practical implications to investors as it helps them in identifying when their portfolio is likely to move toward a point beyond which they should be watchful about the investment activities carried out by their fund managers. The deviations beyond this threshold level may expose them to risk adversely affecting their investment portfolio.

The final essay of this thesis, Essay Three, investigates the relationship between the frequency of mutual fund holdings disclosure and style drift. This essay uses a difference-in-difference test to examine the impact of disclosure frequency on the style drift of mutual funds. The evidence suggests that style drift decreases with an increase in disclosure frequency and vice versa. The essay provides implications for the standard setting authorities, such as the Securities and

Exchange Commission, to consider the impact of disclosure frequency on the style drift of mutual funds when determining optimal disclosure frequency.

Keywords: Mutual Funds, Investment Style, Style Drift, Style Enhancement, Style Misclassification, Risk-Shifting Behavior, Style Misclassification, Investment Style, Performance, Tracking Error Mutual Funds; Portfolio Holdings Disclosure; Portfolio Disclosure Frequency, Style Drift, SEC Regulation, Difference-In-Difference Test

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"Read! In the Name of your Lord, Who has created (all that exists)."

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List of Abbreviation

AR	Active Return
e.g.	For example
CAPM	Capital Asset Pricing Model
EDGAR	Electronic Data Gathering, Analysis, and Retrieval
HBSA	Holding Based Style Analysis
HML	Return Differential Of High And Low Book-To-Market Stocks
i.e.	That is
LB	Large-cap Blend
LG	Large-cap Growth
LV	Large-cap Value
MB	Mid-cap Blend
MG	Mid-cap Growth
MOM	Return Differential Of Positive Momentum And Negative Momentum Stocks
MV	Mid-cap Value
SB	Small-cap Blend
RBSA	Return Based Style Analysis
SDS	Style Drift Score
SEC	Securities and Exchange Commission
SG	Small-cap Growth

SMB	Return Differential Amongst Small And Large-Capitalization Stocks
SV	Small-cap Value
TE	Tracking Error
TE2	Tracking Error Squared
TNA	Total Net Assets
TURN	Turnover
U.S.	United States

Chapter 1: Introduction and Overview

This dissertation investigates the phenomenon of style drift within the mutual funds industry. Style drift occurs when funds invest in stocks that are different from their declared investment strategy. As a result, fund investors' risk and return profiles are disrupted and the issue of information asymmetry inherent within the mutual funds industry is exacerbated.

Chapter 2 of this thesis makes the first attempt to review the existing literature associated with fund managers' style deviating practices to develop a more comprehensive understanding of the underlying concept. Next, it addresses investors' misconceptions by discussing various aspects of the notion and examines the consequences of each. Then, it analyzes the U.S. mutual funds industry from 1990-2019, demonstrates key differences among active and passive managers, and establishes that not all deviations from the indicated investment style of the fund are alike. Finally, it introduces a conceptual framework to present a fuller picture of the phenomenon. This framework introduces style enhancement, presents a newer way of viewing style drift, and utilizes style misclassifications already present within the literature.

According to the framework proposed in Chapter 2, style enhancement occurs when a fund manager deviates from the funds’ originally stated style to explore their own skill and generate superior risk-adjusted returns for their clients. Style drift occurs when fund managers push the boundaries of style enhancement resulting in slightly more deviations than usual. In comparison, style misclassification arises when fund managers engage in excessive risk-taking activities altering the fund's overall investment style. Thus, the proposed framework offers insights beyond the traditional notion that classifies all types of deviations under one broad phenomenon of "style drift."

The primary advantage of this new conceptual framework is to distinguish between different levels of deviation and acknowledge the importance of style deviations for fund investors by transforming the current one dimensional context into a newer and more objective framework. In addition, this segregation is likely to control for the psychological biases of investors and promote the efficient functioning of the funds' management industry.

Using the Morningstar database, Chapter 3 further identifies the threshold level of deviation beyond which a fund exhibits the properties of a misclassified fund. Previous studies explore the presence of misclassified funds within the U.S. mutual funds industry. Some propose a metric to determine the level of style deviation of a fund and define the relationship between style misclassification and fund performance. However, none to date has attempted to determine whether there exists a threshold level of deviation from which investors can classify a fund as a "misclassified fund." We argue that it is crucial to determine the existence of this threshold level as misleading funds send false signals to investors and lead to suboptimal decision-making.

Therefore, within our statistical analysis, we evaluate the existence of a threshold level of deviation where we can classify a fund as misclassified. To do this, we use tracking errors as a proxy to measure the level of style deviations of a fund and examine its relationship with various performance metrics. We do this by fitting the quadratic regression equation of a parabola and assuming a concave relationship between fund performance and tracking errors. We then consider this threshold level of deviation an inflection point where the relationship between performance and tracking errors changes from positive to negative.

Chapter 3 determines this threshold level and indicates a concave relationship between fund returns and tracking errors. We find our results to be economically significant and they remain robust even after dividing our sample into small and large funds. Furthermore, this relationship remains intact when we employ the Fama MacBeth (1973) regression analysis. However, the results of the Fama Macbeth (1973) analysis are not statistically significant.

This particular chapter provides practical implications to investors as it assists them in detecting when their portfolio is likely to move toward a point that they should be vigilant about the investment activities carried out by their fund managers. The deviations beyond this threshold level may expose them to risk adversely affecting their investment portfolio.

Chapter 4 utilizes the data from the Morningstar database and examines the relationship between the frequency of mutual funds holdings disclosure and style drift. The study attempts to determine whether an increase in disclosure frequency is effective in containing style drift within mutual funds. To test our hypothesis, we examine disclosure frequency before and after the regulatory changes by the SEC in 2004 and then again in 2019.

This chapter uses a difference-in-difference test covering the sample period from January 1995-December 2010 to investigate the relationship mentioned above. It considers previously semi-annual funds that had to disclose every quarter after 2004 as the treatment group and funds that disclosed quarterly throughout as the control group. The findings indicate that the style drift of previously semi-annual funds has dropped by about 0.79 points a month after 2004. These results are economically significant and in line with our conjecture that an increase in the disclosure frequency tends to limit style drift within mutual funds. Our findings remain robust while analyzing the 2019 regulatory change when the mandatory disclosure frequency was changed again from quarterly to monthly utilizing data from January 2009-December 2021. We again use a difference-in-difference regression to determine whether the shift to a more frequent portfolio regime has contained style drift in previously quarterly disclosing funds. We find our results to be robust in the recent framework suggesting style drift decreases by 0.51 points with the increase in the disclosure frequency.

This chapter provides implications for standard setting authorities, such as the Securities and Exchange Commission, around the globe for any further changes in the disclosure frequency in the future. It may be wise for them to consider an optimal frequency of disclosure given its benefits and costs.

Structure of the Dissertation

The core part of this dissertation is comprised of three essays. Each focuses on the phenomenon of style drift within the mutual funds industry. To present the dissertation logically, the core three essays will appear as three independent studies. The structure of this dissertation is as follows.

Chapter 2 critically evaluates the style deviating phenomenon and presents a conceptual framework differentiating between various levels of deviation using the three distinct concepts of style enhancement, style drift, and style misclassification. Chapter 3 builds upon the second chapter and attempts to determine a threshold level of deviation to identify style misclassification in funds. The final chapter of this dissertation, Chapter 4, examines the impact of holding disclosure frequency on the style drift of mutual funds.

Chapter 2: Style Drift: A Longitudinal Perspective

Abstract

This paper attempts to address investor misconceptions relating to the style deviating behavior of fund managers. It achieves this by examining the dynamics and consequences of some key theoretic issues present in the literature. Notably, the study advances the understanding of the concept of "style drift" by providing insights beyond the traditional notion that categorizes all types of deviations under one broad phenomenon of style drift. In contrast, we present a fuller picture by developing a conceptual framework that separates normal, not-so-normal, and excessive deviations. Our framework depends on how far these deviations are from the benchmark and the economic motivation behind the risk-shifting behavior. Within this framework, we revisit the current definition of style drift, introduce the concept of' style enhancement, and critically discuss the concept of misclassification in the existing literature.

Keywords: Investment style, style drift, style enhancement, style misclassification, risk-shifting behavior

2.1. Introduction

The use of style classifications and investment objectives is common within the mutual funds industry to highlight the “investment style” of the fund managers. This investment style illustrates key investment tactics and establishes the outlook for long-term performance. In turn, this promotes the fund to investors who wish to pursue a related investment style and with a particular type of market focus (Cooper, Gulen, & Rau, 2005). However, many funds do not entirely adhere to their style profiles over time. This is a phenomenon known as “style drift” in literature.

The financial services industry defines style drift as a deviation of a fund’s actual portfolio holdings from the fund's stated investment strategy as per its offering documents (U.S. Securities and Exchange Commission). Investors generally perceive these style drifting activities quite negatively (Cumming, Fleming, & Schwienbacher, 2009) as they expect fund managers to invest their funds according to the rules and objectives set out within the contracting documents of the fund. When the fund manager’s style deviates, they essentially invest in securities that contradict these documents. As a result, investors often associate this practice with something wrong, unjust, and immoral.

But are all deviations necessarily unethical on the part of fund managers? The answer is no. They can be either fair or unfair on the part of “active” managers. They are fair in that they partially relate to the job of active managers. That is, to beat the benchmark index and to generate superior risk-adjusted returns for their clients. One possibility to beat the benchmark index is by taking positions that are different from it, deviating from it to a certain extent. Sometimes, the choices made to pursue this objective can surpass the style classifications of a fund. Also, sometimes they may arise unintentionally when the underlying characteristics of an investment change over time. An example is when small-cap companies grow to the point that they no longer fit small-cap stocks (Bams, Ottem, & Ramezanifar, 2017).

Alternatively, these deviations can be unfair in certain case. When active managers stray from the benchmark style, this non-conformity with the initially stated style could alter the risk and return characteristics of the fund investments (Ainsworth, Fong, & Gallagher, 2008; Kurniawan, How, & Verhoeven, 2016). Consequently, it disrupts the risk-return expectations of fund investors, sending a clear signal to them that they may not achieve what they fairly anticipate from their investments (Bams et al., 2017). Additionally, these deviations may also represent the agency-prone behavior of the fund managers that encourages them to invest in securities other than the stated investment style. Usually, the fund managers' compensation depends upon their asset base. The larger the assets under management, the higher their remuneration (Brown, Harlow, & Starks, 1996). In other words, their reward is affected by the movement of money in or out of the fund. As investors typically invest in funds with superior prior performance, fund managers are likely to style deviate and switch to an asset class expected to outperform in the short run. Moreover, the presence of information asymmetry facilitates this situation as the information on the funds' investments is only accessible to investors with time lag and noise (Wermers, 2012). Thus, fund managers can take advantage of these discrepancies by indulging in unnecessary risk-taking behavior to enhance their own personal wealth.

However, the term style drift possibly creates the misperception that every deviation is unjust. This may not necessarily be the case. Therefore, we believe that the current description is one dimensional and inadequate. Accordingly, this paper seeks to facilitate investors in developing a better understanding of the concept of style drift. For this purpose, we develop a conceptual framework that sets reasonable and unreasonable deviations apart. Our segregation criteria depend on how far these differences are from the benchmark to differentiate between “typical,” “not so typical,” and “excessive” deviations.

We achieve this by revisiting the current definition of style drift, introducing the concept of style enhancement, and using the notion of style misclassification in the literature. Initially, we classify deviations that are closer to the benchmark under the umbrella of “style enhancement.” These deviations are reasonable to be expected of active managers. It provides them the flexibility to employ their skill, perform their job, and pursue their objective of superior risk-adjusted performance. Since these deviations are close to the benchmark, they are unlikely to hamper the original risk profile of fund investors. However, style drift occurs when active managers stretch the boundaries beyond style enhancement. These are the set of not so reasonable deviations and may lie just outside fund managers' mandate. However, these deviations may just only be slightly outside the fund managers' mandate, but tend to change the risk profile of a fund to a point where even a small external shock can lead to catastrophic outcomes. As a result, these variations from the benchmark index are naturally undesirable on the part of fund managers. Finally, “style misclassification” occurs when a fund deviates so far from its original stated style that it is no longer meaningful to categorize the fund under the same investment style (Kim, Shukla, &Tomas, 2000; Dibartolomeo & Witkowski, 1997; Bams et al., 2017). These excessive levels of deviation seriously disturb the risk profile of fund investors and usually reflect agency issues on the part of fund managers (Huang, Sialm, & Zhang, 2011; Gil-Bazo & Ruiz-Verdu, 2009; Bams et al., 2017).

Accordingly, these deviations are clearly detrimental for fund investors and obstruct the use of the style classification framework present within the funds' management industry.

We conduct an analysis of the U.S. mutual funds industry from 1990-2019 to demonstrate the key differences between active and passive managers and to show that some deviations are part of an active manager's job. We further analyze active managers to demonstrate that not all variations are alike and that extreme levels of deviations are likely to feature fund managers pursuing off-mandate investment strategies that ultimately raise the risk levels of a portfolio.

Many researchers in the past have highlighted this dilemma of style deviations in one way or another. Cumming et al. (2009) discuss the benefits and drawbacks of these deviations concerning private equity investments. Advantages include a diverse range of projects from which to select possible lucrative investments and greater diversification. However, the authors also pinpoint some significant drawbacks associated with them including probable lawsuits and harm to the reputational capital (i.e., usually when these deviations lead to unsuccessful outcomes). Yet the focus of their study was to examine the impact of these deviations on fund performance. Huang et al. (2011) discuss the twofold motivations behind this risk-shifting behavior. They are either skill or agency-prone issues. However, the primary focus of their study was to explore the performance consequences of this risk-shifting behavior. Similarly, DiBartolomeo and Witkowski (1997) and Kim et al. (2000) attempt to group funds into either well-classified or misclassified groups, and provide evidence of misclassified funds present within the U.S. mutual funds industry.

Alternatively, our study makes a first attempt to devise an objective definition to address misconceptions associated with the style deviating practices of fund managers. It achieves this by discussing different aspects of the phenomenon and examining the consequences of each. Notably, the study advances the understanding of the issue by providing insights beyond the traditional notion that categorizes all types of deviations under one broad phenomenon of style drift. This study presents a fuller picture by distinguishing between varying levels of deviations and develops a conceptual framework by revising the current definition of style drift and introducing the concept of style enhancement in the literature.

The development of this conceptual framework is essential within the funds' management industry for several reasons. First, if investors view style deviating activities negatively, they are then likely to report these to the regulatory authorities upon discovering them. However, it may become frustrating for them as the U.S. Securities and Exchange Commission only regards "material" drift without prior consent and/or notification to fund investors as fraud (Jacobs, 1973). Section 35(d)(1) explicitly gives the fund's manager flexibility to invest 20% of the fund's assets in securities other than the asset type and/or geographic location highlighted by the fund's name (Investment Company Names, 2001). Therefore, legal action may only be applicable in specific scenarios.

In addition, owing to human psychology, investors will only file potential litigation cases when they find that these deviations result in inferior investment returns. Generally, individuals are more upset by prospective losses than being happy by equivalent gains (Tversky & Kahneman, 1979) and tend to weigh losses twice as heavily as gains. As a result, they are only critical about these deviations when facing unfavorable investment outcomes. However, rationally speaking, the reaction to both superior and inferior investment results should be the same and depend on whether it was a result of fair or unfair investment practices by fund managers. The positive outcomes can be a result of fund managers' utilization of skills or just good luck.

Finally, adverse outcomes may be a consequence of the agency-prone behavior of fund managers, but it may also indicate that the fund managers' use of skill did not pay off. One must not forget that the investment choices made within style deviating funds rest on forecasts, and there is no guarantee that the use of skill will always translate into superior investment outcomes. Thus, these psychological biases are likely to hinder the efficient functioning of the fund management industry.

2.2. Literature Review

When investors choose to invest in the funds' management industry, they typically use the information present within the fund prospectuses as their initial reference point to make comparisons among various fund managers. These fund prospectuses are legally binding documents describing the investment objectives, strategy, and style of the fund. This document guides investors about the investment approach of the fund managers (i.e., such as income or growth). It enables them to select funds that match their needs so that they can better manage their long-term risk/return objectives.

Despite fund prospectuses clearly stating these investment objectives, there is no guarantee that the fund managers would perfectly adhere to them (Cao, Iliev, & Velthuis, 2017). Funds often and do deviate from their stated investment behavior, a phenomenon known as style drift in the literature. The U.S. Securities and Exchange Commission describes style drift as a deviation of a fund’s actual portfolio holdings from the stated investment strategy of the fund as per its offering documents. Wermers (2012) defines it as a shift in loadings on priced style factors (Fama & French, 1993) or style characteristics (Daniel & Titman, 1997) for a portfolio over time. Cummings & Johan (2014) address it as a deviation from the initial investment objectives of a fund. Kurniawan et al. (2016) define it as a fund's deviation from its stated style objective to some other investment style.

As style deviation involves investment in securities contradicting the offering documents of the fund, investors may perceive it quite negatively (Cao et al., 2017). It showcases the prevalence of agency problems to them as investors expect the risk and returns of their portfolio to resonate with their chosen investment styles. Examples include growth, value, small-cap, mid-cap, or large-cap investments.

When a fund manager changes a fund’s style, they do not remain true to its label. There is no doubt that style deviations may be the result of the agency-prone behavior of the fund managers who may choose to invest in securities conflicting with the choices made by fund investors to maximize their own remuneration. As the remuneration model of the fund, managers’ rewards depend on the breadth of assets under management. Thus, the greater the assets under management, the higher their remuneration. This naturally creates an incentive for fund managers to attract higher fund flows (Brown et al., 1996). Another dominant feature of this compensation scheme is the bonus payment. A portion of a fund manager's compensation is directly tied to fund returns in the form of an annual bonus (Evans, 2008).

Naturally, investors prefer to direct fund flows according to the performance of a fund. Sirri and Tufano (1998) find an increase in fund flows to the performance of a fund. The higher the performance ranking of a portfolio, the higher the fund inflows in succeeding periods. Bogle (1998) and Ippolito (1992) demonstrate that investors allocate funds based on their past performance by observing more significant fund flows to winning funds than to the losing funds. Sirri and Tufano (1998) find that investors disproportionately allocate more funds to better performing funds. Grinblatt, Titman, and Wermers (1995) report 77% of mutual funds are inclined to purchase past winners. Lynch and Musto (2003) note that investors disregard consistently underperforming funds. Berk and Green (2004) also suggest fund investors be “star chasers” and follow higher ranking managers with superior past performance. Likewise, Sensoy (2009) finds investors' preference for direct fund flows correspond to their' performance.

Fund managers are, therefore, susceptible to enhancing the performance numbers of their portfolios and to shifting to an asset class that is expected to outperform in the short run. For example, when a fund manager of small-cap stocks assumes the dwindling performance of these stocks, they may start selling small-cap stocks and buying large-cap stocks with an expectation of beating the small-cap benchmarks (Brown et al., 1996). Many studies acknowledge these compensation arrangements affect the investment behavior of fund managers (Grinold & Rudd, 1987; Golec, 1996; Kritzman, 1987). Jans and Otten (2008) and Taylor (2003) illustrate a positive relationship between the compensation arrangement of fund managers and the magnitude of their risk-taking behavior. Brown et al. (1996), Chevalier and Ellison (1995), Dijk et al. (2014), and Taylor (2003) find that fund managers gamble on short-term returns to generate higher personal income for themselves. Thus, these style deviations may be the result of fund managers’ temptation to boost their performance ranking, to attract more fund flows, and to generate higher income for themselves. This behavior alters the risk-return profile of fund investors, who may consequentially be unable to achieve their long-term investment objectives.

In the past, these issues have led to some prominent scandals in the mutual funds industry, severely damaging investors' trust in the mutual fund sector. Some of these scandals include the lawsuits against the Manhattan Investment Fund, Beacon Hill Asset Management, Lancer Management, Woods River Funds, and Solaris Management, LLC.

In 2000, investors reported the Manhattan Investment Fund to the regulatory authorities. The reason behind it was that the fund manager invested more than 25% in technology stocks even though the offering documents did not allow for more than 25% investment in any given sector. In 2002, the investors' accused Beacon Hill Asset Management of misrepresentation and fraudulent statements. The justification behind their accusation was that the fund was promoting itself as a neutral market fund (i.e., to protect the fund investors from interest rate movement). However, the fund invested entirely in interest rate floaters, which was opposite to its claim. In 2003, investors took action against Lancer Management after discovering misrepresentations made in the offering memoranda. The fund memoranda restricted the investments to listed stocks only. However, most of the investments were made on unlisted exchanges.

Similarly, in 2005, the investors of the Woods River Fund found the fund to be moving away from its strategy of broad diversification and holding no more than 10% in any given stock by investing 65% of funds' assets in just one small-cap stock (i.e., End Wave Corporation). Likewise, in 2011, investors reported a case against Patrick G. Rooney of Solaris Management, LLC. The fund manager misused its funds' assets to further his interests. He did this by deviating from the fund's strategy of broad diversification and investing 80% of the funds' holdings in Positron, a financially troubled company where he served as the Chairman.

While it is true that agency considerations may lead to style deviations, this may not always be the case. Style deviations are common within the mutual fund industry. Specifically, style and selection form the basis of active portfolio management (Sharpe, 1992). Thus, it is the job of active fund managers to beat the benchmark index and rigorously manage the client's portfolio, perform analytical research, identify over- or under-valued securities present in the market, and modify asset allocations according to market conditions. The only possibility to beat the benchmark index is by taking positions that are different from it (i.e., by deviating from it). Fund managers attempt to do this in two general ways: stock selection and factor timing.[1] From time to time, the choices made within factor timing may deviate away from the style classifications of a fund.

Nonetheless, it is the investment style of active managers that differentiates them from passive managers as the objective of passive managers is simply to track the performance of some pre-defined market index. Passive managers can mimic the performance of the index by procuring either all or just a sample of securities that are part of the index. The type of funds in which passive managers invest is known as "index funds."[2] Another category of passive funds is enhanced index funds that also attempts to chase the performance of an index. However, unlike index funds, they

[1] Stock selection is the ability of active managers to choose winning stocks by making use of stock-specific information. Factor timing refers to their ability to overweight or underweight securities to take advantage of movement in common market factors (Sharpe 1992; Aragon & Ferson, 2007).

[2] For example, the S&P 500 Index is comprised of 500 of the largest companies listed on the NASDAQ or NYSE weighted by their market capitalization.

seek to outperform the index by either lowering volatility or adding value through selective stock picking (Morningstar).

Many researchers, as well as industry professionals, support these style deviations within active funds. Don Phillips, President of Morningstar, says, "Style drift is one of the best ways to demonstrate to a client the value of what a professional brings to the equation. It is the kind of work that is very difficult for an investor to do on their own." Wermers (2002) endorses these deviations as he finds an information ratio of 0.37 for high deviating managers and only 0.18 for low deviating managers highlighting the stock picking ability of high deviating managers. Ainsworth et al. (2008) justifies style deviations due to their ability to generate higher average returns. Cumming et al. (2009) argue for these deviations as essential for fund managers as they give fund managers access to an enormous pool of investments to choose from and take advantage of potentially profitable opportunities available in the market. Cremers and Petajisto (2009), Wermers (2012), and Amihud and Goyenko (2013) focus on these deviations proving that added management activity capitalizes on the manager's skill and is the only way through which a fund can beat its benchmark. Thus, style deviations can be encouraging for fund investors as they relate to activeness and the superior skill of fund managers. Moreover, sometimes these deviations may also be a result of unintentional management decisions (Bams et al., 2017) as when the underlying characteristics of an investment change over time (e.g., when small-cap companies grow to the point that they no longer fit small-cap stocks).

In other words, not all style deviations are similar and different strategies lend themselves to varying levels of risk. As style deviations enable active managers to utilize their skill, some variations are perennial and reasonable to expect of active fund managers. Nevertheless, these deviations should still remain within the boundaries of funds' mandate. When the fund manager chooses to deviate too far from the benchmark, it can lead to fund style misclassification where the effectiveness of the style classification within the fund prospectus remains of little or no use (Bams et al., 2017). Therefore, it becomes crucial for investors to be aware of the level of these deviations to determine whether the risk-return characteristics of their portfolio still meet their investment objectives in the long run (Bams et al., 2017). Accordingly, it is useful to set “usual,” “not so typical,” and “excessive” deviations apart.

Previous studies have differentiated between high deviating and low deviating funds by grouping them into well-classified or misclassified groups. DiBartolomeo and Witkowski (1997) determine misclassified (i.e., out-of-mandate) funds using Sharpe's (1988) return-based style analysis on U.S. equity mutual funds from 1990-1995. Specifically, they regress fund returns against the performance of six objective indices. They then categorize a fund as misclassified (i.e., out-of-mandate) if the index receiving the dominant weight is outside its stated objective group. Using this approach, they determine that almost 31% of sample funds are somewhat misclassified, while 9% are extremely misclassified. While Kim et al. (2000) use discriminant analysis depending upon fund attributes (including fund characteristics, investment style, and risk-return features) to identify misclassified (out-of-mandate) funds, they use confidence intervals based on the mean of each objective group to assign a fund to its matching objective group. This group may or may not correspond to the stated investment style of the fund. They then discover that over 50% of mutual funds do not adhere to their attribute-based objectives. They also identify approximately 33% of the funds to be extremely misclassified.

Yet, the financial services industry still categorizes all levels of deviation under one broad phenomenon of style drift. We argue that the current way of describing this style deviating concept is not operational as it contributes to investors' misperceptions by merely providing a one-dimensional depiction of these deviations.

2.3. Analysis of U.S. Mutual Funds Industry

In this section, we first illustrate that not every departure from the stated investment style is unjust as some deviations are a part of an active manager's job and a characteristic that substantially differentiates active fund managers from passive ones. Thus, we examine the difference in fund characteristics between index, enhanced index, and active funds. We further assess style deviations by analyzing 50th, 75th, 90th and 95th percentile of tracking error and present a case that there is a difference between typical, not-so-typical, and excessive deviations. We note that the percentiles used to conduct the above analysis do not suggest absolute cut-off points for segregating between different types of deviations but are rather used to support the qualitative conceptual framework presented in Section 2.4. We attempt to establish the tracking error threshold level in Chapter 3 using a more structured approach, appropriate methodologies and multivariate analysis.

A mutual fund presents its investment strategy within its prospectus document. For instance, a "typical" index fund would state its investment strategy to correspond to the performance of some pre-defined index. The Vanguard Small-Cap Growth Index fund states that it seeks to follow the performance of CRSP U.S. Small Cap Growth. These fund prospectuses do provide some flexibility to enhanced index and active fund managers to invest in securities other than the stated investment style of a fund. Typically, enhanced index and active funds' investment strategy is to spend at least a certain percentage (i.e., usually 80%) of its assets in equity securities of small, medium, or large capitalization stocks under normal circumstances. If the prospectus objective is growth, then it will state that the investment seeks growth of capital. At the same time, if it is equity income, it will state that the investment seeks current income, as well as capital appreciation. For example, the fund prospectus of the Walden Equity fund describes itself as a growth fund and states its benchmark to be the S&P 500. It further notes that it would commonly invest at least 80% of its assets in the common stocks of large capitalization companies giving them the flexibility of investing 20% of the assets elsewhere.

However, this is not so for typical funds. They may be more precise in stating their investment strategy or vague in expressing their investment objectives. The “more specific” funds would explain what they consider as small/medium or large capitalization companies. AllianzGI Opportunity Fund explains which universe its small companies are comparable to, which is the Russell 2000 Index. Likewise, SunAmerica Focused Equity Strategy states that it seeks growth of capital by allocating 80%-100% of its assets in domestic equity stocks, 0%-5% in fixed income stocks, 0%-20% in alternate strategies, and 0%-30% in foreign equity stocks. In contrast, less precise funds would express their investment strategy loosely and simply state that it will invest in equity securities that the advisor believes are capable of achieving superior growth in earnings. An example of a less price fund is the Shelby Fund.

The finance literature suggests a variety of return-based and holding-based techniques to determine the style deviations within a fund. Idzorek and Bertsch (2004) propose a return-based style metric, namely, the style drift score, to determine the volatility in fund style changes over time. The statistic makes use of return-based style analysis as introduced by Sharpe (1988, 1992) to examine numerous rolling windows and then calculates the variance of the asset class coefficients over time to approximate a style drift score as the square root of the sum of these variances. Alternatively, Wermers (2012) develops a holding-based style drift measure using market capitalization, the book to market value ratio, and momentum. He creates a metric to determine the total style drift of a fund. Yet, these style deviating measures only capture the volatility in fund style shifts over time and are unable to ascertain how far these funds are away from their stated investment strategy/style. For instance, the style drift score of a value fund manager who consistently pursues growth investment policies would be approximately equal to zero over time even though the fund manager is pursuing strategies that are far and away from his actual duties. Moreover, fund holdings are only available to investors after a long gap and perhaps with noise. Hence, these measures may not be entirely suitable to measure the style deviations of a fund.

Therefore, we use tracking errors relative to the benchmark index as a proxy to gauge style deviations and the degree of active management of a fund. It is the time-series standard deviation of the difference between the return of a fund and the return of a benchmark index (see e.g., Grinold and Kahn, 2000) and measures funds' risk relative to a benchmark index.[3] The former represents the volatility of the difference amid fund returns and its associated benchmark index returns. It is a measure of funds' risk relative to the benchmark index. Higher levels of tracking errors imply a

[3] We calculate tracking errors using the primary prospectus benchmark index corresponding to the offering memorandum of the fund and where this information was missing. We use the Morningstar Index. Morningstar uses the analysis of the prospectus to assign this benchmark index to the fund under consideration.

greater degree of active management and, as such, higher levels of risk. We calculate the tracking errors as follows:

$$Tracking\ Error = \sigma\ \ (R_{fund\ ,t} - R_{benchmark\ index,t}) \qquad (2.1)$$

We further calculate the information ratio for each of the funds under analysis to assess the level of skill among various fund managers. The information ratio represents fund returns over the benchmark index returns conditional upon the deviation of these returns (Goodwin, 1998). Simply put, it is the additional return per unit of increase in risk. We calculate the information ratio as follows.

$$Information\ Ratio = \frac{R_{fund\ ,t} - R_{benchmark\ index,t}}{\sigma\ \ (R_{fund,t} - R_{benchmark\ index,t})} \qquad (2.2)$$

Theoretically, index funds will exhibit a tracking error of zero percent as there is no deviation involved at all in these types of funds.[4] Enhanced index funds, as well as active funds, will exhibit a tracking error of greater than zero percent. This is because as soon as fund managers deviate from the benchmark, tracking errors go up, along with the costs of managing the fund.

Our research is based on the data for all U.S. open-ended equity funds (including index, enhanced index, and active funds) from the Morningstar Direct database from January 1990-December 2019.[5] We then collect data for all mutual funds that fall into the nine Morningstar categories

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[4] In the real world, the values for tracking errors cannot be zero percent, even for index funds. This is because fund managers cannot rebalance their positions at exactly closing prices to reflect a change in the index.

[5] We use information from Morningstar to categorize funds into the index, enhanced index, and active funds. Morningstar provides this information according to the information present within fund prospectuses.

including small-cap value (SV), small-cap blend (SB), small-cap growth (SG), mid-cap value (MV), mid-cap blend (MB), mid-cap growth (MG), large-cap value (LV), large-cap blend (LB), and large-cap growth (LG). We include only the oldest available equity share class to prevent double counting multiple share classes and consider both dead and alive funds. The observations for which the date of the observation is preceding the inception date of the fund are excluded to preclude any possibility of incubation bias within our data.

For each of these funds, we extract the daily returns data to compute monthly active returns, monthly tracking errors, the monthly information ratio, and the monthly risk-adjusted returns including CAPM, three-factor, and four-factor adjusted returns of the fund.[6] We calculate active returns using the primary prospectus benchmark index corresponding to the offering memorandum of the fund. If this information was missing, we use the Morningstar index. Thus, to qualify for the sample, a fund must have either the primary prospectus benchmark or the corresponding Morningstar Index.

Also, these funds need to have at least 12 days of trading data in a month so we can calculate its active return, tracking error, information ratio, and risk-adjusted returns every month. We also extract data on monthly raw returns, total net assets, expense ratio, and turnover ratio. We present monthly data on raw returns, active returns, risk-adjusted returns, tracking error, information ratio, total net assets, turnover ratio and expense ratio.

[6] Active Return is also referred to as "Excess Return" in the finance literature, but we prefer to use the term active return as a return in excess of the risk-free rate, also referred to as an excess return. Thus, we prefer to use Active Return to avoid ambiguity.

With the above screening criteria, the final sample includes 533,813 fund-month observations and 3,808 distinct funds, of which 3,477 are active, 68 enhanced index funds, and 263 index funds, respectively.

Table 2.1: Mean Mutual Fund Characteristics By Fund Type

This table reports the mean values for mutual fund characteristics including expense ratios, turnover ratios, total net assets, raw returns, active returns, risk-adjusted returns (including CAPM returns), three-factor returns, and four-factor returns, tracking errors, and information ratios grouped by fund type for open-ended U.S. equity mutual funds from 1990-2019 of index funds, enhanced index funds, and active funds. The raw return is the change in monthly net asset value reinvesting all income and capital gains distribution within that month and dividing it by the beginning net asset value of that month. The active return is the mean of the difference between the daily return of a fund and the daily performance of its benchmark index within a given month. The risk-adjusted return is alpha generated by the CAPM, three-factor, and four-factor using the daily returns data for each month. The tracking error is the time-series standard deviation of the daily active return for each month. The information ratio is the mean monthly active return divided by the monthly tracking errors of a fund. The expense ratio is the percentage of fund assets paid for management fee and operating expenses, including 12b-1 fees, management fees, administrative fees, and any other asset-based costs that the fund incurs. The turnover ratio is the lesser of sales or purchases divided by the average monthly net assets of a fund. We calculate all of the values at the fund-month level and convert them into equivalent annualized units.

	Index Funds	**Enhance- Index Funds**	**Active Funds**
Total number of funds (#)	263	68	3,477
Fund Performance (Raw Return, %)	8.47	8.39	8.60
Fund Performance (Active Return, %)	-0.46	-0.86	-0.58
Fund Performance (CAPM, %)	-1.06	-1.01	-1.09
Fund Performance (3-Factor, %)	-0.43	-0.46	-0.69
Fund Performance (4-Factor, %)	-0.40	-0.68	-0.87
Tracking Error (%)	1.62	3.60	5.83
Information Ratio (%)	-1.43	-0.30	-0.17
Expense Ratio (%)	0.50	0.86	1.14
Turnover Ratio (%)	70.15	119.93	78.07
Total Net Assets ($ millions)	5,634.49	410.80	1,453.95

Table 2.1 reports the total number of funds and the mean values of the primary fund characteristics including the expense ratio and the turnover ratio, and total net assets including tracking errors, the information ratio, and various performance metrics (e.g., raw returns, active returns, and risk-adjusted returns) for the index, enhanced index, and active funds. As style deviations are generally

prevalent within active funds and are attributes that substantially differentiate these funds from passive funds, we primarily examine the differences in fund characteristics for active versus passive funds.

The table indicates that there are a greater number of active funds than index or enhanced index funds in the U.S. open-end equity mutual funds market. Average monthly returns are the higher (8.60%) for active funds than those of index funds (8.47%) and enhanced index funds (8.39%). However, average active returns, although negative, are -0.46% (highest) for index funds and -0.86% (lowest) for enhanced index funds, while active funds are around -0.58%. Alternatively, typical CAPM alpha is highest for enhanced-index funds (-1.01%) among the three fund categories. However, three-factor, and four-factor adjusted returns are highest for index funds at -0.43% and -0.40%, respectively, when compared to the active or enhanced index funds.
Additionally, the typical values for tracking errors are close to 5.83% for active funds, which are higher than the average values for the enhanced index (around 3.60%) and index (close to 1.62%) funds. As expected, tracking errors are the highest for active managers and lowest for index managers with enhanced index managers lying somewhere in between. This resonates with the duties of different fund managers, where active fund managers must be substantially different from their benchmark indices to pursue active management strategies. At the same time, index fund managers attempting to mimic the benchmark index seek to remain close to the index and are likely to generate lower tracking error levels.

Likewise, the average information ratio although negative is the highest (-0.17%) for active funds and the lowest (-1.43%) for index funds. This suggests that active fund managers are more skillful than passive fund managers are and are typically able to produce more returns above the benchmark when compared to the index and enhanced index funds. It is also in line with the literature suggesting that is skill a characteristic of active managers rather than passive managers.

Moreover, active funds charge an expense ratio of 1.14%, which is higher than the expense ratio of a conventional enhanced index fund that charges around 0.86%. This figure is only 0.50% (the lowest) for index funds. This is in line with what we have discussed previously; that is, the greater the degree of active management, the higher the fund management costs.

We then analyze the index, enhanced index, and active funds in more detail. Table 2.2 provides the summary statistics for various fund performance measures, tracking errors, and the information ratio from 1990-2019.

The analysis of Table 2.2 indicates that active funds can generate as high as 74.86%, 26.56%, 21.14%, and 20.97%, enhanced index funds produce as high as 72.36%, 16.39%, 12.53%, and 12.37%, while index funds are delivering as high as 71.14% in raw returns, and 16.22%, 10.15%, and 9.97% in CAPM, three-factor, and four-factor adjusted returns, respectively, as suggested by the upper tail (90^{th} percentile) of the data. It is evident that amongst the three fund categories, active funds exhibit the highest return characteristics with index funds being the lowest. This is in line with theoretical expectations where outperformance relates to active funds only. Also, the skewness values for all these performance matrices are close to zero suggesting that these return distributions are approximately symmetric for all (i.e., index, enhanced index, and active) fund types. However, they exhibit positive excess kurtosis implying heavier tails than normally distributed data and a greater probability of frequent medium to large changes around the mean.

Likewise, the highest active returns are associated with active funds (22.81 %) followed by enhanced index funds (10.75%) and then index funds (0.68%) as illustrated by the 90th percentile of the data. Furthermore, the active return distribution is nearly symmetrical for active and enhanced index funds as indicated by the skewness values that are close to zero. However, their distribution is leptokurtic and suggestive of fat tails. Alternatively, the active return distribution for index funds is leptokurtic and positively skewed implying fat tails with most of the values lying below the mean value of -0.46%. As a result, we can infer that active returns for index funds are typically negative. Even the values occurring at the 90th percentile of the data (0.68%) are very low (close to 0%). This is not surprising as index funds aspire to generate active returns of 0% as their objective is to copy the index. In contrast, active funds seek to generate as high active returns as possible as it would showcase the managers' skill and justify the higher management costs of these types of funds.

Correspondingly, the analysis of the 90th percentile of tracking error levels reveals tracking error levels of 10.84% (highest) for active funds and 2.33% (lowest) for index funds. In comparison, they are 7.46% for enhanced index funds. Again, these values are in line with theoretical expectations as active managers must deviate much more than passive managers managing index and enhanced index funds. Moreover, the tracking error distribution is leptokurtic and positively skewed for all of the fund categories including, index, enhanced index, and active funds indicating that most of the values lie above the mean values. However, it is worth noting that there is more significant outlier potential, especially for active funds, as it is associated with the highest excess kurtosis value.

Similarly, for the 90th percentile group, the information ratio is 4.36% (highest) for active funds, followed by 3.86% for enhanced index funds, and 0.99% (lowest) for the index funds. The distribution of the information ratio is almost symmetrical for the active and enhanced indexes with the tails practically identical to the normally distributed data funds as evidenced by the skewness and kurtosis values in Table 2.2. The index funds are still negatively skewed and have fat tails. This indicates that for index funds, the information ratio is typically lower than its mean value of -1.43% and there are numerous medium-to-large changes around the mean. Overall, this implies that index fund managers are staying close to their benchmark index, while active funds are generating returns over their benchmark given the increased risks taken. This is in line with the duties of these fund managers where we expect only the active managers to generate returns over their benchmark index.

In summary, these return, risk, and skill characteristics are in line with what we should expect from active and passive fund managers. That is, active managers generate higher active returns, tracking errors, and information ratios as compared to the index and enhanced index funds. This is due to the objective of active management to achieve outperformance by utilizing skill and is only possible by deviating from the benchmark. In contrast, passive management seeks to mimic the benchmark index, which is only possible by strictly following the index. Thus, it is typical for the index and enhanced index funds to have lower tracking errors, active returns, and information ratios when compared to active funds. These values are in line with the objective of these types of funds.

We now analyze active funds in more detail. This is achieved by identifying possible out-of-mandate active managers. We conjecture those fund managers with extreme levels of tracking errors relative to their benchmark index are possibly out-of-mandate managers who choose to deviate much higher than the normal levels of deviation.[7] For this purpose, we first explore the fund characteristics of active funds for different fund styles (including growth, value, and blend investment styles) and different fund sizes (small, medium, and large). We then investigate these possible out-of- mandate managers and show how these extreme levels of tracking errors raise the overall risk profile of a fund.

[7] We consider extreme deviations when tracking error levels are at the 95th percentile or above and normal deviations when tracking error levels are at the mean tracking error levels within our data.

Table 2.2: Mutual Fund Summary Statistics by Fund Type

This table reports values for the number of observations (N), mean, standard deviation, 10^{th}, 50^{th}, and 90^{th} percentiles, as well as skewness and excess kurtosis values, for mutual fund characteristics including the raw return, active return, risk-adjusted return (including CAPM return, 3-Factor return, and 4-Factor return), tracking errors, and the information ratio grouped by fund type for open-ended U.S. equity mutual funds from 1990-2019. We group funds into index funds, enhanced index funds, and active funds. We calculate all of the values at the fund-month level and convert them into equivalent annualized units.

Index Funds	**N**	**Mean**	**Std**	**P10**	**P50**	**P90**	**Skew**	**Ex. Kur**
Fund Performance (Raw Return, %)	33,900	8.47	56.15	-66.37	14.62	71.14	-0.58	2.52
Fund Performance (Active Return, %)	33,900	-0.46	5.27	-2.05	-0.32	0.68	0.93	115.39
Fund Performance (CAPM, %)	33,900	-1.06	18.24	-19.72	-0.34	16.22	-0.26	9.79
Fund Performance (3-Factor, %)	33,900	-0.43	11.88	-11.17	-0.36	10.15	0.02	22.49
Fund Performance (4-Factor, %)	33,900	-0.40	11.95	-11.24	-0.35	9.97	-0.05	17.56
Tracking Error (%)	33,900	1.62	5.40	0.16	0.47	2.33	8.64	104.83
Information Ratio (%)	33,900	-1.43	3.17	-4.35	-0.80	0.99	-2.31	8.86
Enhanced Index Funds								
Fund Performance (Raw Return, %)	7,658	8.39	56.27	-66.27	13.22	72.36	-0.61	2.18
Fund Performance (Active Return, %)	7,658	-0.86	15.81	-12.75	-0.48	10.75	0.01	20.06
Fund Performance (CAPM, %)	7,658	-1.01	18.33	-19.33	-0.76	16.39	-0.27	8.38
Fund Performance (3-Factor, %)	7,658	-0.46	13.66	-13.47	-0.49	12.53	-0.14	11.76
Fund Performance (4-Factor, %)	7,658	-0.68	14.28	-13.71	-0.51	12.37	-1.67	36.43
Tracking Error (%)	7,658	3.60	4.97	0.94	2.04	7.46	5.95	57.30
Information Ratio (%)	7,658	-0.30	3.37	-4.51	-0.23	3.86	-0.05	0.62
Active Funds								
Fund Performance (Raw Return, %)	492,255	8.60	60.47	-66.82	13.70	74.86	-0.45	3.28
Fund Performance (Active Return, %)	492,255	-0.58	25.08	-24.01	-0.71	22.81	0.39	40.37
Fund Performance (CAPM, %)	492,255	-1.09	27.71	-29.25	-0.85	26.56	0.60	29.48
Fund Performance (3-Factor, %)	492,255	-0.69	22.56	-22.79	-0.71	21.17	0.33	76.52
Fund Performance (4-Factor, %)	492,255	-0.87	22.72	-22.92	-0.88	20.97	0.75	119.78
Tracking Error (%)	492,255	5.83	5.08	2.13	4.48	10.84	9.39	608.67
Information Ratio (%)	492,255	-0.17	3.62	-4.69	-0.18	4.36	0.03	0.58

Table 2.3 reports the risk and return characteristics for active funds according to their investment styles. Across our entire sample period, the mean tracking error for all active funds is 5.83%. Yet, across different style categories, it is highest (6.46%) for the growth investment style as compared to tracking error levels of the blend (5.35%) or value (5.34%) investment styles. Characteristically, tracking error distribution for all investment styles, including growth, value, and the blend, is positively skewed with fat tails. It suggests that the tail on the right side of the distribution is lengthier than in a normal distribution, most of the values lie above the mean value, and the probability of extreme outcomes is more than normally distributed. However, the skewness and kurtosis values are the highest for growth fund style suggesting a much greater tendency within these funds to exhibit extreme tracking error levels. As such, it makes sense to expect more style deviating managers among the growth fund style.

Furthermore, growth funds are more capable of generating higher raw returns, active returns, CAPM alpha, and three-factor adjusted returns than the value or blend investment styles. However, the four-factor adjusted return seems to be the highest for value funds. Overall, the analysis of returns data suggests that growth funds tend to yield much better return outcomes than any other fund style as indicated by positive skewness and fatter tails. The value investment style is less likely to yield better investment returns as suggested by the negative skewness values, as well as the fatter tails of its return distribution.

Correspondingly, the mean information ratio is also -0.06% (greatest) for growth funds, followed by -0.25% for the blend funds, and -0.26% (lowest) for the value funds. The information ratio distribution is symmetrical and slightly fatter for all investment styles. Overall, this implies that growth fund managers are more capable of generating returns above their benchmark given the increased risk taken when compared to value or blend fund managers.

We also explore the mean tracking error levels for active funds in for each style category. Figure 2.1 illustrates that the tracking error levels were unusually high during the time of the dot.com bubble (1999-2001) and the global financial crisis (GFC) (2007-2009). In addition, the tracking error for growth funds has been typically higher than all other style categories before the occurrence of the GFC. However, during the GFC, the tracking error levels of value funds were slightly higher than growth and blend funds, while following the GFC, the mean tracking error levels of the value and blend funds have been just slightly lower than the growth funds.

Figure 2.1: **Mean Tracking Error Levels from 1990-2019**

This figure reports the mean annualized tracking error levels associated with growth, value, and blend funds for active U.S. open-ended equity mutual funds over the full thirty-year period from 1990-2019.

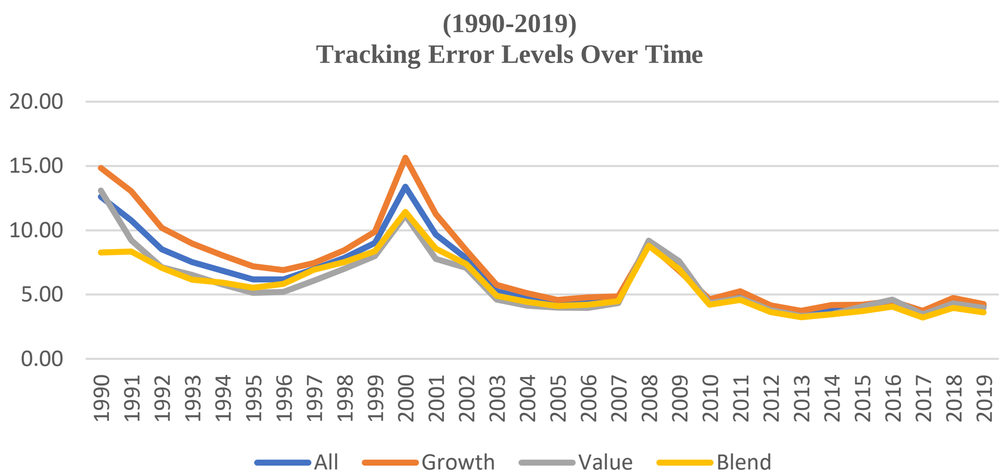


Table 2.3: Mutual Fund Summary Statistics by Fund Style

This table reports the values for the number of observations (N), the number of funds, means, standard deviations, 10th, 50th, 75th, 90th, and 95th percentiles, as well as skewness and excess kurtosis values for mutual fund characteristics including the raw return, active return, risk-adjusted return (including CAPM return, three-factor return, and four-factor return), tracking errors, and information ratios grouped by fund style for active open-ended U.S. equity mutual funds during the sample period from 1990-2019. We group fund style into growth funds, value funds, and blend funds. We calculate all of the values at the fund-month level and convert them into equivalent annualized units.

All Active Funds	**N**	**# of funds**	**Mean**	**Std**	**P10**	**P50**	**P75**	**P90**	**P95**	**Skew**	**Ex. Kurt**
Fund Performance (Raw Return, %)	492,255	3477	8.60	60.47	-66.82	13.70	43.56	74.86	95.37	-0.45	3.28
Fund Performance (Active Return, %)	492,255	3477	-0.58	25.08	-24.01	-0.71	9.38	22.81	34.80	0.39	40.37
Fund Performance (CAPM, %)	492,255	3477	-1.09	27.71	-29.25	-0.85	11.12	26.56	39.31	0.60	29.48
Fund Performance (3-Factor, %)	492,255	3477	-0.69	22.56	-22.79	-0.71	9.21	21.17	31.02	0.33	76.52
Fund Performance (4-Factor, %)	492,255	3477	-0.87	22.72	-22.92	-0.88	8.98	20.97	31.04	0.75	119.78
Tracking Error (%)	492,255	3477	5.83	5.08	2.13	4.48	6.94	10.84	14.36	9.39	608.67
Information Ratio (%)	492,255	3477	-0.17	3.62	-4.69	-0.18	2.15	4.36	5.76	0.03	0.58
Growth Funds											
Fund Performance (Raw Return, %)	215,038	1,499	8.87	65.10	-73.16	13.83	47.29	79.86	101.74	-0.34	2.89
Fund Performance (Active Return, %)	215,038	1,499	-0.22	27.71	-26.17	-0.40	11.08	25.67	38.83	0.81	38.39
Fund Performance (CAPM, %)	215,038	1,499	-0.90	31.04	-32.58	-0.59	13.34	30.03	43.38	0.94	30.63
Fund Performance (3-Factor, %)	215,038	1,499	-0.47	25.58	-25.91	-0.56	11.03	24.48	35.71	0.85	61.47
Fund Performance (4-Factor, %)	215,038	1,499	-1.13	25.74	-26.37	-1.10	10.30	23.68	34.95	1.35	104.99
Tracking Error (%)	215,038	1,499	6.46	5.52	2.47	4.98	7.63	11.85	15.80	11.13	849.00
Information Ratio (%)	215,038	1,499	-0.06	3.66	-4.60	-0.09	2.27	4.52	5.94	0.06	0.62
Value Funds											
Fund Performance (Raw Return, %)	138,151	939	8.39	55.71	-59.27	13.55	40.30	68.97	89.77	-0.63	3.99
Fund Performance (Active Return, %)	138,151	939	-0.86	22.37	-22.55	-0.93	8.41	20.63	31.33	-0.46	49.80
Fund Performance (CAPM, %)	138,151	939	-1.18	24.43	-26.37	-1.06	10.03	23.74	35.42	-0.36	18.84
Fund Performance (3-Factor, %)	138,151	939	-0.92	19.58	-20.72	-0.83	8.29	18.68	27.19	-1.81	130.39
Fund Performance (4-Factor, %)	138,151	939	-0.49	19.52	-20.06	-0.62	8.52	19.24	28.02	-2.01	173.14
Tracking Error (%)	138,151	939	5.34	4.33	2.04	4.12	6.41	9.97	13.05	5.89	184.84
Information Ratio (%)	138,151	939	-0.26	3.61	-4.79	-0.25	2.07	4.26	5.65	-0.01	0.51
Blend Funds											
Fund Performance (Raw Return, %)	139,066	1,039	8.40	57.51	-64.01	13.69	41.94	71.73	91.43	-0.54	3.09
Fund Performance (Active Return, %)	139,066	1,039	-0.86	23.26	-22.11	-0.88	7.97	20.30	31.35	0.00	30.47
Fund Performance (CAPM, %)	139,066	1,039	-1.28	25.19	-26.73	-0.96	9.12	23.41	35.99	0.42	26.11
Fund Performance (3-Factor, %)	139,066	1,039	-0.79	20.21	-20.22	-0.74	7.70	18.42	27.20	0.54	61.13
Fund Performance (4-Factor, %)	139,066	1,039	-0.84	20.57	-20.35	-0.88	7.72	18.68	27.81	1.22	92.29
Tracking Error (%)	139,066	1,039	5.35	4.95	1.83	4.08	6.35	9.96	13.35	7.91	243.47
Information Ratio (%)	139,066	1,039	-0.25	3.57	-4.70	-0.26	2.04	4.21	5.59	0.02	0.57

We also explore fund characteristics of active funds for various fund sizes including fund size less than $10m, fund size between $10m and $100m, and fund size greater than $100m. We categorize these funds as small, medium, and large, respectively. Table 2.4 reports tracking errors, raw, active, and risk-adjusted returns, as well as information ratios for various fund sizes.

Table 2.4 reveals that mean tracking error levels are highest for small funds (size <$10m), followed by medium ($10m<size<$100m) and then large funds (size>$100m) and is 8.04%, 6.49%, and 5.31% respectively. However, these higher levels of deviations from the benchmark are not translating into higher returns for the small and medium-sized funds when compared to the large funds with the lowest tracking error levels. It is evident from the mean raw, active, and risk-adjusted returns, which are highest for the large funds and lowest for the small funds. Additionally, the tracking error distribution for all of the fund sizes is leptokurtic (fat tails) and positively skewed suggesting that many tracking error values lie above their average value. With greater outlier potential, there is a greater chance for extremely low or high values, especially for small funds that have skewness and kurtosis values much higher than the medium and large funds.

We now attempt to identify extreme style deviating (i.e., possible out-of-mandate) active managers in more detail. For this purpose, we further explore tracking error characteristics for active funds across each fund style and size. It is evident in Tables 2.3 and 2.4 that the 75th percentile of the tracking errors is not much different from the mean tracking error levels. However, the 90th percentile is somewhat different from the mean. In contrast, the 95th percentile is much different from the mean tracking error levels. Thus, fund managers surpassing the 95th percentile of the tracking errors are most likely indulging in out-of-mandate style deviating activities. We represent the characteristics of these possible extreme style deviating (i.e., possible out-of-mandate) active managers in Table 2.5.

Table 2.4: Mutual Fund Summary Statistics by Fund Size

This table reports the values for the number of observations (N), number of funds, means, standard deviations, 10^{th}, 50^{th},75^{th}, 90^{th} and 95^{th} percentile as well as skewness and excess kurtosis values for mutual fund characteristics, including the raw return, active return, risk-adjusted return (including CAPM return, three-factor return, and four-factor return), tracking errors and information ratios grouped by fund size for active open-ended US equity mutual funds during the sample period from 1990-2019. We group fund style into small funds, medium funds, and large funds. We calculate all of the values at the fund-month level and convert them into equivalent annualized units.

Small Funds	**N**	**# of funds**	**Mean**	**Std**	**P10**	**P50**	**P75**	**P90**	**P95**	**Skew**	**Ex. Kurt**
Fund Performance (Raw Return,%)	36,450	1,603	5.88	66.24	-75.94	11.27	43.50	77.93	100.73	-0.34	4.02
Fund Performance (Active Return,%)	36,450	1,603	-0.83	33.62	-32.02	-1.04	12.53	30.59	46.12	1.76	72.65
Fund Performance (CAPM, %)	36,450	1,603	-1.70	34.84	-35.99	-1.31	13.12	31.82	47.63	2.18	85.76
Fund Performance (3-Factor,%)	36,450	1,603	-0.86	32.41	-29.34	-0.94	11.69	27.30	40.61	2.42	113.61
Fund Performance (4-Factor,%)	36,450	1,603	-1.05	33.17	-29.67	-1.09	11.43	27.26	41.13	4.07	199.37
Tracking Error (%)	36,450	1,603	8.04	8.24	2.84	6.12	9.48	14.58	19.31	18.11	1063.57
Information Ratio (%)	36,450	1,603	-0.17	3.56	-4.63	-0.19	2.12	4.29	5.70	0.05	0.54
Medium Funds											
Fund Performance (Raw Return,%)	132,336	2,575	7.91	61.53	-68.86	13.07	43.48	75.17	96.80	-0.47	2.72
Fund Performance (Active Return,%)	132,336	2,575	-0.64	26.80	-26.66	-0.94	10.49	25.48	38.65	0.24	16.66
Fund Performance (CAPM, %)	132,336	2,575	-1.06	28.89	-30.96	-0.93	11.87	28.40	42.56	0.20	11.20
Fund Performance (3-Factor,%)	132,336	2,575	-0.80	24.02	-24.88	-0.84	10.02	23.01	33.75	0.01	36.96
Fund Performance (4-Factor,%)	132,336	2,575	-0.97	24.06	-25.04	-1.03	9.85	22.93	33.84	-0.03	34.19
Tracking Error (%)	132,336	2,575	6.49	5.17	2.48	5.04	7.74	12.03	15.74	3.70	29.39
Information Ratio (%)	132,336	2,575	-0.20	3.61	-4.69	-0.20	2.09	4.31	5.73	0.03	0.59
Large Funds											
Fund Performance (Raw Return,%)	323,461	2,371	9.19	59.33	-64.97	14.18	43.59	74.43	94.28	-0.45	3.37
Fund Performance (Active Return,%)	323,461	2,371	-0.53	23.15	-22.09	-0.62	8.70	20.90	31.70	0.00	35.59
Fund Performance (CAPM, %)	323,461	2,371	-1.03	26.26	-27.76	-0.77	10.62	25.22	37.10	0.40	18.79
Fund Performance (3-Factor,%)	323,461	2,371	-0.63	20.50	-21.32	-0.64	8.70	19.77	28.74	-0.41	61.65
Fund Performance (4-Factor,%)	323,461	2,371	-0.81	20.60	-21.31	-0.81	8.44	19.55	28.77	-0.36	91.77
Tracking Error (%)	323,461	2,371	5.31	4.44	1.98	4.12	6.32	9.78	12.96	5.49	116.69
Information Ratio (%)	323,461	2,371	-0.16	3.63	-4.69	-0.17	2.18	4.39	5.78	0.03	0.58

From Table 2.5, we can infer that a total of 2,129 (61%) active funds indulged in possible out-of-mandate style deviating practices at one point or another from 1990-2019. A significant proportion of these out-of-mandate funds relates to growth funds style (47%), followed by blend (27%), and value (26%) style. It is in line with our findings above that a growth fund style seeks to pursue a higher level of style deviating activities than other fund styles. It is also in line with the finance literature that suggests growth funds tend to indulge in higher levels of style deviation (Wermers, 2012). Moreover, a greater number of large funds (Size>$100m) are indulging in extreme style deviating activities than small (Size<$10m) or medium ($10m<Size<$100m) size funds. Yet the tracking error level of small funds is the highest indicating the more significant potential of these funds to deviate in comparison to their peer funds. Correspondingly, the mean tracking error of possible out-of-mandate funds is above 20% and is typically associated with negative return characteristics across all fund styles and sizes. At the same time, the information ratio is either negative or close to zero except for medium size funds where active returns are positive and the information ratio is greater than zero. However, even if out-of-mandate funds generate positive returns, they are making them at the expense of a very different risk profile than what their investors would prefer (Holmes & Faff, 2007).

Overall, our assessment of tracking errors for various fund styles and sizes indicates that growth and small funds to exhibit higher tracking error levels when compared to their peers. Also, these are funds that show the highest positive skewness and kurtosis signaling that more tracking error observations lie above the mean values and that there is more outlier potential among these fund types. It further suggests that out-of-mandate fund managers are more likely associated with these fund types.

Table 2.5: Summary Statistics of Extreme Style Deviating (Possible Out-of-Mandate) Fund Managers

This table reports the mean values for mutual fund characteristics, including the raw return, active return, risk-adjusted return (including CAPM return, three-factor return, and four-factor return), tracking errors and information ratios of extreme style deviating (possible out-of-mandate) active open-ended U.S. equity mutual funds from 1990-2019 for various fund categories, fund categories segregated by fund style including growth, value, and blend funds, and fund categories segregated by fund size including small, medium and large funds. We calculate all of the values at the fund-month level and convert them into equivalent annualized units.

	All Funds	**Growth**	**Value**	**Blend**	**Small**	**Medium**	**Large**
Number of funds	2129	997	551	581	596	1150	1445
Fund Performance (Raw Return,%)	-10.35	-9.23	-12.33	-11.21	-9.45	-8.27	-8.63
Fund Performance (Active Return, %)	-0.71	-0.39	-0.16	-1.95	-1.99	0.70	-0.13
Fund Performance (CAPM,%)	-1.84	-2.18	-0.37	-2.37	-4.15	-0.78	-1.81
Fund Performance (3-Factor ,%)	-0.38	0.32	-1.53	-0.99	-1.93	-0.88	-1.20
Fund Performance (4-Factor ,%)	-0.91	-0.45	-1.13	-1.81	-2.56	-1.51	-1.83
Tracking Error (%)	21.42	21.66	20.33	21.83	23.71	21.13	21.92
Information Ratio (%)	-0.01	0.00	0.01	-0.07	-0.13	0.04	-0.01

We further demonstrate how these extreme levels of tracking errors raise the overall risk profile of a fund. To illustrate this, we assess mean raw, active, and risk-adjusted returns across different tranches of tracking errors. Table 2.6 reports that for our whole sample of data from 1990-2019, fund performance is typically inferior as the fund crosses the 95th percentile threshold (Tracking Error >14%) of the data. Additionally, active returns and the information ratio initially rise from lower to higher levels of tracking errors, but then fall again. This trend remains the same across different subperiods of our data. The only exception is from 1995-1999, where active returns tend to increase with increasing levels of tracking errors. Moreover, the active returns and the information ratio are typically negative beyond 14%, (i.e., extreme levels of tracking errors). The only exception was between 1995-1999 and 2000-2004.

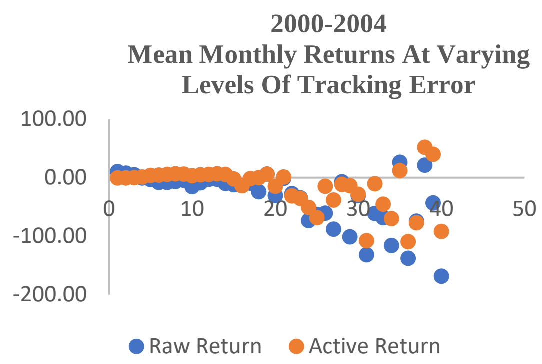
Table 2.6: Mean Mutual Fund Characteristics by Tracking Error Tranches

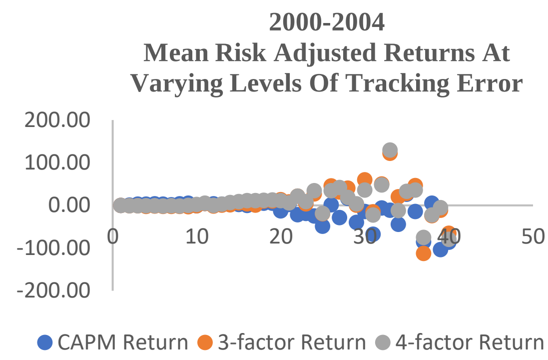
This table reports the mean values for mutual fund characteristics including the raw return, active return, risk-adjusted return (including CAPM, three-factor, and four-factor alpha), and information ratios associated with different tranches of tracking error active open-ended U.S. equity mutual funds during the full sample period from 1990-2019, as well as for five-year subperiods within the thirty-year sample period. We calculate all of the values at the fund-month level and convert them into equivalent annualized units.

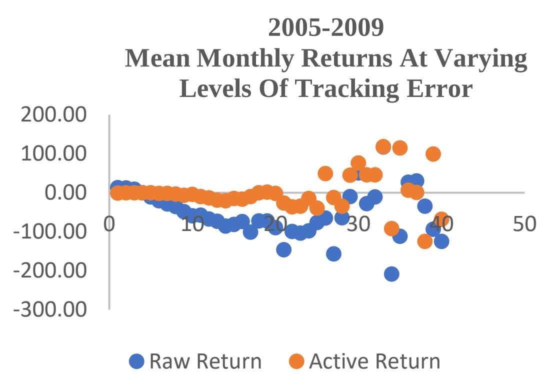
1990-2019	***0-2%***	***2-4%***	***4-6%***	***6-8%***	***8-10%***	***10-12%***	***12-14%***	***>14%***
Fund Performance (Raw Return, %)	15.52	13.54	10.52	5.49	1.23	-2.88	-5.27	-10.03
Fund Performance (Active Return, %)	-0.59	-0.77	-0.69	-0.58	-0.10	0.04	0.77	-0.60
Fund Performance (CAPM, %)	-1.02	-1.18	-0.81	-1.07	-0.89	-1.38	-1.38	-1.85
Fund Performance (3-Factor, %)	-0.70	-0.64	-0.57	-0.97	-0.85	-0.92	-0.56	-0.46
Fund Performance (4-Factor, %)	-0.80	-0.73	-0.68	-1.02	-1.21	-1.69	-1.39	-0.97
Information Ratio (%)	-0.39	-0.27	-0.14	-0.09	-0.01	0.00	0.06	-0.01
1990-1994	***0-2%***	***2-4%***	***4-6%***	***6-8%***	***8-10%***	***10-12%***	***12-14%***	***>14%***
Fund Performance (Raw Return, %)	5.52	7.62	9.66	11.71	11.92	14.67	17.04	15.06
Fund Performance (Active Return, %)	-1.14	-0.63	0.50	0.94	2.03	2.45	3.27	-0.85
Fund Performance (CAPM, %)	-3.34	-0.30	1.29	2.82	3.08	3.86	6.35	4.07
Fund Performance (3-Factor, %)	-1.83	-1.16	-0.74	-0.41	-0.37	-0.37	0.68	1.26
Fund Performance (4-Factor, %)	-1.90	-1.24	-1.22	-1.12	-0.94	-1.06	-0.50	-0.52
Information Ratio (%)	-0.89	-0.21	0.10	0.13	0.23	0.23	0.26	-0.02
1995-1999	***0-2%***	***2-4%***	***4-6%***	***6-8%***	***8-10%***	***10-12%***	***12-14%***	***>14%***
Fund Performance (Raw Return, %)	24.28	24.86	21.78	18.33	18.51	21.24	23.51	36.31
Fund Performance (Active Return, %)	-1.07	-2.06	-1.87	-1.82	-2.54	-1.59	-1.67	3.79
Fund Performance (CAPM, %)	-1.15	-0.38	-0.69	-1.93	-1.35	-0.70	0.14	6.70
Fund Performance (3-Factor, %)	-1.72	-1.40	-1.01	-0.24	1.00	3.55	4.95	6.58
Fund Performance (4-Factor, %)	-1.21	-1.20	-1.14	-0.87	-0.23	1.07	2.72	1.88
Information Ratio (%)	-0.69	-0.66	-0.38	-0.26	-0.29	-0.15	-0.13	0.15
2000-2004	***0-2%***	***2-4%***	***4-6%***	***6-8%***	***8-10%***	***10-12%***	***12-14%***	***>14%***
Fund Performance (Raw Return, %)	10.05	7.39	4.48	-0.60	-3.73	-8.20	-8.40	-10.26
Fund Performance (Active Return, %)	-1.00	-0.97	0.00	0.86	3.36	3.93	5.34	2.40
Fund Performance (CAPM, %)	-0.03	0.83	2.97	2.92	3.66	2.64	1.58	1.72
Fund Performance (3-Factor, %)	-0.40	-0.83	-1.34	-2.62	-1.90	-2.77	-2.19	0.30
Fund Performance (4-Factor, %)	-0.55	-0.73	-0.61	-1.34	-1.05	-1.50	-1.18	2.46
Information Ratio (%)	-0.67	-0.35	0.00	0.12	0.38	0.36	0.41	0.20
2005-2009	***0-2%***	***2-4%***	***4-6%***	***6-8%***	***8-10%***	***10-12%***	***12-14%***	***>14%***
Fund Performance (Raw Return, %)	13.04	12.09	9.17	-0.26	-10.37	-20.30	-28.81	-53.06
Fund Performance (Active Return, %)	-0.41	0.06	0.53	0.14	-0.05	-1.23	-1.54	-6.60
Fund Performance (CAPM, %)	-0.48	-0.06	0.44	-1.08	-2.03	-4.01	-5.72	-13.42
Fund Performance (3-Factor, %)	-0.53	0.59	1.27	0.52	0.00	-0.94	-1.80	-5.20
Fund Performance (4-Factor, %)	-0.68	0.24	0.47	-0.50	-1.49	-3.21	-4.05	-6.74
Information Ratio (%)	-0.26	0.00	0.11	0.02	-0.01	-0.11	-0.12	-0.34
2010-2014	***0-2%***	***2-4%***	***4-6%***	***6-8%***	***8-10%***	***10-12%***	***12-14%***	***>14%***
Fund Performance (Raw Return, %)	20.56	17.51	11.98	7.09	1.73	0.34	-8.56	-11.41
Fund Performance (Active Return, %)	-0.63	-1.15	-1.48	-1.57	-2.43	-4.41	-5.20	-9.22
Fund Performance (CAPM, %)	-1.15	-1.59	-2.03	-2.63	-3.92	-6.01	-6.91	-13.22
Fund Performance (3-Factor, %)	-0.85	-1.20	-1.46	-1.99	-2.53	-3.90	-4.08	-10.40
Fund Performance (4-Factor, %)	-0.97	-1.19	-1.30	-1.47	-1.72	-3.37	-3.74	-9.60
Information Ratio (%)	-0.42	-0.39	-0.31	-0.23	-0.28	-0.40	-0.41	-0.49
2015-2019	***0-2%***	***2-4%***	***4-6%***	***6-8%***	***8-10%***	***10-12%***	***12-14%***	***>14%***
Fund Performance (Raw Return, %)	12.69	10.34	7.89	4.13	1.29	-6.04	-5.87	-11.77
Fund Performance (Active Return, %)	-0.54	-0.74	-1.34	-1.80	-2.48	-2.79	-3.17	-2.06
Fund Performance (CAPM ,%)	-1.40	-2.48	-3.95	-5.16	-7.07	-8.42	-8.68	-10.40
Fund Performance (3-Factor, %)	-0.63	-0.81	-1.06	-1.43	-2.59	-3.24	-2.29	-4.18
Fund Performance (4-Factor, %)	-0.70	-0.89	-1.05	-1.21	-2.39	-3.21	-2.89	-4.23
Information Ratio (%)	-0.35	-0.25	-0.27	-0.26	-0.28	-0.26	-0.24	-0.20

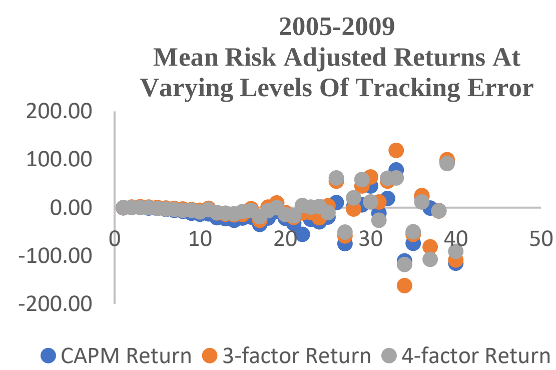
Figure 2.2: Mean Monthly Return At Varying Levels of Tracking Error

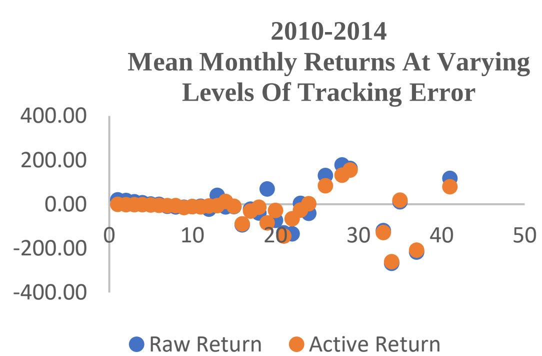
This figure reports mean fund performance associated with different levels of tracking error for active US open-ended equity mutual funds over the full thirty-year period from 1990-2019 as well as for 5-year sub-periods between the thirty years from 1990-2019.

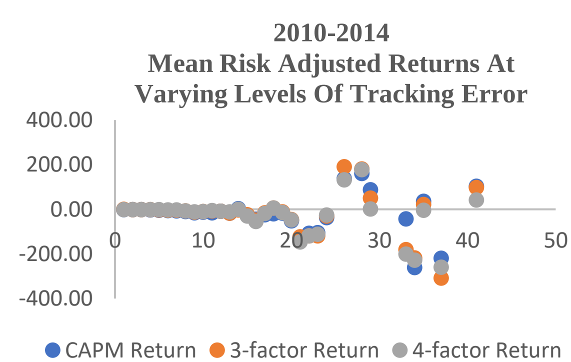

2000-2004
Mean Monthly Returns At Varying Levels Of Tracking Error
100.00
0.00
-100.00
-200.00
0
10
20
30
40
50
Raw Return
Active Return

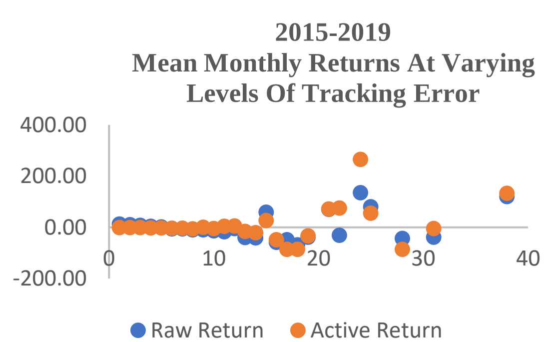

2000-2004
Mean Risk Adjusted Returns At Varying Levels Of Tracking Error
200.00
100.00
0.00
-100.00
-200.00
0
10
20
30
40
50
CAPM Return
3-factor Return
4-factor Return

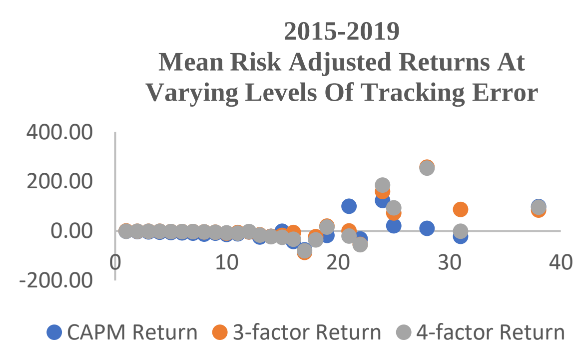

2005-2009
Mean Monthly Returns At Varying Levels Of Tracking Error
200.00
100.00
0.00
-100.00
-200.00
-300.00
0
10
20
30
40
50
Raw Return
Active Return


2005-2009
Mean Risk Adjusted Returns At Varying Levels Of Tracking Error
200.00
100.00
0.00
-100.00
-200.00
0
10
20
30
40
50
CAPM Return
3-factor Return
4-factor Return


2010-2014
Mean Monthly Returns At Varying Levels Of Tracking Error
400.00
200.00
0.00
-200.00
-400.00
0
10
20
30
40
50
Raw Return
Active Return


2010-2014
Mean Risk Adjusted Returns At Varying Levels Of Tracking Error
400.00
200.00
0.00
-200.00
-400.00
0
10
20
30
40
50
CAPM Return
3-factor Return
4-factor Return


2015-2019
Mean Monthly Returns At Varying Levels Of Tracking Error
400.00
200.00
0.00
-200.00
0
10
20
30
40
Raw Return
Active Return


2015-2019
Mean Risk Adjusted Returns At Varying Levels Of Tracking Error
400.00
200.00
0.00
-200.00
0
10
20
30
40
CAPM Return
3-factor Return
4-factor Return

We further examine how the riskiness of the portfolio is changing from lower to higher levels of tracking errors. For this purpose, we provide a visual depiction of how mean fund performance is changing with increasing levels of tracking errors. We use Figure 2.2 to illustrate the relationship between mean fund performances associated with different levels of tracking errors in the form of a scatter plot.

The analysis of the scatter plot indicates that the level of risk increases with extreme levels of tracking errors. It is possible that the variation in fund performance tends to increase with lower to higher levels of tracking errors. More specifically, this variation is minimal for tracking error levels that are less than 14% (e.g., within the upper tail of our data). However, this variation increases significantly as the fund manager crosses the upper tails of the data. This extreme behavior of fund performance relative to tracking errors remains the same, even when we break down our data into smaller subperiods of five-years as illustrated in Figure 1. It reflects a gambling scenario where one can expect either very high returns or meager returns. For example, a tracking error level of 32% could yield 14.96 in mean active returns. However, at a tracking error level of 33%, it could yield -15.08% in mean active returns during the same period. This behavior remains the same even during the time of the dot.com bubble and during the global financial crisis.

The analysis of the U.S. mutual funds industry above confirms that active managers must deviate from the benchmark to showcase their skills. This is what distinguishes active managers from passive managers. However, this style-deviating activity must remain within the bounds of the fund for active managers to follow their investment mandate. This is because extreme levels of deviation showcase fund managers that could make choices outside of their directives increasing the riskiness of the portfolio.

2.4. Our Conceptual Framework

Within this section, we propose an analytical framework that sets different levels of deviation apart. This framework separates varying degrees of aberrations depending upon how far these deviations are from the benchmark and the economic motivation behind the risk-shifting behavior.

Take ABC value fund as an example set up to invest in value stocks. As a part of an active manager's job, from time to time they must somewhat deviate from pursuing its objective of outperformance. Therefore, when its fund manager chooses to invest 5% of the funds' assets in growth stocks (for hedging purposes) and the remaining 95% in value stocks, the fund's overall strategy somewhat remains adherent to the value investment style of the fund. This it is not a substantial deviation from the fund's objectives. However, when the manager chooses to allocate 50% of the funds' assets in value stocks and the remaining 50% in growth it becomes an example of substantial deviation. The fund has now become susceptible to growth market risks in opposition to what value fund investors would expect. Thus, a deviation of 5% is very different from a variation of 50%. It becomes crucial for fund investors to understand the difference between varying levels of deviation and to differentiate between standard and not so standard deviations.
Following the above conceptual framework, we propose categorizing deviations that are closer to the benchmark under the phenomenon of style enhancement. We revise the current definition of style drift by classifying deviations stretching the boundaries of style enhancement as style drift. At the same time, we refer to variations that are too far away from their specified investment style that they no longer fit their original investment style as style misclassification. We present the details of these concepts below.

2.4.1. Style Enhancement

Style enhancement refers to deviations from the benchmark that gives fund managers the flexibility to utilize their skills and generate outperformance for fund investors. These deviations typically lie within fund managers' mandate and could be beneficial for fund investors as they ensure that fund managers are doing their job. An essential feature of these deviations is that they maintain the original risk profile of the investors. Disclosure of these types of irregularities should ideally be present within fund prospectuses. For example, the Lockwell Small Cap Value Fund clearly states that it will invest at least 80% of the fund's assets in small-cap stocks, but may choose to spend 20% of its assets in REITs within its fund prospectuses. Therefore, when it invests 85% of the fund assets in small-cap stocks and the remaining 15% in REITs, it remains consistent with its overall investment style as dictated by its fund's prospectus. Fund managers pursuing style enhancement remain consistent with the general investment strategy of the fund. These deviations could be healthy on the part of active managers as it ensures that fund managers are doing their job by using their specialist investment management skills.

Yet, style enhancement and style consistency are two separate phenomena, and one should not be confused with the other. A fund can be style consistent even when it is farther away from its benchmark. More explicitly, the XYZ growth fund can be style consistent by constantly pursuing value investment strategies over time that are farther away from its indicated investment style.

2.4.2. Style Drift

Style drift occurs when a fund manager’s style deviates by pushing the boundaries of style enhancement and by straying just outside their mandate. It is likely to happen when, for example, the Lockwell Small Cap Value Fund starts investing 21% or 22% in REITs. These are a set of not so reasonable deviations as they lie just outside the boundaries of style enhancement. Although these deviations are unlikely to alter the risk-return profile of fund investors significantly, these deviations could be bad on the part of active managers as they can lead to devastating outcomes if the market experiences adverse economic conditions. It is the type of behavior that led to the demise of Long Term Capital Management (LTCM) who managed over $4.8 billion in capital. The style drifting behavior of its Nobel Prize winning managers put too large a bet on the convergence of interest rates bringing it to the verge of default. It is different from the traditional style drift concept as it does not include all deviations under style drifting phenomenon. Instead, it is only comprised of departures stretching the margins of style enhancement as style drift.

2.4.3. Style Misclassification

Style misclassification lies at the farther end of our conceptual framework. These are deviations that are so far from their stated investment style that it is no longer remains meaningful to categorize the fund under the same investment style. This is likely to happen when a fund starts investing farther away from its initial stated objectives. For example, the XYZ small-cap value fund starts investing more and more in large-cap growth investment strategies. It is also likely to happen when a fund investing in real estate starts purchasing more and more commodities. In the case of the Lockwell Small Cap Value Fund, it happens when its fund manager starts investing around 40% in REITs in opposition to its fund's prospectus. We can think of these deviations as “ugly” as they considerably alter the risk levels of a portfolio and generally highlight the presence of agency issues between fund managers and fund investors.

2.5. Conclusion

Traditionally, the financial services industry defines the style deviating activities of fund managers under one broad concept leading to misinterpretation by investors who associate it with something appalling, unjust, and immoral. However, style deviating behavior is not necessarily alarming, but could be a desirable attribute while choosing to allocate funds between active vs. passive fund managers. In certain cases, it indicates that a fund manager can utilize their skill to adapt to changing market conditions. Alternatively, it can also be harmful to fund investors in certain scenarios. This is likely to occur in the case of excessive or more than typical deviations from the initially stated style of a fund as it tends to change the risk profile of fund investors.

This chapter attempts to provide a clearer picture regarding investor misconceptions concerning the risks by revisiting the current one-dimensional definition of style deviating behavior. We achieve this by proposing an analytical framework that segregates between different levels of deviations as some aberrations are necessary, while others are not. For this purpose, we introduce the concept of style enhancement, present an alternative way of defining style drift, and use the idea of style misclassification.

Style enhancement arises when a fund manager deviates from its original stated style to use their skill to generate superior risk-adjusted returns for their clients. Style drift occurs when fund managers push the boundaries of style enhancement resulting in slightly more deviations than usual. In comparison, style misclassification is present when fund managers engage in excessive risk-taking behavior that alters the overall investment style of the fund.

Reforms in fund mandates are needed to clear investors' misconceptions and increase their financial literacy. We believe that one way of doing this is to break down the style deviation phenomenon into subgroups of style enhancement, style drift, and style misclassification. The primary benefit of our proposed analytical framework is to distinguish between different levels of deviation for fund investors by transforming the current one-dimensional view into a newer and more objective framework. Fund management companies may also consider incorporating the level of style enhancement, style drift and style misclassification within their investment memorandum (the offering documents of the fund) in order tofurther help and control the psychological biases of investors, mitigate the risk of excessive deviations and promote the efficient functioning of the funds' management industry.

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Chapter 3: Mutual Funds, Agency Issues, and Style Misclassification

Abstract

This chapter investigates the presence of a threshold level of deviation beyond which we can classify a fund as a misclassified fund. To determine the presence of this threshold level, we use quadratic regression analysis on a sample of 3,431 open-ended U.S. equity mutual funds from 1991-2019 and regard the threshold level of deviation as the inflection point from where the relationship between tracking errors and fund performance changes from positive to negative. Our results suggest the existence of a concave relationship between fund performance and tracking errors implying that a threshold level of deviation does exist beyond which we can categorize a fund as a misclassified fund.

Keywords

Mutual Funds, Style Misclassification, Investment Style, Performance, Tracking Error

3.1. Introduction

With more than $54 trillion in total worldwide assets under management, the mutual fund industry remains one of the most significant financial intermediaries around the globe. As of the year-end December 2019, 45% of these assets were invested in equity funds alone. Within the worldwide capital market, the U.S. mutual funds industry plays a dominant role by managing more than $21 trillion in total global assets. In the past ten years, the industry was able to attract $232 billion in net new cash flows. A significant portion (53%) of these assets is committed to equity funds. Given the sheer size of equity investments, it is crucial to monitor whether the industry delivers what it promises to its investors. This is because not only businesses and institutional investors, but also about 101.8 million individual investors and 58.5 million U.S. households rely on them to achieve their long-term financial objectives (Investment Company Fact Book, 2020).

Within the mutual fund industry, the investor makes their investment decisions by referring to fund prospectuses. This document presents information on the investment style of the fund and the investment strategy of its fund manager. Nevertheless, many mutual funds exhibit behavior that is contrary to their stated investment strategy/style. If investment managers excessively deviate from their stated investment style, over time, their original style could become materially different from what is stated in its fund prospectus. Consequently, this can lead to the issue of style misclassification with a fund exposing individual investors to risk levels that are fundamentally irreconcilable with their risk-return objectives.

These extreme levels of style deviation expose fund investors to unexpected risks that may adversely affect fund performance along with other fund attributes. In the worst case scenario, it may lead investors to consume grossly inferior investment returns in opposition to their expectations based on the stated fund objectives. Alternatively, even if the investment returns are not materially different or are superior to investors' expectations, they are the result of a risk profile that is in direct opposition to investor preferences (Holmes & Faff, 2007). As such, investors should be genuinely interested in the issue of style misclassification and be aware of the level of these deviations to ensure that they are still conforming to their long-term investment objectives. Subsequently, it is critical to determine whether there exists a threshold of deviation where a fund starts exhibiting characteristics of a misclassified fund.

Accordingly, this study seeks to answer the following research question. Does a threshold level of deviation exist at which a fund no longer remains representative of its stated investment style?

It is crucial to determine this threshold level as a misleading classification system sends false signals to investors and leads to suboptimal investment allocations (DiBartolomeo & Witkowski, 1997; Castellanos & Alonso, 2005). As a result, investors may choose funds that are inconsistent with their needs and entrust their money to those who are not necessarily competent enough to manage it. For example, an income fund investing a large portion of its assets in small, growth-oriented securities is likely to have risk-return considerations that are unsuitable for retirees. Moreover, the performance evaluation of fund managers relates to the performance benchmark concerning their self-declared investment style. The assessment of growth fund managers is against a growth benchmark, while the appraisal of small-cap funds is against a small-cap benchmark (Buncic, Eggins, & Hill, 2015). However, this performance evaluation will produce misleading results if there is a divergence between the funds' actual investment strategy and its stated investment style. Thus, it is important to distinguish between the stated style and the actual stock holdings to determine the realistic investment style of the fund to ensure that benefits accrue to fund investors. The objective of this research is to identify a threshold level of deviation at which a fund starts exhibiting the properties of a misclassified fund.

This study attempts to contribute to the literature in several ways. To the best of our knowledge, no one to date has attempted to determine the threshold level of deviation from which investors can classify a fund as a misclassified fund. DiBartolomeo and Witkowski (1997) and Kim, Shukla, and Tomas (2000) explore the existence of misclassified funds within the U.S. mutual fund industry. Bams, Otten, and Ramezanifar (2017) propose a metric to determine the level of style deviation of a fund and determine the relationship between style misclassification and fund performance on a long-term basis. While, other studies, such as Brown, Harlow, and Zhang (2009), Huang, Sialm and Zhang (2011), and Wermers (2012) study the relationship between style consistency, risk shifting and/or style drift, and other fund attributes. Our study presents a non-linear relationship between style deviations and fund performance unlike previous studies that consider whether a linear positive or a negative association exists between style deviations/drift and fund performance (Brown et al., 2009; Huang et al., 2011; Wermers, 2012; Holmes & Faff, 2007; Bams et.al., 2017).

We believe that determining this threshold level of deviation will help mutual fund investors to identify when their investment portfolio is likely to move toward the issue of style misclassification and when they should be watchful about the investment activities of their fund managers. Within this empirical analysis, we assess the presence of a threshold level of deviation from the benchmark where we can categorize a fund as a misclassified fund. To do so, we use tracking errors as a proxy to measure the level of style deviation of a fund and examine its relationship with various performance metrics by fitting the quadratic regression equation of a parabola and assuming a concave relationship between fund performances and tracking errors. We then consider this threshold of deviation to be an inflection point from where the relationship between performance and tracking errors changes from positive to negative.

Our results suggest the existence of such a threshold and indicate a concave relationship between fund returns and tracking errors. These results are statistically significant and robust even when we divide our sample into small and large funds. Furthermore, this relationship also remains intact when we employ the Fama MacBeth (1973) regression analysis.

We arrange this chapter as follows. Section 3.2 discusses the literature concerning the evidence of style misclassification, its association with agency-related motivation of fund managers, and its impact on fund performance. Section 3.3 reports the data and variables. Section 3.4 presents a discussion of model selection, results, and empirical results, while Section 3.5 provides our conclusions.

3.2. Literature Review and Hypothesis Development

Mutual fund companies hire fund managers to provide specialist investment management services to fund investors who do not have either the time or knowledge to participate in the financial markets on their own. The delegation of this portfolio management from fund investors (principle) to fund managers (agents) creates a principle-agent relationship within the mutual fund industry. The terms and conditions of this contracted relationship are present within an investment management mandate that dictates how a fund manager is to construct a portfolio of assets by investing only in a specific asset class and style, the characteristics of which resonate with the investors' risk-return preferences.

Although the regulatory authorities require mutual funds to stick to their indicated investment objectives, some variations from them are still likely to occur. While some deviations (at smaller levels) are inevitable to make use of active managers' skills, some are a consequence of unintentional management decisions (e.g., when the underlying characteristics, such as market capitalization of an investment, change over time). Still others result from the agency driven actions of the fund managers. However, considerable deviation from the indicated investment style can lead to style misclassification within mutual funds. These frequent departures that are farther away from the benchmark signal that the fund has veered away from its original style and has moved to a point where it can no longer be categorized under that same investment style exposing the fund to style misclassification.

Several researchers refer to and identify the issue of style misclassification within the mutual fund industry. DiBartolomeo and Witkowski (1997) find that style misclassification occurs when a fund starts exhibiting behavior that no longer coincides with its indicated asset class/investment style. They explore whether style misclassification is present within the mutual fund industry, whether it is random, and if it creates a hindrance to fund investors. For this purpose, they use an iterative application of Sharpe's (1992) return-based style analysis, regress the fund's return against the returns of indexes representative of numerous investment approaches, and categorize the fund under the objective group providing the best fit. The results of their study suggest that around 40% of the funds do not correspond to their original style group.

Similarly, Kim et al. (2000) suggest that style misclassification occurs when the actual activities of a fund do not correspond to what it states within its fund prospectus. They use discriminant analysis and fund attributes, including investment style, characteristics, and risk/return measures, to determine whether funds with similarly stated objectives are comparable. They find that the attributes of more than 50% of the funds do not match their original objectives and discover that nearly 33% of the funds are critically different from their original style group.

At the same time, Bams et al. (2017) suggest that style misclassification occurs when a fund moves so much farther away from its original stated style that its fund investors are unlikely to meet their long-term investment objectives. They find that 14% of the equity mutual funds within the U.S mutual fund industry exhibit style misclassification.

Sensoy (2009) analyze U.S equity mutual funds and find that approximately one-third of these funds do not adhere to their stated investment styles. The Standard & Poor's Indices vs. Active scorecard found almost half of U.S equity funds experience style-shifting behavior from 2005-2009 (S&P Dow Jones Indices, 2010; S&P Financial Services, 2013). Similarly, Cao, Iliev, and Velthuis (2017) find that U.S. small-cap funds allocate 35% of their fund assets in large-cap securities in 2009.

The finance literature indicates that style misclassification is likely to occur for several reasons. The current system of preparing the fund's offering documents is broad. Although every fund typically describes its investment strategy in a particular manner, there is usually wording that allows fund managers enough leeway to execute investments outside the bounds of the stated investment strategy of a fund. Many researchers conjecture the possible reasons behind these vague objectives. Investment strategies and objectives are deliberately left ambiguous to provide flexibility to its fund managers. Another explanation is to make it challenging for investors to identify the risks associated with the investment accurately. Additionally, it enables fund managers to time the market through temporary deviations from the stated style (Watson, Allen, Phoon, & Wickramanayake, 2010).

In addition, style misclassification may also arise due to the misalignment of interests between fund managers and fund investors (i.e., the agency problem). Typically, fund investors expect their fund managers to maximize returns with the pre-specified investment style as this style tends to resonate with their risk preferences and investment goals. However, fund managers motivated to raise their compensation may desire to alter the risk profile by investing in securities that fall outside the bounds of this pre-stated investment style (Elton, Gruber, & Blake, 2001; Brown & Goetzmann, 1997; Chevalier & Ellison, 1995). This occurs because investors tend to direct fund flows based on the past performance of a fund (Ippolito, 1992; Sirri & Tufano, 1998; Patel, Zeckhauser, &d Hendricks 1992; Berk & Green, 2004; Sensoy, 2009). Because Morningstar, Thomson Reuters, Bloomberg, and other fund resources generally publish fund performance in rank order, they use this relative performance ranking to invest in star funds (Schwarz, 2011). It creates intense competition in the marketplace as fund managers must present evidence of stellar performance over their counterparts (DiBartolomeo & Witkowski, 1997; Kim et al., 2000). One tactic to beat competitors is to take on additional risk. Thus, fund managers are likely to sway from their stated investment style and alter the risk profile of their fund by investing in securities that are outside their mandate in an attempt to increase their remuneration (Elton et al., 2001; Brown & Goetzmann, 1997; Chevalier & Ellison, 1995).

Finally, the career concerns of fund managers may also lead to the style misclassification of a fund. Chan, Chen, and Lakonishok (2002) study a sample of 3,336 funds from 1976-1997 and discover style shifts to be most prevalent for funds with poor historical performance and career concerned fund managers. They explain their results to coincide with the agency issue explanation. Lakonishok, Shleifer, and Vishny (1994) also determine that money managers' fears about their career encourage them to sway toward growth securities.

The presence of style misclassification poses a significant issue within the mutual fund industry. If equity fund managers adhere to some other investment style, then the inferences drawn by investors based on their designated investment style will be misleading. For example, investors may choose a fund that declares its objective as growth, but practices investment strategies similar to that of value funds. This situation is likely to expose investors' portfolios to unexpected risk as each investment style exemplifies unique risk-return characteristics and experiences unpredictable cycles in which the market either rewards or punishes these styles. As a result, portfolios containing misclassified styles are likely to hurt investors' as fund managers straying outside the bounds of their mandated range expose investors to risk. As such, they may not realize their personal investment goals. Given the turbulent environment of the financial markets and the catastrophic impact of the global financial crisis 2008, it is essential that fund managers not to stray too far from their stated investment style. In worst case scenario, it can lead to devastating consequences for its fund’s investors (Watson et al., 2010).

Alternatively, the existing literature suggests that style deviations lead to either positive or negative investment returns. Nevertheless, the evidence from a study by Bams et al. (2017) indicates that style misclassification (i.e., the farther level of these deviations) leads to inferior fund performance.

Prior studies indicate that fund managers with inconsistent investment styles are more prone to commit asset allocation errors, be affected by higher turnover, and lead to poor investment returns when compared to peer funds (Gallo, Phengpis, & Swanson, 2007; Brown et al. 2009).

A study conducted by Bams et al. (2017) examines the relationship between style deviation and fund performance on a long-term basis by constructing a sample of 1.866 U.S. equity mutual funds from 2003-2016 and find misclassified funds perform worse than well-classified funds by approximately 0.92% per annum.

Other studies propose that managers with inconsistent styles relative to their mandated style typically exhibit overall poor fund performance in contrast to peer funds. Brown et al. (2009) use holding- and return-based style analysis techniques on a sample of 2,621 U.S. mutual funds from of 1980-2006. Their findings indicate funds with inconsistent styles underperform peer funds on a risk-adjusted basis owing to the greater likelihood of making asset allocation errors and higher turnover.

Furthermore, Huang et al. (2011) investigate the performance consequences of risk-shifting funds using the holdings data of 2,979 U.S. equity mutual funds from 1980-2009. The results of their study indicate risk-shifting funds worsen portfolio performance. They also find that those funds with more significant incentives to take risks are more prone to increased risk resulting in inferior performance on the risk-adjusted basis after increasing risk. They suggest that these actions are a result of the agency-driven behavior of the fund managers, which eventually translates into poor fund performance in style-shifting funds. The opportunistic style-shifting behavior of the fund managers prevents them from concentrating on their actual investment goal. Namely, to invest in promising securities and generate maximum returns for their clients. When the style-shifting activity of fund managers is motivated by agency issues, it is unlikely to serve in the best interests of the fund's investors. Their findings are consistent with Sensoy (2009), who finds evidence that style misclassification is likely a result of agency-driven behavior on the part of fund managers who may mismatch styles to improve inflows. Accordingly, the premise of this literature is that fund managers should avoid style misclassification as it may prove to be detrimental for a fund's investors.

However, these studies do not negate the likelihood that equity managers following a style-timing strategy can be profitable. In addition, there are studies in the finance literature that suggest style deviations lead to superior fund performance. Wermers (2012) analyzes a sample of 2,892 U.S. mutual funds from 1985-2000 using a holding-based style deviation measure and find style deviating managers to be good at selecting superior momentum securities that contribute positively to future portfolio performance. At the same time, Holmes and Faff (2007) study a sample of 198 Australian multisector trusts from 1990-1999 to determine the relationship between style drift, fund flow, and fund performance. Their findings suggest a positive correlation between style deviations and fund performance and can be indicative of the superior selectivity skills of style deviating fund managers. Similarly, Cumming and Flemming (2004) assess the impact of style drift on private equity investments and study a sample of 11,871 U.S. VC-backed companies from 1985-2003. The findings of their study suggest a positive relationship between style deviations and fund performance.

Our study contributes to the current literature by going beyond the traditional linear relationship between style deviation/drift/consistency and risk-adjusted performance that is commonly assumed in the previous research. Within our study, we seek to find the threshold level of deviation at which a fund is most likely to exhibit the properties of a misclassified fund. We conjecture a concave (non-linear) relationship between style deviation and fund performance. As explained in our first chapter, fund managers employ style enhancement to make use of their skills and market timing ability and they cannot achieve outperformance without deviating from the benchmark. We must give fund managers the flexibility to utilize their skills below the threshold of deviation and expect a positive association between style deviation and fund performance.

> H_1: Fund performance increases as the fund deviates from its benchmark until it reaches a threshold level of deviation.

However, once a fund starts to deviate further from the benchmark and reaches this threshold level of style deviation, the fund is likely to exhibit the properties of the misclassified fund. Once a fund reaches this level, we would expect the relationship between style deviation and fund performance to become negative.

> H_2: Fund performance decreases as the fund continues to deviate from its benchmark style beyond a certain level.

Our hypothesis is in line with the finance literature that suggests style deviations lead to positive fund performance and allows fund managers the ability to use their skills (Holmes & Faff, 2007; Cumming & Flemming 2009; Wermers, 2012). However, deviations farther from the benchmark lead to style misclassification within a fund and are representative of agency-driven behavior of fund managers. When this is the case, one should not expect superior investment returns (Huang et al., 2010, Bams et al., 2017). Consequently, it is reasonable to expect an inverted U-Shaped relationship between fund performance and style deviations of a fund.

3.3. Data and Variables

3.3.1. Measuring Style Deviation

The literature suggests two distinct approaches to identify style deviations within mutual funds. These include the return-based approach and the holding-based approach.

The return-based approach uses fund returns to infer style deviations within a fund. Sharpe (1988) first introduced this technique of style analysis. His method suggests deconstructing the historical funds' returns into the returns of passively constructed reference portfolio returns and then calculating factor loading concerning a set of each benchmark indices. Sharpe's (1988) approach can determine the style deviation of a fund since the value of these factor loadings is the effective asset mix of a portfolio, and the style deviation of a portfolio is the evolution of these asset class coefficients over time. Thus, any researcher can effectively perform style analysis using this approach providing they are successful in obtaining historical returns data on the portfolio under investigation and on passive indexes. Researchers including Fama and French (1992, 1993), Busse (2001), Chan, Chen, and Lakonishok (2002), and Brown et al. (2009) have extensively used Sharpe's (1988) approach.

Other measures of the return-based approach include Idzorek and Bertsch's (2004) style drift score (SDS) that measures the style deviation of a fund in a single statistic. This score makes use of the return-based style analysis technique as introduced by Sharpe (1988,1992) to examine numerous rolling windows and then calculates the variance of the asset class coefficients over time to approximate a style drift score as the square root of the sum of these variances. A high style drift score highlights a high degree of style drift, while low SDS emphasizes vice versa. They calculate it using the following formula:

$$SDS = \sqrt{\sum_{k=1}^{k} \sigma_k^2} \qquad (3.1)$$

where σ_k^2 = Var [$c_{k,1}, c_{k,2}, c_{k,3}, \ldots\ldots, c_{k,T}$] (i.e., the variance of the *k*th asset class coefficient). Tracking errors relative to the benchmark index is another return-based style deviation measure to estimate the style deviation of a fund. It is an estimate of a fund's volatility in returns relative to its benchmark index returns. More specifically, it is the time-series standard deviation of the active returns of a fund, where the active returns of a fund are simply the difference between the performance of a fund and the benchmark index return. The formula to calculate tracking errors is as follows;

$$Tracking\ Error = \sigma \ (R_{fund} - R_{benchmark\ index}) \qquad (3.2)$$

Alternatively, the holding-based approach uses the actual portfolio holdings of a fund at different points in time to infer the style deviations of a fund. The researcher ranks these securities according to various characteristics (e.g., the book-to-market ratio and market capitalization) that defines their style and then aggregates them together at the fund level to assess the style of a fund as a whole. Many researchers, including Grinblatt and Titman (1989), Wermers (2012), and Brown et al. (2015) measure style volatility using this approach.

However, this study will only explore tracking errors, a traditional returns-based style deviation measure, to estimate the style deviation of a fund. We calculate it as the time-series standard deviation of the daily active returns of a fund for each month, where the active returns of a fund are simply the difference between the daily performance of a fund and its primary prospectus benchmark index return. Where the information on the primary prospectus benchmark was missing, we use the Morningstar Index as the benchmark index[8]. The Morningstar analyzes the funds' prospectus to assign this benchmark index to the funds under consideration.

$$Tracking\ Error = \sigma\ \ (Active\ Return) \qquad (3.3)$$

That is,

$$Tracking\ Error = \sigma\ \ (R_{fund,t} - R_{\ benchmark\ index,t}) \qquad (3.4)$$

where R_{fund} represents the daily return of fund and $R_{\ benchmark\ index}$ represents the daily return of the benchmark index.[9]

Tracking errors serve as a reasonable proxy for style bets (Cremers & Petajisto, 2009) and is a good reference point to examine whether a fund deviated from its declared investment style. Low levels of tracking errors indicate a better match between the fund and the associated benchmark index (Buncic, Eggins, & Hill, 2015), which, in turn, highlights low levels of style deviation. We use tracking errors as our proxy for measuring style deviations for two main reasons. First, it can

[8] Morningstar assigns benchmark to each fund within a Morningstar category. Normally, when a fund has a Primary Benchmark, the Morningstar Benchmark is similar to it.
[9] We convert the tracking errors into equivalent annualized units considering 250 trading days in a year.

measure how far a fund is from its initial stated benchmark unlike other style drift measures that only gauge the volatility in portfolio style changes over time. For example, the style drift score of a value fund consistently pursuing growth investment strategies would be nearly zero over time, but the tracking errors of such a fund would be quite high. It is because tracking errors can capture both the consistent set of style bets away from the stated benchmark and a set of changing style bets over time (Idzorek and Bertsch, 2004). In addition, the holdings data of the fund is only available to investors after a long gap and that too with noise.

3.3.2. Measuring Fund Performance

This study employs five different performance measures. For each fund under analysis, we calculate the active return and the risk-adjusted performance of a fund using the alpha scores generated after regressing the excess returns of a fund over the risk-free rate by the CAPM one-factor capital asset pricing model, the Fama and French (1993) three-factor model, and the Carhart (1997) four-factor model.[10] We also use the raw net return of each fund within our analysis[11].

We estimate each of these performance measures using the following specifications:

i. $AR = (R_{fund} - R_{benchmark\ index})$ (3.5)

ii. $R_{i,t} - R_{ft} = \alpha_{i,t} + \beta_1(R_m - R_f)_t + \varepsilon_{i,t}$ (3.6)

[10] We convert the active return and the risk-adjusted return (including CAPM, three-factor, and four-factor) into equivalent annualized units considering 250 trading days in a year.

[11] We extract the raw net return data from the Morningstar database every month and multiply it by 12 to convert it into equivalent annualized units.

iii. $R_{i,t} - R_{ft} = \alpha_{i,t} + \beta_1(R_m\text{-}R_f)_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_{i,t}$ (3.7)

iv. $R_{i,t} - R_{ft} = \alpha_{i,t} + \beta_1(R_m\text{-}R_f)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \varepsilon_{i,t}$ (3.8)

The dependent variable for Equation (3.2) is the active return of a fund, while the dependent variable for Equations (3.3), (3.4), and (3.5) represents the difference between the daily return of fund *i* (R_i) and the risk-free rate (R_f) for day *t* from the CAPM, the Fama French three-factor model, and the Carhart four-factor model. In contrast, the independent variables showcase the daily return series of the zero investment factor portfolios. The terms (R_m-R_f), SMB, HML, and MOM denote excess returns of the market portfolio over the risk-free rate, the return differential among small and large capitalization stocks, the return differential of high and low book-to-market stocks, and the return differential of positive momentum and negative momentum stocks, respectively. β_1, β_2, β_3, and β_4 represent expected fund loadings associated with each factor. The error term $\varepsilon_{i,t}$ represents the portion of returns unexplained by these four factors. The intercept term of this regression (i.e., α) corresponds to the alpha scores of a fund and is a measure of the risk-adjusted performance of a fund. We calculate these alpha scores using daily data for each fund every month. We require each fund to have a minimum of 12 days of trading data within a month for the alpha score estimation. We extract the daily factor realizations data from the Fama-French website. The positive values of alpha indicate excess risk-adjusted performance, while negative values indicate deficient risk-adjusted performance. More explanations of these models are outside the scope of this study.

3.3.3. Control Variables

Our study controls for numerous variables that have been identified by the finance literature to correlate with fund style deviation. These include fund age, fund size, expense ratio, turnover ratio, and fund flow.

The fund age is the number of years from the inception date of the fund, and fund size represents the total net assets managed by the fund. The age and size are likely to shape the ability of the fund to control for style deviations. The expense ratio is the yearly fee charged by the fund to its investors. The turnover ratio represents the trading activity within a fund. It is the lesser of sales or purchases divided by the average monthly net assets of a fund. It controls for the impact of the fund's management activity on the level of its style deviation. In contrast, fund flow represents the percentage growth of the total net assets of a fund due to additional investments. We calculate fund flow for each month using the following formula used by Sirri and Tufano (1998).

$$TNA_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + r_{i,t})}{TNA_{i,t-1}} \qquad (3.9)$$

$TNA_{i,t}$ represents the total net assets of a fund for fund *i* in month *t*, $TNA_{i,t-1}$ signifies the previous period's total net assets of the same fund, while $r_{i,t}$ is the fund return for fund *i* in month *t*. We winsorize fund flow at 1% and 99% to prevent a potential impact from extreme observations.

3.4. Data Cleaning, Sample Construction, and Description

We construct our data by identifying all active U.S. equity (open-ended) mutual funds from the Morningstar Direct database from January 1991-December 2019. Morningstar Direct database provides comprehensive data on mutual funds and is widely used by financial advisors, retail investors, and researchers (see e.g., Kurniawan et al., 2016; Gregory-Allen et al., 2019).

We then collect data for all mutual funds that fall into the nine Morningstar categories including small-cap value (SV), small-cap blend (SB), small-cap growth (SG), mid-cap value (MV), mid-cap blend (MB), mid-cap growth (MG), large-cap value (LV), large-cap blend (LB), and large-cap growth (LG). We include only those funds that have a fund size greater than $10 million and have either an associated primary prospectus benchmark or the Morningstar Index (where the information on the associated primary prospectus benchmark was missing) as defined by Morningstar.[12] We include only the oldest available equity share class to prevent double-counting of multiple share classes and use data for both dead and alive funds to eliminate survivorship bias. We also exclude observations for which the date of the observation is preceding the inception date of the fund to preclude any possibility of incubation bias within our data.

We then collect data for each eligible fund that has at least 12 days of trading daily returns data availability for itself and its associated benchmark within a month. For each of these funds, we calculate monthly tracking errors, monthly active returns, and risk-adjusted returns using the daily returns data of the fund and the benchmark indices. We also extract data on each of the eligible funds for its total net assets every month and the expense ratio and turnover ratio on an annual basis from Morningstar.[13] We then calculate fund age and fund flow for each fund within our

[12] Morningstar reports the primary prospectus benchmark corresponding to the offering memorandum of a fund.

[13] We estimate the regression models every month and assign the annual expense ratio and the turnover ratio to all months in that year.

analysis. The final data set in our study contains a sample of 3,431 funds and 467,456 observations.[14]

Table 3.1 provides the summary statistics for our sample of funds at the fund-month level converted into equivalent annualized units. Panel A reports the summary statistics relating to the primary fund characteristics including the expense ratio, turnover ratio, total net assets, fund age, and fund flow. A typical fund generates 8.81% raw returns each month, is about 14.15 years old, incurs an expense ratio of 1.11%, has around $1,535 million in assets under management, and a turnover ratio of around 77%. Panel B presents the summary statistics relating to various performance matrices at the fund-month level converted into equivalent annualized units. A typical fund generates 8.81% and -0.63% in raw net returns and active returns, respectively. Using the CAPM, we find average risk-adjusted returns to be -1.11%, while the three-factor and four-factor adjusted returns are around -0.72% and -0.90%, respectively. Panel C reports the tracking error statistics at the fund-month level converted into equivalent annualized units. We find an average actively managed fund to have a tracking error level of around 5.63%. High levels of standard deviation indicate large variability across the funds.

Table 3.2 reports the mean statistics for our sample of funds from the first month of 1991 to the last month of 2019. We find observations at the year level by taking the average of annualized monthly raw net returns, the expense ratio, the turnover ratio, total net assets, fund age, and fund

[14] Note the data set in consideration is an unbalanced panel data set, and some funds come in for a shorter period than others do.

flow for the sample of funds in that particular year. We also provide the number of funds present in a specific year denoted by N. For each year, the amount of funds present varies with 314 funds in 1991 and 1,251 funds in 2019 highlighting an overall increasing trend. The number of funds declines during 2003 and 2004 highlighting the impact of the dot.com bubble. We also see significant negative raw net returns coinciding during the period of the dot.com bubble and the financial crisis.

Table 3.1: Summary Statistics of Actively Managed Funds

Panel A reports the mean, the standard deviation, the 25th percentile, the median, and the 75th percentile for mutual fund characteristics including expense ratio, turnover ratio, total net assets, fund age, and fund flow. Panel B reports the mean, the standard deviation, the 25th percentile, the median, and the 75th percentile for fund performance metrics including the raw net returns, active returns, and risk-adjusted returns (including CAPM returns, three-factor returns, and four-factor returns) for 3,431 U.S. actively managed funds from 1991-2019. The raw return is the change in monthly net asset value reinvesting all income and capital gains distribution within that month and dividing it by the beginning net asset value of that month. The active return is the mean of the difference between the daily return of a fund and the daily performance of its benchmark index within a given month. The risk-adjusted returns are alpha generated by the CAPM, the three-factor, and the four-factor using the daily returns data for each month. Panel C reports the mean, the standard deviation, the 25th percentile, the median, and the 75th percentile for tracking errors of the fund. The tracking error is the time-series standard deviation of the daily active return for each month. We convert all of the values into equivalent annualized units.

Panel A: Fund Characteristics	**Mean**	**Std**	**P25**	**Median**	**P75**
Expense ratio (%)	1.11	0.41	0.87	1.06	1.30
Turnover ratio (%)	77.13	88.19	31.00	58.00	98.00
Total Net Assets ($ millions)	1,535.08	5,762.21	76.77	273.41	1,020.17
Fund Age (year)	14.15	13.20	5.34	10.72	18.35
Fund Flow (%)	5.37	59.25	-15.98	-3.53	13.33
Panel B: Performance Metrics					
Fund Net Return (%)	8.81	60.23	-21.55	13.86	43.65
Active Return (%)	-0.63	24.45	-10.67	-0.73	9.14
CAPM Return (%)	-1.11	27.30	-12.95	-0.86	10.96
3-Factor Return (%)	-0.72	21.63	-10.60	-0.73	9.03
4-Factor Return (%)	-0.90	22.06	-10.69	-0.90	8.80
Panel C: Style Deviation Measure					
Tracking Error (%)	5.63	4.65	2.95	4.38	6.72

However, on average, raw net return has been around 8.81% for our whole sample period from 1991-2019. A mutual fund investor, on average, incurs an average expense ratio of 1.11 from

Table 3.2: Summary Statistics of Actively Managed Funds Over Time

This table represents the summary statistics from 1991-2019 for 3,431 U.S. actively managed funds. The cross-sectional mean values are calculated for fund characteristics that include the number of funds existing each year (N), the average raw net return, the expense ratio, the turnover ratio, total net assets, fund age, and fund flow. We calculate all of the values at the fund-month level and convert them into equivalent annualized units.

Year	N	Raw Net Return (%)	Expense Ratio (%)	Turnover Ratio (%)	Total Net Assets ($M)	Fund Age (Years)	Fund Flow (%)
1991	314	33.58	1.20	81.17	533.59	16.40	19.22
1992	352	10.91	1.17	72.21	621.66	15.85	26.16
1993	543	13.37	1.16	71.63	678.70	14.71	24.38
1994	645	-0.59	1.15	73.89	688.69	13.53	15.86
1995	745	28.04	1.16	76.92	802.40	12.74	16.97
1996	831	18.92	1.17	82.68	1,010.05	12.09	20.22
1997	937	23.54	1.16	84.23	1,216.84	11.97	22.35
1998	1,085	16.39	1.16	88.04	1,378.47	11.30	14.86
1999	1,220	25.30	1.17	91.40	1,516.49	11.05	10.20
2000	1,310	2.71	1.17	110.51	1,675.60	10.83	16.05
2001	1,366	-6.40	1.18	98.82	1,395.09	11.51	15.75
2002	1,615	-22.31	1.20	94.96	1,068.45	11.07	11.07
2003	905	31.06	1.23	91.35	1,019.62	10.63	12.43
2004	906	13.61	1.12	75.71	1,817.96	12.54	13.29
2005	1,887	7.76	1.17	75.86	1,306.18	11.73	8.80
2006	2,029	12.47	1.13	81.46	1,380.44	11.82	7.83
2007	2,068	6.79	1.11	82.19	1,512.51	12.13	4.12
2008	2,084	-44.83	1.11	93.94	1,219.47	12.68	-0.86
2009	1,904	31.08	1.13	94.12	1,028.37	13.77	0.98
2010	1,889	19.84	1.11	77.78	1,260.76	14.38	1.38
2011	1,838	-0.54	1.09	72.67	1,431.17	14.89	1.17
2012	1,792	14.64	1.08	66.01	1,481.98	15.68	-2.77
2013	1,804	30.72	1.06	62.83	1,768.46	16.02	6.29
2014	1,827	8.26	1.05	60.84	2,023.92	16.31	2.11
2015	1,821	-1.07	1.04	60.72	2,060.06	16.92	-1.28
2016	1,790	12.17	1.03	60.66	2,009.83	17.72	-6.62
2017	1,774	17.87	1.01	57.13	2,256.28	18.09	-5.35
2018	1,734	-6.59	0.98	59.35	2,440.98	18.57	-3.14
2019	1,251	26.07	0.96	62.37	2,447.07	19.13	-6.63
1991-2019	3,431	8.81	1.11	77.13	1,535.08	14.15	5.37

1991-2019. The mean value of the expense ratio varies during the initial period of the sample, but shows a downward trend from 2009-2019. In 2009, the average expense ratio was 113 basis points or 113 cents for every $100 invested. By 2019, this value fell to 96 basis points, a decline of 17 cents for every $100 spent. The average turnover ratio for the entire sample of funds is around 77.13 from 1991-2019. The turnover ratio was relatively higher for the time periods coinciding with the dot.com bubble and the global financial crisis.

The average value of fund size, as indicated by the total net assets of a fund, increases from $534 million starting from the beginning of the period to $2,447 million in 2019. The average age of the fund is around 16.40 years at the beginning of our sample period. It fell to 10.83 years in the early 2000s and tended to increase after that. Over 1991-2019, monthly fund flows decrease from 19.22% in 1991 to -6.63% in 2019, and the time-series average for the whole sample period is 5.37% for all of the funds under consideration.

To gauge how the overall fund tracking errors change over time, we plot Figure 3.1 with the yearly cross-sectional mean, median, and standard deviation, as well as the values for the upper and lower quartiles of tracking errors from 1991-2019. Table 3.3 reports the summary statistics for tracking errors related to Figure 3.1. The average tracking error value is around 5.64% for the entire sample of funds with a standard deviation of approximately 4.65%. There are two apparent spikes around 2000 and 2008 coinciding with the period of the dot.com bubble and the 2008 financial crisis.

Figure 3. 1: The Time Trend of Tracking Error

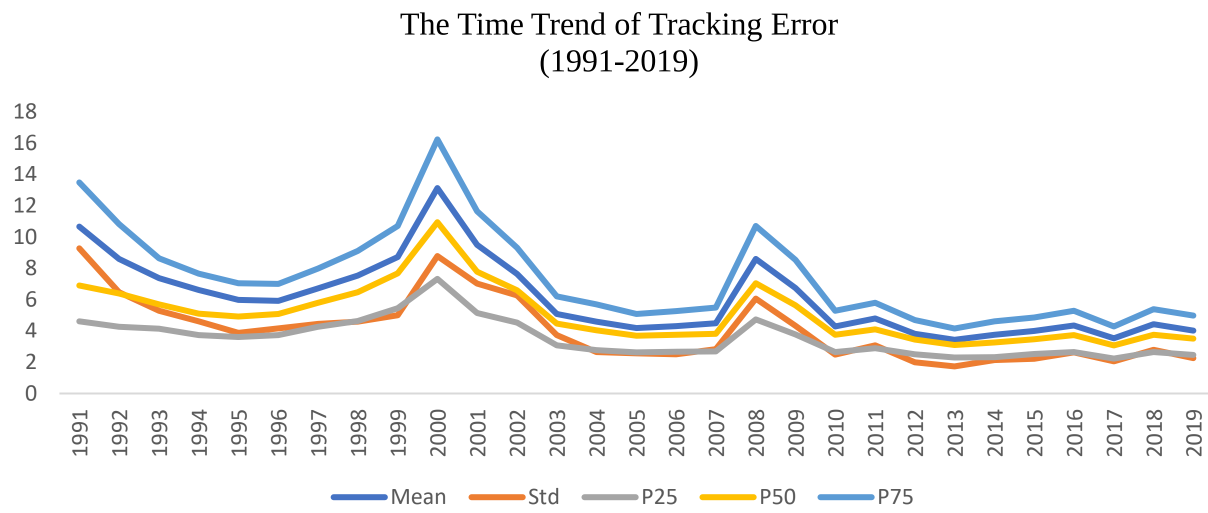

Table 3.4 demonstrates fund characteristics relating to each style category for the sample of funds under consideration. We report the mean values for raw net returns, tracking errors, expense ratio, turnover ratio, total net assets, fund age, and fund flow for each style category at the fund-month level converted into equivalent annualized units. The tracking error is lowest (4.63%) for large-cap value funds and highest (7.15%) for mid-cap growth funds. Overall, large-cap funds experience smaller tracking errors relative to other style categories. That is, they more strictly follow their benchmark index as compared to others. Alternatively, all growth funds exhibit high tracking errors (i.e., a more significant deviation from their stated style). The average raw net return for the large-cap funds are weaker than small-cap and mid-cap funds. The highest average raw net returns relate to small-cap growth funds at 9.56%. The highest expense ratio of 1.29% is associated with small-cap growth funds, while the lowest relates to large-cap value funds at 0.99%. A turnover ratio of 99.21% is the highest for small-cap growth funds, followed by mid-cap growth funds at 99.15%, and the lowest for large-cap value funds at 59.26%. The most significant fund

size is associated with large-cap funds and the smallest fund size with small-cap funds and ranges between \$588m to \$2,328m. Overall, mid-to-smaller funds are associated with higher tracking error levels, higher expense ratios, and higher turnover ratios

Table 3.3: The Time Trend of Tracking Error

This table summarizes the cross-sectional mean, standard deviation, 25*th* percentile, median, and the 75*th* percentile for tracking errors at the end of each year, as well as over the entire sample period from 1991-2019 for 3,431 U.S. actively managed funds. We calculate all of the values at the fund-month level and convert them into equivalent annualized units.

Year	Mean	Std	P25	P50	P75
1991	10.65	9.27	4.60	6.90	13.47
1992	8.60	6.46	4.27	6.38	10.83
1993	7.36	5.29	4.13	5.70	8.64
1994	6.61	4.60	3.72	5.10	7.66
1995	5.98	3.87	3.61	4.91	7.05
1996	5.92	4.16	3.73	5.07	6.99
1997	6.71	4.45	4.27	5.80	7.99
1998	7.54	4.59	4.63	6.47	9.10
1999	8.71	5.00	5.44	7.67	10.69
2000	13.12	8.78	7.32	10.94	16.23
2001	9.50	7.03	5.15	7.77	11.65
2002	7.64	6.27	4.52	6.59	9.31
2003	5.08	3.73	3.08	4.46	6.21
2004	4.58	2.64	2.77	4.04	5.70
2005	4.18	2.57	2.63	3.69	5.08
2006	4.30	2.50	2.67	3.75	5.26
2007	4.49	2.84	2.68	3.81	5.48
2008	8.60	6.05	4.73	7.05	10.70
2009	6.73	4.32	3.77	5.64	8.53
2010	4.29	2.48	2.65	3.75	5.28
2011	4.79	3.08	2.89	4.09	5.80
2012	3.82	1.99	2.50	3.45	4.69
2013	3.43	1.73	2.29	3.09	4.15
2014	3.75	2.14	2.31	3.25	4.61
2015	3.99	2.22	2.52	3.47	4.86
2016	4.35	2.63	2.64	3.72	5.29
2017	3.52	2.06	2.23	3.07	4.28
2018	4.43	2.78	2.65	3.76	5.38
2019	4.01	2.26	2.47	3.51	4.98
1991-2019	5.64	4.65	2.95	4.38	6.72

Table 3.4: Summary Statistics of Actively Managed Funds by Fund Style

This table summarizes the cross-sectional mean for raw net returns, tracking errors, and fund characteristics including expense ratio, turnover ratio, total net assets, fund age, and fund flows for 3,431 U.S. actively managed funds from 1991-2019. We calculate all of the values at the fund-month level and convert them into equivalent annualized units.

Style category	Raw Net Return (%)	Tracking Error (%)	Expense Ratio (%)	Turnover Ratio (%)	Total Net Assets ($M)	Fund Age (Years)	Fund Flow (%)
LB	8.26	4.64	1.02	70.49	1,838.13	16.06	5.30
LG	8.80	5.69	1.08	81.86	2,327.66	16.43	4.31
LV	8.15	4.63	0.99	59.26	1,877.47	14.42	5.44
MB	8.96	6.36	1.22	79.08	781.79	11.12	4.35
MG	9.30	7.15	1.17	99.15	1,055.13	14.52	5.19
MV	9.39	5.60	1.09	68.75	1546.76	11.34	8.95
SB	9.15	5.77	1.17	71.42	655.61	10.67	6.24
SG	9.56	6.88	1.29	99.21	588.87	11.69	5.53
SV	9.37	6.08	1.23	65.94	683.06	11.16	6.42

3.5. Model Selection, Results, and Empirical Analysis

3.5.1. Model Selection

To investigate the presence of a threshold level, we hypothesize a concave relationship between tracking errors and fund performance. For this purpose, we fit a quadratic regression equation of a parabola and regress various performance metrics of a fund on its tracking errors, both with and without the addition of control variables. We include the quadratic term, TE2, to see if the relationship between fund performance and tracking errors is concave.

With the addition of control variables, we mitigate any concern that the relationship between performance and tracking errors may be due to their relationship with other characteristics of a fund. The control variables include expense ratio, turnover ratio, the natural logarithm of total net assets, the natural logarithm of fund age, and fund flows. We also control for time and fund fixed-effects.

Our model is specified as follows:

$$Perf_{it} = \beta_1 TE_{it} + \beta_2 TE2_{it} + \beta_3 EXP_{it} + \beta_4 TURN_{it} + \beta_5 LogTNA_{it} + \beta_6 LogAGE_{it} + \beta_7 FLOW_{it} + TIME_t + FUND_t + e_{it}$$

where $Perf_{it}$ represents the raw net return, active return, or the risk-adjusted return under the CAPM, the Fama-French three-factor model, or the Carhart four-factor model of fund *i* in month *t*. TE_{it} is the tracking error of fund *i* in month *t*. $TE2_{it}$ represents the square of the tracking error. The control variables include the following. EXP_{it} represents the expense ratio of a fund in month *t*. $TURN_{it}$ represents the turnover ratio of fund *i* in month *t*. $LogTNA_{it}$ is the natural logarithm of the total net assets (in million dollars) of fund *i* in month *t*. $LogAGE_{it}$ is the natural logarithm of the age of the fund in month *t*. $FLOW_{it}$ is the net percentage growth in fund assets from *t*-1 to *t* as defined in Equation (3.7). $TIME_t$ (time dummies) is indicative of time fixed effects and $FUND_t$ indicates fund fixed effects.

If β_2 is positive, the parabola shapes up (is convex), but when β_2 is negative, the parabola shapes down (is concave). Since we are interested at the point where the relationship between tracking errors and risk-adjusted returns changes from positive to negative, we would expect the threshold level of deviation to exist if the coefficient of TE is positive and TE2 is negative. We can easily find this threshold level of tracking errors using the following mathematical formula:

$$\text{TE-Threshold} = \frac{-\beta 1}{2\beta 2} \qquad (3.10)$$

3.5.2. Results and Empirical Analysis

This section examines the relationship between performance and tracking errors using multivariate regression analysis. We test this relationship by regressing fund performance on tracking errors with and without controlling for fund characteristics that may affect fund performance and using style and time fixed effects.

In each month, we regress different performance measures on tracking errors (TE) and tracking errors squared (TE2). A positive β_2 coefficient is indicative of a convex relationship between performance and tracking errors, while a negative β_2 coefficient is indicative of a concave relationship between the two. Since we are interested in finding the inflection point where the effect of tracking errors changes from positive to negative, we expect β_1 to be positive and β_2 to be negative.

Table 3.5 presents the multivariate regression results for pooled cross-sectional regressions from 1991-2019, both with and without the impact of the control variables. The first four columns of the table report raw net returns and active returns as the dependent variable, respectively, while the last six columns use CAPM, three-factor, and four-factor risk-adjusted returns as the dependent variable, respectively. The model tends to examine how tracking errors are related to the raw net returns, the active returns, and the CAPM, three-factor, and four-factor risk-adjusted returns of a fund. That is, the effect of deviating and moving away from the benchmark index on the performance of a fund. We introduce time fixed effects to limit the impact of any unobserved heterogeneity on the cross-section of funds due to the passage of time and fund dummies to limit the effect of time invariant unobservable fund characteristics. We focus on the coefficient estimate of tracking errors (TE) and tracking errors squared (TE2) (i.e., β_1 and $\beta_{2,}$ respectively) to test our hypothesis.

The linear tracking error (TE) variable is significant and positively relates to annualized monthly fund performance in all models at a 1% significance level. The quadratic tracking error (TE2) variable is significantly and negatively associated with annualized monthly fund performance in all model specifications at a 1% significance level. Moreover, the linear tracking error (TE) variable is economically significant with magnitudes of the estimate for β_1 ranging between 0.09 and 0.85 depending upon the use of the performance metric and the model specification used. Similarly, the quadratic tracking error (TE2) variable is economically significant with magnitudes of the estimate for β_2 ranging between -0.01 and -0.02 depending upon the use of the performance metric and the model specification used. Considering Model specification (2), where we have raw returns as our dependent variable, initially fund performance increases by 0.23% with every 1% increase in tracking errors. However, as soon as the fund crosses the threshold level of tracking error, which is 13%, fund performance starts decreasing by 0.01% with every 1% increase in tracking errors. For model specifications (4), (6), (8) and (10) where we have active returns, CAPM, three-factor and four-factor risk adjusted returns as our dependent variables, the tracking error threshold comes out to be 16%, 6%, 25% and 22% respectively. These results strongly support our hypothesis. Fund performance increases as the fund deviates from its benchmark, while fund performance decreases as the fund continues to deviate from its benchmark beyond a certain threshold.

The analysis above suggests that the threshold level for excessive deviations could be different under different model specifications. The investors can thus rely on the asset pricing model specification that they deem most appropriate for their evaluations to adjust for systematic (non-diversifiable) risks. For instance, retail investors may prefer simple CAPM model specification, which relies on just market risk premium as independent variable that serves as a catch-all proxy for economic cycles. On the other hand, institutional investors may choose to apply either three-factor or four-factor asset pricing model depending on whether they perceive the fourth factor (momentum factor) as a valid proxy for another non-diversifiable risk.

In addition, the expense ratio is significantly and negatively associated with fund performance in Columns (4) and (5) model specifications and the turnover ratio is significantly and negatively associated with fund performance in all of the model specifications. This is in line with earlier studies by Bogle (1998), Carhart (1997), and Gil-Bazo and Ruiz-Verdu (2009). A study conducted by Huang et al. (2011) also indicates severe performance consequences for higher expense ratio funds. The literature explains that the negative relationship between fund performance and turnover is because active funds indulge in more information processing and higher trading increasing the expenses of a fund in a way that may diminish the relative performance of it. We further find that the fund flow is significantly and positively related to fund performance in all of the model specifications. Again, these findings are in line with literature that suggests investors' preferences to invest in high performing funds (Sirri & Tufano, 1998; Ippolito, 1992; Bogle, 1998). At the same time, we find the age of the fund to be positively related to fund performance and the total net assets of a fund to be negatively related to fund performance (Chen et al., 2004; Yan, 2008).

Table 3.5: Pooled Regressions with Time and Fund Fixed Effects for the Sample Period (1991-2019)

This table explores the relationship between tracking errors and the performance of funds. The dependent variable is raw net returns, active returns, and the risk-adjusted returns obtained through the CAPM, the three-factor model, and the four-factor model. We control for expense ratio, turnover ratio, the natural logarithm of total net assets, the natural logarithm of age, and fund flow. We further control for time and fund fixed effects. We report t-values in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

$Perf_{it} = \beta_1 TE_{it} + \beta_2 TE2_{it} + \beta_3 EXP_{it} + \beta_4 TURN_{it} + \beta_5 Log\ (TNA)_{it} + \beta_6\ Log\ (AGE)_{it} + \beta_7 FLOW_{it} + \mathrm{TIME}_t + \mathrm{FUND}_{t\,+}\ e_{it}$

	Raw Return		**Active Return**		**CAPM**		**3 -Factor**		**4-Factor**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TE	0.2456***	0.2332***	0.2868***	0.2784***	0.1031***	0.0914***	0.4957***	0.4906***	0.8466***	0.8452***
	(14.43)	(13.72)	(19.47)	(18.91)	(6.57)	(5.83)	(38.53)	(38.14)	(65.03)	(64.91)
TE2	-0.0092***	-0.0092***	-0.0087***	-0.0087***	-0.0071***	-0.0071***	-0.0099***	-0.0099***	-0.0192***	-0.0192***
	(47.88)	(-47.99)	(-52.11)	(-52.15)	(-39.98)	-(40.09)	(-67.74)	(-67.94)	(-130.47)	(-130.67)
EXP		0.3745		0.0894		0.7834***		-0.2344***		-0.1080***
		(1.41)		(0.39)		(-3.20)		(-1.17)		(-0.53)
TURN		-0.0011***		-0.0013**		-0.0026***		-0.0035***		-0.0052***
		(-1.59)		(-2.04)		(-3.89)		(-6.53)		(-9.52)
Log (TNA)		-1.0348***		-0.9684***		-0.9585***		-0.6622***		-0.8612**
		(-18.78)		(20.30)		(18.88)		(15.89)		(20.42)
Log (AGE)		0.6261***		0.2950***		0.1624*		0.0381		0.1510*
		(5.92)		(3.22)		(1.67)		(0.48)		(1.86)
FLOW		0.0317***		0.0200***		0.0294***		0.0182***		0.0124***
		(42.77)		(31.29)		(43.06)		(32.51)		(21.80)
TE-Threshold		13%		16%		6%		25%		22%
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	467,456	467,456	467,456	467,456	467,456	467,456	467,456	467,456	467,456	467,456
R-Squared	0.7947	0.7957	0.0672	0.0703	0.1507	0.1553	0.0910	0.0940	0.1051	0.1071

3.5.3. Robustness Tests

In this section, we test for the robustness of our main results by considering several alternatives for the main tests.

3.5.3.1. Fama-MacBeth Regression

In this section, we conduct Fama-MacBeth (1973) regression analysis to best gauge the relationship between our variables of interest. We consider time-varying betas to further test the role of tracking errors on fund performance. There are two main reasons to incorporate this approach. It accounts for the time-varying betas and it estimates standard errors by eliminating the issue of heteroskedasticity and correlation among errors.

For each year, from 1991-2019, we regress fund performance on tracking errors (TE) and tracking errors squared (TE2) and control for different fund characteristics. We then calculate the average of these parameter estimates across the entire sample period. Table 3.6 provides the estimation results using the Fama-MacBeth (1973) regression. The first four columns represent coefficient estimates from the raw net returns and the active returns, while the last six columns represent coefficient estimates from the CAPM, three-factor, and four-factor risk-adjusted returns, respectively. The focus of our analysis is on the parameter estimates of the tracking errors (TE) and the associated quadratic term (TE2).

We find results using the model specifications, both with and without the use of control variables. We find the linear tracking error (TE) variable to be positively related to the annualized monthly fund performance. However, this relationship was only significant within Model Specifications (2), (3), and (4) at the 5%, 1%, and 5% levels of significance, respectively. Also, we find the quadratic tracking error (TE2) variable to be negatively associated with annualized monthly fund performance metrics across all of the model specifications except Models (3), (9), and (10). Moreover, we do not find this variable to be economically significant at any model specification within the Fama-MacBeth (1973) analysis.

Overall, seven of the ten model specifications support our hypothesis that there is a concave relationship between fund performance and the style deviation of a fund suggesting that fund performance increases as the fund deviates from its benchmark. However, fund performance decreases as the fund continues to deviate from its benchmark beyond a certain threshold level. However, we find little evidence that this relationship is statistically significant under the Fama-MacBeth (1973) analysis.

Table 3.6: Fama-MacBeth Multivariate Regression for the Sample Period (1991-2019)

This table explores the relationship between tracking errors and the performance of funds using Fama and MacBeth (1973) regression analysis. The dependent variable is raw net returns, active returns, and the risk-adjusted returns obtained through CAPM, three-factor, and the four-factor models. We control for expense ratio, turnover ratio, the natural logarithm of total net assets, the natural logarithm of age, and fund flow. We report t-values in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

$Perf_{it} = \beta_1 TE_{it} + \beta_2 TE2_{it} + \beta_3 EXP_{it} + \beta_4 TURN_{it} + \beta_5 Log\ (TNA)_{it} + \beta_6\ Log\ (AGE)_{it} + \beta_7 FLOW_{it} + e_{it}$

	Raw Return		**Active Return**		**CAPM**		**3 -Factor**		**4-Factor**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TE	0.3071	0.3547**	0.1811*	0.2248**	0.1198	0.1768	0.0644	0.1063	0.0060	0.0629
	(1.64)	(2.09)	(1.72)	(2.17)	(0.62)	(1.01)	(0.65)	(1.09)	(0.06)	(0.66)
TE2	-0.0078	-0.0103	0.0001	-0.0018	-0.0057	-0.0073	-0.0001	-0.0001	0.0011	0.0006
	(-0.99)	(-1.34)	(0.02)	(-0.28)	(-0.74)	(-0.96)	(-0.02)	(-0.02)	(0.20)	(0.11)
EXP		-0.5451*		-0.7236***		-0.5811**		-0.6482***		-0.6418
		(-1.88)		(-2.97)		(-2.13)		(-4.42)		(-4.30)
TURN		0.0019		0.0019		-0.0035		-0.0036**		-0.0070
		(0.76)		(0.93)		(-1.55)		(-2.04)		(-4.79)
Log (TNA)		0.1110		0.0969		0.0494		0.0788		-0.0163
		(0.96)		(1.16)		(0.57)		(1.43)		(-0.31)
Log (AGE)		0.0854		0.0248		-0.0213		-0.0668		-0.0595
		(0.60)		(0.29)		(-0.18)		(-1.05)		(-0.93)
FLOW		0.0240***		0.0171***		0.0234***		0.0172***		0.0135***
		(8.57)		(9.93)		(9.39)		(12.04)		(11.64)

3.5.3.2. Panel Regression for Small and Large Funds

We further test the robustness of the main results by partitioning the full sample into large and small funds. To partition funds each month, we split the funds based on the sample median of the size (i.e., total net assets) of the funds. We then define funds below the median size (i.e., total net assets) as small funds and funds above the median size (i.e., total net assets) as large funds.

The results related to this analysis are present in Table 3.7. We find the relationship between the linear tracking error (TE) variable to be positively related to the annualized monthly fund performance in all models. This relationship is also statistically significant at the 1% level across all of the model specifications except Specification (6). The quadratic tracking error (TE2) variable is significantly and negatively associated with annualized monthly fund performance in all model specifications at the 1% significance level. The β_1 estimate for the economically significant linear tracking error coefficient ranges between 0.01 and 1.04 subject to the performance metrics used within various model specifications.[15] The β_2 estimate for the economically significant linear tracking error coefficient ranges between -0.01 and -0.02 subject to the performance metrics used within the various model specifications.[16]

The results are very similar to the primary sample using fixed effects regression and support our hypothesis. Fund performance increases as the fund deviates from its benchmark; however, fund

[15] The magnitude of the impact is more than what we find (about 0.0914 to 0.8466) in Table 3.5, which considers the full sample of funds.
[16] The magnitude of the impact is more than what we find (about -0.0071 to -0.0192) in Table 3.5, which considers the full sample of the fund.

performance decreases as the fund continues to deviate from its benchmark beyond a certain threshold level.

Table 3.7: Pooled Regression with Time and Fund Fixed Effects for Small and Large Funds (1991-2019)

This table reports the relationship between tracking errors and the performance of funds. The dependent variable is raw net returns, active returns, and the risk-adjusted returns obtained through the CAPM, the three-factor, and the four-factor models. We control for expense ratio, turnover ratio, the natural logarithm of total net assets, the natural logarithm of age, and fund flow. We further control for time and style fixed effects. We report t-values in the parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

$Perf_{it} = \beta_1 TE_{it} + \beta_2 TE2_{it} + \beta_3 EXP_{it} + \beta_4 TURN_{it} + \beta_5 Log\ (TNA)_{it} + \beta_6\ Log\ (AGE)_{it} + \beta_7 FLOW_{it} + \mathrm{TIME}_t + \mathrm{FUND}_{t} + e_{it}$

	Raw Net Return		Active Return		CAPM Return		3 Factor		4 Factor	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
TE	0.3698***	0.0079	0.3497***	0.1394***	0.1816***	-0.1077	0.4749***	0.4579***	1.0442***	0.5308***
	(15.16)	(0.31)	(16.20)	(6.49)	(8.07)	(-4.59)	(25.03)	(24.60)	(54.05)	(28.51)
TE2	-0.0087***	-0.0102***	-0.0081***	-0.0096***	-0.0075***	-0.0065***	-0.0102***	-0.0095***	-0.0241***	-0.0118***
	(33.39)	(-34.84)	(-35.22)	(-39.11)	(-31.21)	(-24.26)	(-50.78)	(-44.27)	(-117.66)	(-55.18)
EXP	0.4824	0.0671	0.2658	-0.2984	1.0753***	-0.3769	0.3427	-1.9909***	0.4580*	-1.4387***
	(1.41)	(0.12)	(0.88)	(-0.62)	(-3.41)	(-0.72)	(1.29)	(-4.77)	(1.69)	(-3.44)
TURN	-0.0007	-0.0072***	-0.0011	-0.0067***	-0.0019**	-0.0086***	-0.0028***	-0.0085***	-0.0038***	-0.0121***
	(-0.80)	(-4.66)	(-1.53)	(-.5.13)	(-2.44)	(5.99)	(-4.20)	(-7.54)	(-5.53)	(-10.64)
Log (TNA)	-1.2819***	-1.0114	-1.1395***	-0.9885***	-1.0667**	-1.0166***	-0.8488***	-0.6134*	-0.8689***	-0.9851*
	(-10.78)	(-10.13)	(-10.83)	(-11.75)	(-9.72)	(11.07)	(-9.18)	(-8.42)	(-9.22)	(-13.52)
Log (AGE)	1.1412***	0.3761*	0.7202***	0.1604	0.7297***	-0.3965**	0.4292***	-0.2743*	0.4527***	0.0192
	(7.30)	(1.87)	(5.21)	(0.95)	(5.06)	(-2.15)	(3.53)	(-1.87)	(3.66)	(0.13)
FLOW	0.0282***	0.0375***	0.0185***	0.0206***	0.0266***	0.0342***	0.0170***	0.0192***	0.0123***	0.0111***
	(29.24)	(30.03)	(21.62)	(19.53)	(29.84)	(29.75)	(22.59)	(21.10)	(16.08)	(12.16)
Fund Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	233,726	233,726	233,726	233,726	233,726	233,726	233,726	233,726	233,726	233,726
R-Squared	0.7889	0.8080	0.0741	0.0879	0.1761	0.1510	0.0977	0.1118	0.1288	0.1050

3.6. Conclusion

In this study, we attempt to determine the existence of a threshold level of deviation beyond which a fund is likely to exhibit the properties of a misclassified fund. To determine the existence of this threshold level, we hypothesize a concave relationship between fund performance and tracking errors. We use a quadratic regression model and multivariate regression analysis, along with the Fama-MacBeth (1973) regression analysis to determine the presence of this threshold level of tracking errors. The main results of our regression for the sample period from 1991-2019 depicts a consistent concave relationship that exists between various fund performance metrics and tracking errors. These results support our hypothesis and suggest a threshold level to exist beyond which a fund is likely to exhibit the properties of a misclassified fund.

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Appendix A

Table A.1:Description of Variables
This table describes all of the main variables of this study.

Variable	**Description**
Perf	The raw net return, active return, or the risk-adjusted return under the CAPM, Fama-French three-factor model, or Carhart four-factor model.
TE	The tracking error of a fund.
TE2	The square of the tracking error of a fund.
EXP	The percentage of fund assets paid for management fees and operating expenses.
TURN	The lesser of sales or purchases divided by the average monthly net assets of a fund.
Log (TNA)	The natural logarithm of the total net assets under management of a fund.
Log (AGE)	The natural logarithm of the number of years from the inception date of a fund.
FLOW	The percentage growth of the total net assets of a fund due to additional investments.

Chapter 4: Mutual Funds Portfolio Holdings Disclosure and Style Drift

Abstract

This chapter examines the effect of more frequent portfolio disclosures on the style drift of mutual funds. Since 2004, the SEC revised the filing of mandatory portfolio holdings disclosure frequency by requiring all mutual funds to disclose quarterly rather than semi-annually. Then, again in 2019, the SEC changed this requirement of filing mandatory portfolio holdings disclosure from quarterly to monthly. These changes in regulation offer a natural setting to analyze the impact of disclosure frequency on the style drift of mutual funds. To determine the impact of the 2004 regulation change, we use a difference-in-difference test using a sample period from 1995-2010 and find statistically significant evidence that this increase in the disclosure frequency results in decreasing style drift by 0.79 points, on average, for previously semi-annual disclosing funds. Further analysis over the sample period from 2009-2021 for the 2019 regulation change also suggests that the increase in disclosure frequency from quarterly to monthly reduced the style drift in previously quarterly disclosing funds by 0.51 points. These results support our hypothesis that the style drift of funds with a more frequent disclosure regime is lower than the style drift of funds with a less frequent disclosure regime.

Keywords Mutual Funds; Portfolio Holdings Disclosure; Portfolio Disclosure Frequency, Style Drift, SEC Regulation, Difference-in-difference Test

4.1. Introduction

The information present within the mutual fund portfolio holding disclosure is useful to investors for assessing fund investment style, risk-taking, performance, and strategy.[17] The more frequent the disclosure, the easier it is for investors to monitor their securities and keep a track of their portfolios. It enables shareholders to detect any changes to the funds' investment strategy and lower the instances of “style drift” within mutual funds (Ge & Zhang, 2006; Gregory-Allen, Balli, and Thompson., 2019). However, the frequency of mutual fund portfolio disclosure has been a focus of longstanding debate among academics, regulators, and industry participants because of the costs and benefits associated with the disclosure of information to industry participants. This study investigates the relationship between disclosure frequency and style drift of mutual funds. We argue that more frequent disclosure contributes to lower levels of style drift.

Those concerned with the costs of more frequent portfolio disclosure present several arguments against it. They fear that more frequent portfolio disclosure is likely to lower total returns to the shareholders from mutual fund investments. An increase in the front-running activities could subsequently increase fund trading costs raising free-riding activities and restraining the fund’s ability to benefit fully from research and additional costs associated with tax management strategies that provide liquidity to fund shareholders. In fact, mandatory portfolio disclosure

[17] See Wermers (1999, 2000), Grinblatt and Titman (1989, 1993), Daniel, Grinblatt, Titman, and Wermers (1997), Cohen, Coval, and Pastor (2005), Kacperczyk, Sialm, and Zheng (2005, 2008), Kacperczyk and Seru (2007), Alexander, Cici, and Gibson (2006), and Jiang, Yao, and Yu (2007).

frequency was decreased from quarterly to semi-annually by the U.S Securities and Exchange Commission (SEC) in 1985.

Others present several benefits in support of a more frequent disclosure regime. An increase in portfolio holdings disclosure frequency could ease investors' monitoring of their securities in various funds and help build public confidence. It could facilitate asset allocation and diversification choices for their overall portfolios. In addition, it would enable shareholders to detect any changes to the funds' investment strategy and lower the instances of style drift within mutual funds. Investor advocacy groups filed a petition with the SEC requiring more frequent and complete portfolio holdings disclosure to expose any instances of style drift within a fund.[18] Finally, a more frequent disclosure regime could make “window-dressing” strategies that generate differences between the portfolio held on the reporting date and the portfolio held at other times more costly. Long after 1985, the SEC acknowledged the benefits of a more frequent disclosure regime by revisiting the Investment Company Act of 1940 in May 2004 and requiring mutual funds to file their portfolio holdings information every quarter rather than every six months.[19] More recently, in October 2016, the SEC enacted a new rule replacing quarterly disclosures with monthly disclosures.[20] However, the filing of these monthly disclosures through the Electronic

[18] For more information, see https://www.sec.gov/rules/final/33-8393.htm.

[19] See Shareholder Reports and Quarterly Portfolio Disclosure of Registered Management Investment Companies (2004) adopted by the SEC.

[20] For more information on Investment Company Reporting Modernization (2016) see https://www.sec.gov/rules/final/2016/33-10231.pdf.

Data Gathering, Analysis, and Retrieval (EDGAR) system, which is the primary system used by companies and others to file their forms with the U.S. SEC, started in April 2019.[21]

Our study contributes to the finance literature on fund disclosures. There exists a wide strand of the literature examining the costs (i.e., front running, free riding, and lower shareholder returns) of a more frequent disclosure regime (Wermers, 2001; Verbeek & Wang, 2013; Parida & Teo, 2018; Parida, 2019). However, our study attempts to investigate one of the benefits of a more frequent portfolio regime. That is, lowering the instances of style drift within mutual funds. The impact of the disclosure frequency on the style drift of mutual funds is yet to be explored. Most of the previous studies explore the impact of portfolio disclosure on fund returns (Parida & Teo, 2018; Shi, 2017; Gregory-Allen et al., 2019). Other researchers, such as Agarwal, Mullally, and Yang (2015), examine the impact of mandatory portfolio disclosure on stock liquidity and mutual fund performance. In addition, Ge and Zheng (2004) explore the determinants and potential effects of portfolio disclosure frequency by comparing funds providing voluntary quarterly disclosure to funds providing only mandatory semi-annual disclosure. However, to the best of our knowledge, we have not seen a study that explores the impact of the frequency of portfolio disclosure on the style drift of a fund.

In this study, we empirically examine the impact of more frequent portfolio disclosure on the style drift of mutual funds. The fact that the U.S. Securities and Exchange Commission changed the mandatory portfolio holdings disclosure frequency from semi-annual to quarterly in May 2004 and

[21] For more information on the Interim Final Rule: Amendments to the Timing Requirements for Filing Reports on Form N-Port (2019) see https://www.sec.gov/rules/interim/2019/ic-33384.pdf.

then quarterly to monthly in April 2019 provides us with a unique opportunity to explore whether more frequent portfolio disclosure has been effective in containing style drift within mutual funds. We first investigate the 2004 policy change and study U.S domestic equity open-end funds from 1995-2010. Our univariate analysis suggests that before the policy change, from 1995-2003 the style drift score of semi-annually disclosing funds is greater than the quarterly disclosing funds by almost 1.56 points per month. We then find that the style drift score of semi-annually disclosing funds declines and is greater than the quarterly disclosing funds by only 0.07 points a month after 2004 when a shift to more frequent disclosure was made by the SEC. We further run a difference-in-difference test using the sample period from 1995-2010 to establish whether this decrease resulted from the shift in the mandatory disclosure policy. We consider previously semi-annually disclosing funds that had to disclose every quarter after 2004 as the treatment group and funds that disclosed quarterly throughout as the control group. Our findings from the multivariate analysis indicate that the style drift of previously semi-annual funds has declined by about 0.79 points a month after 2004. These findings are in line with our hypothesis that the previously semi-annual funds are now less exposed to the style-drifting activities of the fund managers. In addition, our findings remain robust even when we run a difference-in-difference test for small and large funds, as well as growth and value funds.

We then conduct further analysis under a more contemporary setting using the 2019 policy change to see if the increase in disclosure frequency translates into a decrease in the style drift of mutual funds. For this purpose, we analyze U.S. open-end equity mutual funds from 2009-2021. Our findings suggest a drop in the style drift of quarterly disclosing funds by 0.51 points when these mutual funds were required to move to an even more frequent disclosure regime of monthly reporting. Our findings to remain robust when the dependent variable, the style drift score, is calculated using the Morningstar style indices as opposed to the Russell style indices used in the previous analysis.

We believe that it is important to study the impact of disclosure frequency on style drift for several reasons. It gives us a good indication whether the U.S. SEC has been effective in reaping one of the benefits of a frequent disclosure regime. That is, reducing the instances of style drift (i.e., one of the rationales behind increasing the disclosure frequency). The findings of our study also offer implications for regulatory authorities around the globe regarding changes in their disclosure frequency. It may be wise to consider the optimal frequency of disclosure given its benefits and costs.

We organize the rest of this chapter as follows: Section 4.2 discusses the literature and hypothesis development. Section 4.3 explores the data and variables. Section 4.4 presents a discussion of model selection, results, and empirical results. Section 4.5 conducts further analysis, while Section 4.6 provides our conclusions.

4.2. Institutional Background, Literature Review, and Hypothesis Development

4.2.1. Institutional Background

External oversight of the mutual funds' industry is the responsibility of the Securities and Exchange Commission. This oversight responsibility not only includes investigations and enforcement actions associated with misleading disclosures, but also regular reviews of fund disclosures and inspections of fund operations. Mandatory portfolio holdings disclosure of institutional investors is a crucial part of securities market regulations. Securities market regulations via the Securities Act of 1934 and the Investment Company Act of 1940 require institutional money managers (including mutual funds, closed-end funds, and unit investment trusts) to disclose their portfolio holdings and investment activities via periodic filings to fund investors. This information helps investors make better investment decisions, facilitates governance, improves transparency within capital markets, enhances competition, reduces management fees, and promotes efficiency within the funds' management industry.

Prior to May 2004, the requirement to file mandatory portfolio holdings was semi-annually using Form N-30D. In May 2004, the SEC passed a new rule requiring Form N-30D to be replaced with Form N-CSR that must be filed by the end of the second and fourth fiscal quarters by mutual funds. Form N-Q was also introduced in this new rule requiring portfolio holdings disclosure at the end of the first and third fiscal quarters. This new rule changes the reporting frequency from two to four times a year with each report filed with no more than a 60-day delay. In addition, these forms were to be certified by the principal executive and financial officers of the fund before their submission to the SEC with a requirement to produce audited fiscal year-end portfolios.

In October 2016, a new rule was enacted by the SEC to modernize the standards for risk management and disclosure practices for investment companies (SEC, 2016). This rule created Form N-PORT (replacing Form N-Q) and must be filed on a monthly, rather than a quarterly, basis to the commission with no later than a 30-day delay. This new rule became effective in March 2019 and the first form had to be filed by May 2019 (SEC, 2019). However, the reports on Form N-PORT are only made available to the public for every third month of the fund’s fiscal quarters with no more than a 60-day delay. For the public, the status quo of a quarterly reporting schedule with a 60-day delay was maintained (Calluzzo, Moneta, & Topaloglu, 2021). However, the monthly filing with the SEC would still put pressure on fund managers not to drift.

The other disclosure requirements via Section 13(f) of the Securities Exchange Act of 1934 necessitates mutual fund companies to quarterly disclose their aggregate holdings in Form 13F with a delay of no longer than 45 days. Form N-PORT is at the individual fund level and provides much more detailed information than Form 13F, which only provides information at the company level. Since mutual fund companies typically offer multiple funds, the aggregated data in 13F are less informative. Also, Form 13F filing is only applicable to large investors holding $100 million or more in 13F securities. It provides information on large positions only (with 10,000 shares or a market value over $200,000) in the 13F securities comprised of equities, exchange-listed options, and convertible bonds.[22] Form N-PORT filings are for all types of mutual funds for all securities irrespective of their fund size or the size of the position held in individual securities. Through Form N-PORT, disclosures are more valuable and informative than through Form 13F filed by mutual fund families. Form 13F has always been required quarterly with no regulatory change in its reporting frequency by the SEC.

Mutual funds can also choose to report their portfolio holdings information more often than mandated by their regulatory authorities. These voluntary disclosures can be made via Form N-30B-2 to the SEC or to data vendors, such as Morningstar and Thomson Reuters. Many funds seek

[22] For more information on 13F filings, see http://www.sec.gov/divisions/investment/13ffaq.htm.

to implement their voluntary portfolio disclosure strategies beyond the regulatory mandatory disclosures.

4.2.2. Literature Review and Hypothesis Development

The portfolio holdings information is valuable for both investors and regulators in selecting and monitoring funds. Investors perform asset allocation, style analysis, risk modelling, and performance attribution among other evaluation activities, while it helps regulators in the monitoring of industry trends and conducting enforcement (SEC, 2016). The benefits of portfolio holdings disclosure do not come without costs as with more frequent disclosure requirements, the returns to the shareholders are likely to suffer. Frequent portfolio disclosure may increase front running by industry professionals and speculators.[23] It is also likely to aid copycat (free riding) investment strategies and limit the funds' ability to take advantage of its research fully.[24] Finally, it increases the direct costs of a fund due to increased printing and dissemination of additional reports to the shareholders (Frank et al., 2004; Wermers, 2001; Shi, 2017).

Many empirical studies provide evidence regarding the front running activities in the mutual fund industry. Cai (2003) finds evidence that market makers indulged in front running activities against Long Term Capital Management (LTCM) in the late 1990s. Coval and Stafford (2007) illustrate

[23] Front running occurs when other investors buy (sell) securities in anticipation of buy (sell) trades by a fund.
[24] Free riding is a situation where some other copycat funds mimic the holdings of actively managed funds and re-balance their portfolio holdings based on the disclosures of those actively managed funds.

that mutual funds experiencing large inflows (outflows) choose to increase (decrease) their dominant portfolio positions creating opportunities for other market participants to front run the projected forced trades by funds enduring extreme capital flows. They run a hypothetical front running strategy producing between 0.35% and 1.07% returns a month. Dyakov and Verbeek (2013) illustrate that from 1990-2010, a real-time trading strategy front running the anticipated forced sales by mutual funds suffering extreme capital outflows generates an alpha of 0.5% per month. Aragon, Hertzel, and Shi (2013) find that managers are more susceptible to pursuing confidential treatment of illiquid positions that are more prone to front running and highlight several important benefits of reduced disclosure.

There is also substantial research on “copy strategy.” Wermers (2001) discusses the possibility of lower shareholder returns with more frequent portfolio disclosure due to the free riding problem and front running activities. Frank et al. (2004) examine 812 high expense funds in the 1990s and find that the copycat funds earn statistically indistinguishable and perhaps higher returns (after expenses) than the target actively managed funds. Verbeek and Wang (2013) investigate the performance of copycat funds and determine that, on average, these funds were able to generate performance comparable to their target fund (considering transition costs and expenses). They further find evidence that their relative success substantially increased after 2004 when the SEC increased the disclosure requirements from semi-annual to quarterly. They conclude that the cost of the increase in disclosure is high due to copycat funds receiving additional information on which to free ride.

Ge and Zhang (2006) study the relation between disclosure frequency and fund performance conditional upon the investment skills of a fund. They find the presence of an asymmetric relationship between fund performance and disclosure frequency for past winners and losers. Less frequently disclosing past winners outperform more frequently disclosing past winners, while less frequently disclosing past losers underperform more frequently disclosing past losers. Shi (2017) runs a difference-in-difference regression and finds a decrease in fund performance after hedge funds start filing Form 13F. They argue that portfolio disclosure exposes trade secrets and the cost of portfolio disclosure to performance is economically significant suggesting that the current mandatory disclosure regime needs improvement. Parida and Teo (2018) study the impact of disclosure on fund returns after the policy change in 2004 and discover that before the policy change, successful semi-annual disclosing funds outperform successful quarterly disclosing funds by 17-20 basis points a month. However, after 2004, the performance of successful semi-annual disclosing funds suffers and they no longer outperform successful quarterly disclosing funds.

Nevertheless, a large body of literature has shown that this disclosure information contains valuable information for fund investors. Gregory-Allen et al. (2019) find that these disclosures advance investor monitoring and oversight of their delegated investments. The transparency permits investors to detect any instances of non-compliance of the fund with its stated investment objectives. It enables tracking of the funds' engagement in portfolio manipulation (i.e., portfolio pumping and window dressing). Daniel et al. (1997) state that the portfolio holdings information allows the construction of benchmarks that appropriately capture fund managers' investment styles and makes it easier to determine if the fund managers possess any stock selection or timing skill. Many other pieces of research indicate that mutual fund holdings disclosure provides valuable information to fund investors to assess the style, strategy, performance, and risk-taking within their investments.[25]

One of the SEC's rationales behind the change in disclosure frequency from semi-annually to quarterly and then to monthly was that the increase in disclosure frequency would facilitate the monitoring of investors' securities in various funds and subsequently improve diversification and asset allocation selections for their overall portfolio. Also, more frequent disclosure would help fund investors notice any changes to the funds' investment strategy and detect style drift. Trading violations and deviations from the initial fund objectives are more visible when holding information is regularly provided (Ge & Zhang, 2006, Gregory-Allen et al., 2019). Greater portfolio disclosure requirements enable investors and regulators to monitor fund activities more closely discouraging them from engaging in activities that are not in the best interest of their investors. Furthermore, it will also make it more costly for fund managers to pursue "window dressing" strategies. Da et al. (2010) mention improved governance and the ability to make more knowledgeable investment decisions as some of the potential benefits for fund investors of the increase in disclosure. They analyze the determinants and potential effects of frequent portfolio holding disclosures and compare the funds providing mandatory six-month disclosure vs. the funds providing voluntary quarterly disclosure. For this purpose, they consider U.S. equity funds from 1985-1999 and discover that the funds with higher expense ratios, turnover ratios, and a greater

[25] See, for example, Wermers (1999, 2000), Kacperczyk et al. (2005, 2008), Da, Gao, and Jagannathan (2010), Alexander, Cici, and Gibson (2006), Wermers, Yao, and Zhao (2012), and Huang and Kale (2013).

likelihood of committing fraud tend to disclose their holdings less often. These results align with the agency effect, where funds with more significant agency problems prefer to disclose less often.

Within our study, we examine whether frequent portfolio disclosure has been effective in limiting style drift within mutual funds. In this regard, we conjecture that mutual funds are less likely to engage in style drifting activities if they disclose more often. It is because these periodic shareholder reports not only discuss fund investment strategies and recent performance, but also a variety of other information including a list of the fund's current investments (Wermers, 2001). Within these portfolio disclosures, funds are required to disclose their portfolio investments and they are more likely to stick to the portfolio style suggested within the investment mandate of their funds. Otherwise, they are likely to face investor scrutiny. Thus, an increase in disclosure will lead to less style drift.

> H_1: The incidence of more frequent portfolio disclosure is effective in containing style drift within mutual funds.

To test this hypothesis, we first analyze the May 2004 regulatory event where the SEC changes the mandatory disclosure frequency from semi-annual disclosure to quarterly disclosure. We then test our hypothesis for the May 2019 regulatory event when the SEC again changed this requirement from quarterly to monthly. We address the problem of endogeneity inherent in funds and the choice not to disclose if they are farther away from their prospectus benchmark (more deviation) by using a difference-in-difference approach and studying the regulatory change in holdings disclosure requirements in mandatory portfolio disclosure requirements in 2004 and 2019 as a natural experiment. After 2004 (2019), all funds were required by law to disclose their holdings on a quarterly (monthly) basis. Thus, we consider funds that used to disclose semi-annually (quarterly) before 2004 (2019) as our treatment group and the funds that disclosed quarterly (monthly) even prior to 2004 (2019) as our control group.

4.3. Data and Variables

4.3.1. Measuring Style Drift

We use the style drift score (SDS) as a measure of style drift using style weights from return-based style analysis. The estimation of SDS involves style weights over a number of periods indicating the percentage of fund assets allocated in each style over a certain period of time. These style weights are derived from a process known as "style analysis." Style analysis can be performed either from portfolio holdings [holding-based style analysis (HBSA)] or from fund returns [return-based style analysis (RBSA)]. While the HBSA approach provides valuable insight into the fund's actual asset allocation, the frequency (semi-annual/quarterly) of stockholdings data accessible for this analysis results in a major drawback. This is due to the fact that data on fund holdings during a year is sparse as the U.S. disclosure requirements only mandate funds to report their portfolio holdings either semi-annually or quarterly (before 2019). Consequently, HBSA based on semi-annual/quarterly holdings loses a fair amount of trades and may result in less precise style drift estimates.

In contrast, RBSA (an approach introduced by Sharpe (1988, 1992) determines a fund's style using its return data that are more readily available and in greater frequency. Accordingly, this approach has the capability to produce more frequent style weights as it does not require the funds' actual stockholding data. For this reason, we use RBSA to estimate style weights using the monthly returns data of the funds together with style indexes from the Russell index family.[26] This includes Russell Top 200 Value, Russell Top 200 Growth, Russell Mid Cap Value, Russell Mid Cap Growth, Russell 2000 Value, and Russell 2000 Growth.[27]

Sharpe's RBSA model is expressed in the following manner,

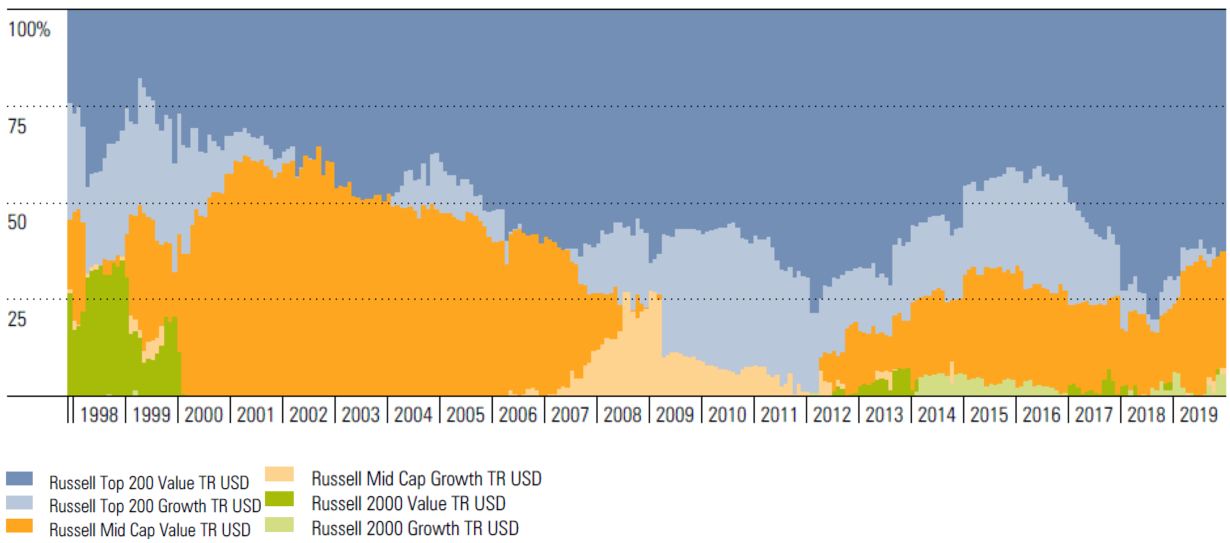
$$R_{im} = W_{1im1}F_{1m} + W_{1im2}F_{2m} + \cdots + W_{iimn}F_{imn} + e_{1im}$$

where R_{im} is the return on fund *i* in month *m*, W_{iimn} is the weight of style n (n=1,2,…,n), F_{imn} is the style *n* (*n*=1,2,…,n) benchmark index return, and e_{1im} is the error term. We find fund style weights (W_{iimn}) by using monthly returns data extending from January 1995-December 2010 for each fund using quadratic programming and the rolling window of 36 months. Following Sharpe (1988, 1992), we constrain W_{iimn} to be non-negative and its sum to be equal to one to represent a long-only portfolio. We use style indexes from the Russell Index family.

[26] We would have ideally used the Morningstar style indexes. However, these indexes were introduced on June 30, 1997 and did not cover our entire sample period.

[27] Russell Top 200 Value (Growth) measures the performance of companies with lower (higher) price-to-book ratios and lower (higher) forecasted growth values and includes 200 of the largest market capitalization firms from the Russell 3000 Index. Russell Mid Cap Value (Growth) measures the performance of companies with lower (higher) price-to-book ratios and lower (higher) forecasted growth values and includes 201-1,000 firms from the Russell 3000 Index based on market capitalization. Russell 2000 Value (Growth) measures the performance of companies with lower (higher) price-to-book ratios and lower (higher) forecasted growth values and includes 2,000 of the smallest market capitalization firms from the Russell 3000 Index.

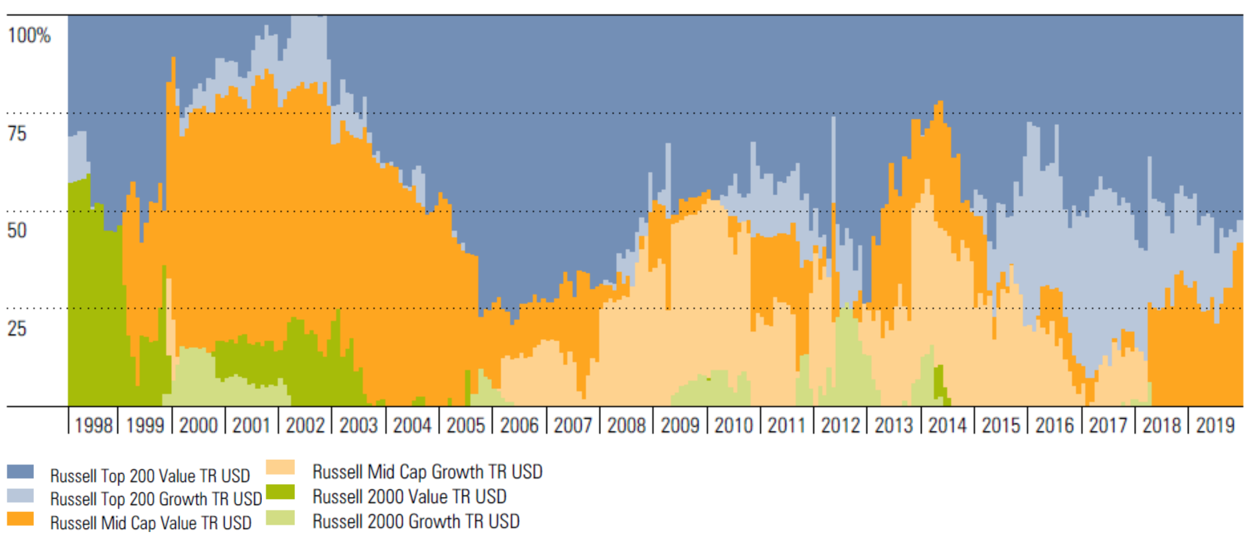
Figure 4.1: Mutual Fund Style Exposure with a Low Style Drift Score
This figure illustrates the style exposure of a fund with a low style drift score.



Source: *Morningstar.com*

Researchers must examine several asset allocation graphs produced by RBSA and map the identified style into a style map. Examples of these style exposure charts are shown in Figures 4.1

Figure 4 2: Mutual Fund Style Exposure with a High Style Drift Score
This figure illustrates the style exposure of a fund with a high style drift score.



Source: *Morningstar.com*

and 4.2. The fund represented in Figure 4.1 has comparatively stable exposure to various styles over the period under consideration. In contrast, the fund represented in Figure 4.2 has drastically changing exposure to various styles for the period under consideration.

Idzorek and Bertsch (2004) introduced the style drift score (SDS) that measures the style drift of a fund in a single statistic eliminating the examination of countless rolling window asset allocation graphs. High SDS highlights a high degree of style drift, while low SDS indicates a less degree. Most of the recent research (Holmes &d Faff, 2007; Kurniawan, How, & Verhoeven, 2016) has used this style drift score (SDS) as it is categorized as one of the best measures for portfolio screening to identify the style consistency of a fund and to monitor its style drift.

Thus, we measure the style drift of a fund using a style drift score that measures the variability within the portfolio investment style through time. We calculate this style drift score using Morningstar's performance reporting module. Morningstar measures style drift score using the following formula.

$$SDS = \sqrt{\sum_{k=1}^{k} \sigma_k^2} \qquad (4.1)$$

where,

σ_k^2 = Var [$c_{k,1}, c_{k,2}, c_{k,3}, \ldots\ldots, c_{k,T}$] (i.e., the variance of the *k*th asset class coefficient)

$$SDS = \sqrt{\frac{1\ \sum_{c=1}^{n} \sum_{t=1}^{T} (W_{c,t} - \overline{W_c})^2}{T-1}} \qquad (4.2)$$

T = total number of periods

n = number of asset classes

$W_{c,t}$ = weight of asset class at time *t*

W_c = average of asset class weight for an asset class

The larger the value of the style drift scores of a fund, the greater the portfolio's style drift.

4.3.2. Measuring Disclosure

We use the Morningstar database to determine the holdings disclosure of a fund. The Morningstar database proactively reports holdings as disclosed by the fund. It uses data from the reports filed by mutual funds with its regulatory authorities. In addition, it also acquires data from the voluntary reports produced by the funds. To determine the holdings frequency of a fund, we use the "Historical Portfolio Date List" to determine the portfolio disclosure dates of a fund. Using the portfolio disclosure dates, we can easily determine whether a fund discloses monthly, quarterly, semi-annually, or discloses its holdings in any other frequency manner.

4.3.3. Control Variables

We control for several variables that have been identified by the finance literature to correlate with the style drift of a fund. These include return rank, fund age, fund size, expense ratio, turnover ratio, and fund flow.

The fund's return rank (relative performance) is its average mid-year return rank relative to its peers. The relative performance of a fund may affect the risk-taking behavior of a fund manager and the style drift within a fund (Chevalier & Ellison, 1995). This is referred to as the tournament effect (Brown, Harlow, and Starks, 1996) where below mid-year performance funds tend to increase their risk in the following six months to catch up with the better performing funds.

The fund age is the number of years from the inception date of the fund, and fund size represents the total net assets managed by the fund. The age and size are likely to shape the ability of the fund to control style drift. Age is a symbol of a fund’s establishment and highlights the constancy in the investment practices that may affect the fund's style drift. The expense ratio is the yearly fee charged by the fund to its investors. The turnover ratio represents the trading activity within a fund. It is the lesser of sales or purchases divided by the average monthly net assets of a fund. It controls the impact of the fund’s management activity on the level of its style drift.

In contrast, fund flow represents the percentage growth of the total net assets of a fund due to additional investments. We calculate fund flow for each month using the following formula as used by Sirri and Tufano (1998).

$$TNA_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + r_{i,t})}{TNA_{i,t-1}} \qquad (4.3)$$

$TNA_{i,t}$ represents the total net assets of a fund for fund *i* in month *t*, $TNA_{i,t-1}$ signifies the previous period's total net assets of the same fund, while $r_{i,t}$ is the fund return for fund *i* in month *t*. We winsorize fund flow at 1% and 99% to prevent the potential impact from extreme observations.

4.4. Data Cleaning, Sample Construction, and Description

We obtain data from the Morningstar Direct database that provides comprehensive data on mutual funds and is used extensively within the mutual fund industry by financial advisors, retail investors, and researchers. Morningstar also provides data on the disclosed holding of funds, as well as the style drift score for each fund under consideration.

The SEC requirements for mandatory portfolio disclosures were semi-annual until 2004 for the mutual fund industry. To capture this event window, we follow Parida (2019) and collect data for the sample period from January 1995-December 2010. Again, following Parida (2019), we split our sample into two periods: 1995-2003 and 2005-2010.[28] We then identify quarterly and semi-annual funds and consider a fund quarterly (or semi-annual) if it discloses every three months (or every six months) at least 75% of the time during its life span.[29]

We focus on actively managed U.S. domestic equity funds to investigate the impact of disclosure frequency on the style drift of the funds. We begin our sample construction by identifying mutual funds that exclusively invest in U.S. equity. Specifically, from the Morningstar Direct database, we retrieve all funds domiciled in the U.S. that belong to the “U.S. Equity” group. We ascertain the equity status using Morningstar’s “Global Broad Category.” We eliminate all index or enhanced index funds and focus only on actively-managed funds. We also exclude funds with the investment objective of investing in securities other than U.S. equity (i.e., Foreign Stock, Money Market, Multi-asset Global, World Stock, Worldwide Bond, Diversified Emerging Markets, Specialty, Balanced, and Government Bond – Treasury). We eliminate survivorship bias using

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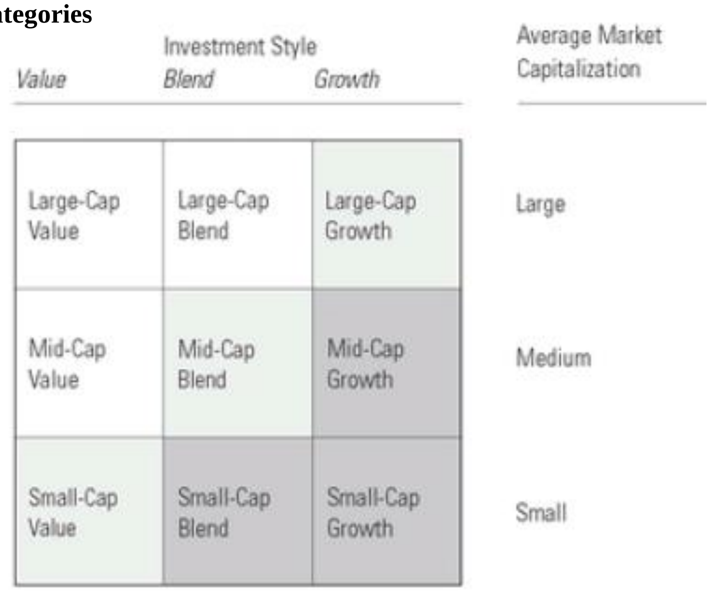
[28] We exclude observations for 2004 to mitigate the concern that our estimates are polluted by funds' anticipated reaction to the shift in regulation.

[29] Due to missing data and reasons including the shift in the fiscal year, we do not see a fund disclosing at the same frequency during its existence. Therefore, we let some of the disclosures occur at different frequencies and still call a fund quarterly/ semi-annual as the case may be. This approach is similar to the approach followed by Parida and Teo (2018).

data from both dead and alive funds. We collect data for funds that fall into the nine Morningstar categories including small-cap value (SV), small-cap blend (SB), small-cap growth (SG), mid-cap value (MV), mid-cap blend (MB), mid-cap growth (MG), large-cap value (LV), large-cap blend (LB), and large-cap growth (LG) grounded on the widely accepted Morningstar Style-box methodology (Morningstar, 2008). These style categories cover greater than 97% of U.S equity market value. Figure 4.3 illustrates the Morningstar style categories for equity funds. We exclude the funds outside the boundaries of the Morningstar categories to ensure homogeneity of the funds' investment style in the same classification.

A fund usually has multiple share classes. These share classes differ slightly in their fees, but their investment portfolio, objectives, and policies are similar (SEC, 2013). We carry out our analysis at the fund level instead of the class level. When a fund has multiple share classes, we only use the oldest to prevent double counting of multiple share classes. To ensure robust statistical inference, we exclude funds with assets less than $10 million. Following Holmes and Faff (2007), we use a rolling window of 36 months to calculate the style drift score of a fund. We exclude funds with

Figure 4.3: Morningstar Style Categories



Source: *Morningstar.com*

less than 36 monthly returns data. Finally, we winsorize all of the variables at 1% and 99% levels. Our final data sample consists of 100 semi-annual disclosing funds and 330 quarterly disclosing funds to analyze the 2004 policy change.

We obtain the data from the Morningstar database (to study the impact of the 2019 policy change) from January 2009-December 2021 using the same criterion as stated above. We then identify quarterly and monthly funds and consider a fund quarterly (or monthly) if it discloses every three months (or every month) at least 75% of the time during its life span. Our final sample is comprised of 2,047 funds, 1,092 of which are quarterly disclosing funds and 955 are monthly disclosing funds.

For each fund, we collect the following data from Morningstar Direct: inception date, fund objective, monthly fund size, year-end turnover, and net expense ratio as reported in the fund annual report, monthly returns on funds, monthly style drift score, style indexes, and historical portfolio dates to determine the portfolio disclosure dates of a fund.

Table 4.1 reports the summary statistics of various fund attributes from 1995-2010 for the analysis of the 2004 policy change. There are 430 funds in our sample. Panel A of the table reports the summary statistics of the style drift score and primary fund characteristics including return rank, expense ratio, turnover ratio, total net assets, fund age, and fund flow. Panel B provides the same statistics for quarterly disclosing funds, while Panel C reports for the semi-annual funds.

Table 4.2 reports the summary statistics of various fund attributes from 2009-2021 to analyze the 2019 policy change. There are 2,047 funds in our sample. Panel A of the table reports the summary statistics of style drift score and primary fund characteristics including return rank, expense ratio, turnover ratio, total net assets, fund age, and fund flow. Panel B provides the same statistics for quarterly disclosing funds, while Panel C reports for the semi-annual funds.

Table 4.3 compares the attributes of all of the funds in the sample with that of the semi-annual and quarterly disclosing funds. It also reports the p-value of the difference in the means of the semi-annual and quarterly disclosing funds. We find that the mean style drift score of a fund is

Table 4.1: Mutual Fund Summary Statistics From 1995-2010

The table reports the mean, median, standard deviation, 25th percentile, and the 75th percentile for the mutual fund characteristics including expense ratio, turnover ratio, total net assets, fund age, and fund flow for 430 U.S. actively managed funds from 1995-2010. We call a fund quarterly (semi-annual) if it discloses every three months (or every six months) for at least 75% of the time during its entire life span.

Panel A: All	**Mean**	**Median**	**Std**	**P25**	**P75**
Style Drift Score	15.13	13.60	8.43	8.90	19.87
Return Rank (percentile)	2.01	2.00	1.42	1.00	3.00
Expense ratio (%)	1.05	1.00	0.37	0.82	1.25
Turnover ratio (%)	75.43	55.76	70.32	26.00	103.00
Total Net Assets ($ millions)	2,868.88	404.35	7,255.65	106.97	1,783.77
Fund Age (year)	15.35	10.37	14.19	6.44	17.62
Fund Flow (%)	0.21	-0.31	4.00	-1.35	1.02
Panel B: Quarterly Disclosing Funds					
Style Drift Score	14.90	13.32	8.40	8.73	19.54
Return Rank (percentile)	2.01	2.00	1.42	1.00	3.00
Expense ratio (%)	1.08	1.06	0.37	0.87	1.29
Turnover ratio (%)	70.82	51.00	67.49	24.97	96.00
Total Net Assets ($ millions)	2,229.92	344.11	6,166.25	100.69	1,398.14
Fund Age (year)	15.31	10.29	14.42	6.35	17.10
Fund Flow (%)	0.19	-0.32	4.01	-1.37	0.99
Panel C: Semi-annual Disclosing Funds					
Style Drift Score	16.12	14.97	8.49	9.72	21.08
Return Rank (percentile)	2.01	2.00	1.41	1.00	3.00
Expense ratio (%)	0.91	0.86	0.29	0.71	1.05
Turnover ratio (%)	94.84	79.00	78.23	36.00	135.00
Total Net Assets ($ millions)	5,560.55	871.28	10,260.86	162.73	5,265.48
Fund Age (year)	15.52	10.79	13.20	6.84	19.53
Fund Flow (%)	0.30	-0.25	3.98	-1.27	1.12

Table 4.2: Mutual Fund Summary Statistics From 2009-2021

The table reports the mean, median, standard deviation, 25th percentile, and the 75th percentile for mutual fund characteristics including expense ratio, turnover ratio, total net assets, fund age, and fund flow for 2,047 U.S. actively managed funds from 2009-2021. We call a fund monthly (quarterly) if it discloses every month (or every three months) for at least 75% of the time during its entire life span.

Panel A: All	**Mean**	**Median**	**Std**	**P25**	**P75**
Style Drift Score	13.91	12.30	7.94	8.06	18.15
Return Rank (percentile)	2.01	2.00	1.41	1.00	3.00
Expense ratio (%)	1.01	1.00	0.35	0.81	1.22
Turnover ratio (%)	60.06	47.00	49.82	26.00	80.00
Total Net Assets ($ millions)	1,234.25	268.10	2,997.60	72.92	978.15
Fund Age (year)	18.16	15.68	12.95	9.76	22.55
Fund Flow (%)	-0.53	-0.59	3.61	-1.49	0.29
Panel B: Monthly Disclosing Funds					
Style Drift Score	12.98	11.47	7.42	7.58	16.83
Return Rank (percentile)	2.02	2.00	1.41	1.00	3.00
Expense ratio (%)	0.98	0.98	0.33	0.79	1.18
Turnover ratio (%)	65.02	52.00	51.61	29.00	85.00
Total Net Assets ($ millions)	1,100.12	278.61	2,531.00	73.90	967.30
Fund Age (year)	18.37	15.84	13.27	10.02	22.63
Fund Flow (%)	-0.56	-0.60	3.67	-1.51	0.31
Panel C: Quarterly Disclosing Funds					
Style Drift Score	14.75	13.09	8.29	8.56	19.32
Return Rank (percentile)	2.01	2.00	1.41	1.00	3.00
Expense ratio (%)	1.05	1.02	0.36	0.83	1.25
Turnover ratio (%)	55.58	42.93	47.69	23.00	74.00
Total Net Assets ($ millions)	1,355.47	259.50	3,359.45	72.21	996.12
Fund Age (year)	17.97	15.55	12.64	9.51	22.49
Fund Flow (%)	-0.51	-0.58	3.56	-1.48	0.27

around 15.13 points, while the mean style drift score of a treatment (i.e., semi-annual/less frequently disclosing) fund is 16.12 points, which is larger than the mean style drift score of 14.90 points for a control (i.e., quarterly/more frequently disclosing) fund. This conforms with our hypothesis that expects less frequently (semi-annually) disclosing funds to have greater levels of style drift than more frequently (quarterly) disclosing funds.

The expense ratio for quarterly disclosing funds is higher than semi-annual disclosing funds. The turnover ratios for semi-annual disclosing funds are larger than the quarterly disclosing funds. When considering the turnover ratio as a proxy for informational advantage to the funds, it is reasonable to infer those funds engaging in information-related trades desire to be semi-annual (Ge & Zhang, 2006). We further note that the semi-annual disclosing funds have more total net assets in comparison to the quarterly disclosing funds. A possible explanation for this is that larger funds are more exposed to front running activities and choose to disclose less often to prevent others from front running their trades (Ge & Zhang, 2006; Parida and Teo, 2018). Moreover, semi-annual funds appear to be older than their quarterly counterparts are. Lastly, flows to the semi-annual disclosing funds are greater than that of the quarterly disclosing funds.

Table 4.3: Summary Statistics: Semi-annual Disclosing Funds vs. Quarterly Disclosing Funds (1995-2010)
The table compares the mean for mutual fund characteristics, including expense ratio, turnover ratio, total net assets, fund age, and fund flow of all the funds in the sample with that of quarterly disclosing and previously semi-annual disclosing funds. We call a fund quarterly (semi-annual) if it discloses every three months (or every six months) for at least 75% of the time during its entire life span.

	All	**Quarterly**	**Semi-annual**	**Qtly-semi**	**p-value**
Number of Funds	430	330	100		
Style Drift Score (%)	15.13	14.90	16.12	-1.22	<0.0001
Return Rank (percentile)	2.01	2.01	2.01	0.00	<0.0001
Expense ratio (%)	1.05	1.08	0.91	0.17	<0.0001
Turnover ratio (%)	75.43	70.82	94.84	-24.02	<0.0001
Total Net Assets ($ millions)	2,868.88	2,229.92	5,560.55	-3,330.63	<0.0001
Fund Age (year)	15.35	15.31	15.52	-0.21	<0.0001
Fund Flow (%)	0.21	0.19	0.30	-0.11	<0.0001

Table 4.4 compares the attributes of all the funds in the sample with that of quarterly disclosing and monthly disclosing funds. It also reports the p-value of the difference in the means of the semi-annual and quarterly disclosing funds. We find that the mean style drift score of all the funds in our sample is around 13.91 points, while the mean style drift score of a treatment (i.e., quarterly/less frequently disclosing) fund is 14.75 points, which is larger than the mean style drift score of 12.98 points for a control (i.e., monthly/more frequently disclosing) fund. This again conforms with our hypothesis that expects less frequently (quarterly) disclosing funds to have greater levels of style drift score than more frequently (monthly) disclosing funds.

The expense ratio for quarterly (less frequently) disclosing funds is higher than that of monthly (more frequently) disclosing funds. If we use expense ratio as a proxy for agency costs, then we are likely to expect that funds disclosing less frequently are more likely to suffer from agency costs. However, this may not necessarily be a correct assumption as marketing and distribution expenses are also included in the expense ratio, and higher marketing and distribution costs may not inevitably result in inferior fund performance (Parida & Teo, 2018). We also find the turnover ratio to be higher for monthly funds than the quarterly funds, quarterly funds to be comparatively younger than monthly funds, and note a higher fund flow to monthly vs. quarterly funds. Moreover, less frequently (quarterly) disclosing funds have more total net assets under management than more frequently (monthly) disclosing funds.

Table 4.4: Summary Statistics: Quarterly Disclosing Funds vs. Monthly Disclosing Funds (2009-2021)

The table compares the mean for mutual fund characteristics, including expense ratio, turnover ratio, total net assets, fund age, and fund flow of all the funds in the sample with that of quarterly disclosing and previously semi-annual disclosing funds. We call a fund monthly (quarterly) if it discloses every month (or every three months) for at least 75% of the time during its entire life span.

	All	**Monthly**	**Quarterly**	**Mtly-Qtly**	**p-value**
Number of Funds	2,047	955	1,092		
Style Drift Score (%)	13.91	12.98	14.75	-1.77	<0.0001
Return Rank (percentile)	2.01	2.02	2.01	0.01	0.1451
Expense ratio (%)	1.01	0.98	1.05	-0.07	<0.0001
Turnover ratio (%)	60.06	65.02	55.58	9.44	<0.0001
Total Net Assets ($ millions)	1,234.25	1,100.12	1,355.47	-255.35	<0.0001
Fund Age (year)	18.16	18.37	17.97	0.40	<0.0001
Fund Flow (%)	-0.53	-0.56	-0.51	-0.05	<0.0001

4.5. Model Selection, Results, and Empirical Analysis

4.5.1. Model Selection

We use a difference-in-difference test to examine the effect of change in the mandatory portfolio disclosure frequency on mutual fund style drift. This is possible because our sample consists of funds that disclosed semi-annually (quarterly) before 2004 (2019), but were forced to disclose quarterly (monthly) subsequently. We can consider this group of funds as our treatment group. Now, some funds had been voluntarily disclosing quarterly (monthly) before the 2004 (2019) regulation change. Thus, the change in the regulation will not affect the style drift of this group of funds. Therefore, we treat this group of funds as our control group.

To examine the relationship between style drift and disclosure frequency for the 2004 regulation change, we estimate the following panel regression.

$$Drift_{it} = \beta_1 Semi_i + \beta_2 POST2004 + \ \beta_3 Semi_i * POST2004 + \beta_4 RETURNRANK_{it} + \beta_5 EXP_{it} + \beta_6 TURN_{it} + \beta_7 LogTNA_{it} + \beta_8 LogAGE_{it} + \beta_9 FLOW_{it} + TIME_t + FUND_t + e_{it}$$

While investigating the association between style drift and disclosure frequency for the 2019 policy change, we estimate the following panel regression.

$$Drift_{it} = \alpha_1 Quar_i + \alpha_2 POST2019 + \ \alpha_3 Quar_i * POST2019 + \alpha_4 RETURNRANK_{it} + \alpha_5 EXP_{it} + \alpha_6 TURN_{it} + \alpha_7 LogTNA_{it} + \alpha_8 LogAGE_{it} + \alpha_9 FLOW_{it} + TIME_t + FUND_t + e_{it}$$

$Drift_{it}$ represents the style drift score of fund *i* in month *t*. $Semi_i$ is a dummy variable that takes the value of one if fund *i* is semi-annual from 1995-2003 and zero if it is quarterly. $Quar_i$ represents a dummy variable and takes a value of one if fund *i* is quarterly from 2009-2018 and zero if it is monthly. POST2004 is also an indicator variable taking a value of one if t is later than 2004 and zero otherwise. POST2019 is an indicator variable taking a value of one if t is later than 2019 and zero otherwise. The control variables include $RETURNRANK_{it}$ representing the average mid-year performance of the fund relative to its peers. EXP_{it} represents the expense ratio of a fund in month t. $TURN_{it}$ represents the turnover ratio of fund i in month t. $LogTNA_{it}$ is the natural logarithm of total net assets (in million dollars) of fund i in month t. $LogAGE_{it}$ is the natural logarithm of the age of the fund in month t. $FLOW_{it}$ represents the percentage growth of the total net assets of a fund due to additional investments of a fund in month t. Our coefficients of interest are β_3 and α_3 capturing the effect of change in the mandatory portfolio disclosure frequency on the style drift of previously semi-annual and quarterly funds, respectively, and we expect it to be negative.

Finally, we include $TIME_t$ (time dummies) and $FUND_t$ (fund dummies) in our regression to capture for time and fund fixed effects. Time fixed effects ($TIME_t$) account for time-varying macroeconomic conditions and trends in our dependent variable, while fund fixed effects ($FUND_t$) control for time invariant unobservable fund characteristics. The inclusion of time and fund fixed effects reduces the potential concern of correlated omitted variables (Bourveau, Li, Macciocchi, & Sun, 2020).

4.5.2. Results and Empirical Analysis

4.5.2.1. Does a Shift in Mandatory Disclosure Frequency From Semi-Annual to Quarterly in 2004 Lower Style Drift in Previously Semi-Annual Funds?

We start with univariate analysis and identify quarterly and semi-annually disclosing funds from 1995-2003 (i.e., the period before the change in regulation). We then compute the style drift scores for these funds, the results of which are reported in Panel A of Table 4.5. The analysis of the table reveals that the style drift score of semi-annual disclosing funds is greater than the quarterly disclosing funds by approximately 1.56 points per month. This supports our conjecture that the semi-annual disclosing funds suffer more from style drifting activities of fund managers than the quarterly disclosing funds prior to 2004. This likely because semi-annual disclosing funds choose to style drift more when there is less monitoring by fund investors and external regulators. If this is true, we should expect the difference in style drift (between previously semi-annual disclosing funds and quarterly disclosing funds) to go down or become insignificant after 2004, as all of the funds are mandated to disclose quarterly since then.

Table 4.5: Pre-2004 vs. Post-2004 Analysis of Disclosure Frequency and Style Drift

Panel A of the table reports the mean style drift scores of active equity mutual funds from 1995-2003. Panel B of the table provides the mean style drift scores of active equity mutual funds from 2005-2010. The table reports the results for all of the funds in the sample and for quarterly disclosing and previously semi-annual funds separately. At the end, it provides the difference in style drift scores between quarterly and previously semi-annually disclosing funds. We call a fund quarterly (semi-annual) if it discloses every three months (or every six months) for at least 75% of the time during its entire life span.

Panel A: (1995-2003)	**All**	**Quarterly**	**Semi-annual**	**Qtly-semi**	**p-value**
Style Drift Score	15.51	15.22	16.79	-1.56	0.0646
Panel B: (2005-2010)					
Style Drift Score	14.76	14.56	15.54	-0.07	0.0014

We compare the style drift of previously semi-annual disclosing funds with quarterly disclosing funds from 2005-2010. The results are reported in Panel B of Table 4.5. We find that the difference in style drift between the previously semi-annual disclosing funds and quarterly disclosing funds have gone down. For example, the difference in style drift score has reduced from 1.56 points a month before 2004 to 0.07 points a month after 2004.

Thus far, we have learned that funds disclosing semi-annually pursued greater style drift than quarterly disclosing funds prior to 2004. We also learned that this difference in style drift (though small, but still significant) disappears after 2004. We need to establish that this is triggered by the shift in disclosure policy in 2004. For this purpose, we extend our analysis to a multivariate setting and perform a difference-in-difference test. We can use a difference-in-difference test because the change in the disclosure policy is an exogenous event and only affects our treatment group (semi-annual disclosing funds) and not the control group (quarterly disclosing funds).

Table 4.6 provides the results of the difference-in-difference test for the whole sample of funds from 1995-2010. We focus on the double-interaction term (Semii*POST2004) that estimates the difference between the semi-annual disclosing (treatment) funds and the quarterly disclosing (control) funds in changes in style drift before and after the SEC (2004) regulation event. In the first column of Table 4.6, we report the estimation of the treatment effect without the inclusion of the control variables using fund and time fixed effects. The reason for doing so is to prevent "bad controls" that may undermine our ability to depict causal inferences (Gormley & Matsa, 2013). We find the treatment effect to be negative and statistically significant at a 1% significance level for our measure of style drift. It corresponds to an average decrease in style drift by 0.82 points after the 2004 regulation change. Column (3), Column (4), and Column (5) show this relationship to remain intact and significant with the inclusion of controls and without fixed effects, with only time fixed effects, and then with only fund fixed effects, respectively.

Finally, Column (5) indicates that the estimated treatment effect remains stable with the inclusion of controls and both fund and time fixed effects. The stability of R-squared across Column (1) and Column (5) gives us confidence that there are no spurious effects from correlated omitted variables (Oster, 2019).

This finding supports our hypothesis that the shift in mandatory disclosure frequency from semi-annual disclosure to quarterly disclosure in 2004 lowers style drift in previously semi-annual funds compared to funds that disclosed quarterly throughout. For instance, the coefficient on $Semi_i$*POST2004 is -0.79 for our main regression indicating that after the change in disclosure policy from semi-annual to quarterly in 2004, the style drift of semi-annual funds dropped by approximately 0.79 points.

In addition, we find expense ratio, turnover ratio, fund size, fund age, and fund flow to be significantly and positively associated with style drift, while return rank is negatively associated with style drift. These findings are in line with the literature. Using return based style analysis, Holmes and Faff (2007) show a positive effect of style drift on the expense ratio of a fund. Frijns, Gilbert, and Zwinkels (2016) and Huang, Sialm, and Zhang (2011) found turnover to be positively related to style drift as it highlights the fund managers' efforts in the search for profitable investment opportunities. Guo and Gao (2018) find a positive association between fund style and fund flows. Their paper suggests that this may be because fund managers actually have some style timing ability (Cremers & Petajisto, 2009) or they are just catering to investors' preferences. Chua and Tam (2020) suggest funds with greater assets under management may be more inclined to style drift given the influence of positive fund flows on their expected remuneration. Kurniawan et al. (2016) find return rank to be negatively associated with the style drift of a fund.

4.5.2.2. Does the Relationship Between Disclosure Frequency and Style Drift Still Hold in a More Recent Setting?

The results above support our hypothesis that an increase in disclosure frequency facilitates to control for style drift in mutual funds. Yet, we wish to conduct further analysis to investigate whether this hypothesis still holds in a different and more recent setting. For this purpose, we again examine the relationship between disclosure frequency and style drift, but this time for the 2019 regulatory change.

Table 4.6: Difference-in-Difference Test for the Sample Period (1995-2010)

This table inspects the impact of the change in disclosure frequency on mutual fund style drift using a difference-in-difference test. The dependent variable is style drift score. $Semi_i$ is a dummy variable and takes the value of one if fund *i* is semi-annual from 1995-2003 and zero if it is quarterly. POST2004 is also an indicator variable taking a value of one if *t* is later than 2004 and zero otherwise. We control for expense ratio, turnover ratio, the natural logarithm of total net assets, the natural logarithm of age, and fund flow. We further use month dummies in the regression. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

$Drift_{it}=\beta_1 Semi_i+\beta_2 POST2004+ \beta_3 Semi_i{*}POST2004+\beta_4 RETURNRANK_{it}+\beta_5 EXP_{it}+\beta_6 TURN_{it}+\beta_7 LogTNA_{it}+\beta_8 LogAGE_{it}+\beta_9 FLOW_{it}+TIME_t+FUND_t+e_{it}$

Semi	15.60***	2.16***	2.28***	5.94	5.88**
	(30.87)	(15.04)	(16.75)	(0.82)	(5.36)
POST2004	-6.04***	-0.22***	3.95***	0.07	-6.61***
	(-12.28)	(-2.55)	(5.81)	(0.63)	(-12.44)
Semi*POST2004	-0.82***	-1.23***	-1.08***	-1.09***	-0.79***
	(4.40)	(-6.37)	(-5.89)	(-5.80)	(-4.32)
Return Rank		0.01	0.00	-0.06**	-0.10**
		(0.23)	(0.01)	(-2.55)	(-2.02)
Expense Ratio		5.10***	3.92***	1.28***	0.94***
		(52.27)	(36.17)	(6.07)	(4.23)
Turnover Ratio		0.01***	0.01***	0.01***	0.01***
		(19.02)	(17.94)	(12.19)	(12.72)
Log (TNA)		0.49**	0.02	0.42***	0.32***
		(50.11)	(0.96)	(8.51)	(6.22)
Log (Age)		-0.46***	0.08	-1.91***	1.08***
		(-7.98)	(1.34)	(-13.68)	(6.33)
Fund Flow		0.05***	0.06***	-0.00***	0.02*
		(5.59)	(6.84)	(-0.32)	(1.95)
Time Fixed Effects	Yes	No	Yes	No	Yes
Fund Fixed Effects	Yes	No	No	Yes	Yes
Observations	48,243	48,243	48,243	48,243	48,243
R-Squared	0.8490	0.7718	0.1370	0.2751	0.8501

We again begin with a univariate analysis and identify monthly and previously quarterly disclosing funds from 2009-2018 (i.e., the period before the change in regulation). We then compute the style drift scores for these funds, the results of which are reported in Panel A of Table 4.7. The analysis of the table reveals that the style drift score of quarterly disclosing funds is greater than the monthly disclosing funds by approximately 1.82 points per month. This supports our conjecture that the less frequently (quarterly) disclosing funds suffer more from style drifting activities of fund managers than the more frequently (monthly) disclosing funds prior to 2019. We would expect this difference in style drift (between previously quarterly disclosing funds and monthly disclosing funds) to decline or become insignificant after the 2019 policy change, as all of the funds are mandated to disclose monthly since then.

Table 4.7: Pre-2019 vs. Post-2019 Analysis of Disclosure Frequency and Style Drift

Panel A of the table reports the mean style drift scores of active equity mutual funds from 2009-2018. Panel B of the table reports the mean style drift scores of active equity mutual funds from 2020-2021. The table provides the results for all of the funds in the sample and for monthly and previously quarterly disclosing funds separately. In the end, it reports the difference in style drift scores between monthly and previously quarterly disclosing funds. We call a fund monthly (quarterly) if it discloses every month (or every three months) for at least 75% of the time during its entire life span.

Panel A: (2009-2018)	**All**	**Monthly**	**Quarterly**	**Mtly-Qtly**	**p-value**
Style Drift Score	14.24	13.29	15.11	-1.82	<0.0001
Panel B: (2020-2021)					
Style Drift Score	12.07	11.30	12.75	-1.45	<0.0001

We compare the style drift of previously quarterly disclosing funds with monthly disclosing funds between 2020 and 2021. The results are reported in Panel B of Table 4.7. We find that the difference in style drift between the previously quarterly disclosing funds and the monthly disclosing funds has declined. For example, the difference in the style drift score has dropped from 1.82 points a month before 2019 to 1.45 points a month after 2019.

We now extend our analysis and again perform a difference-in-difference test to examine the effect of change in the mandatory portfolio disclosure frequency on mutual fund style drift. This is possible because our sample consists of funds that were disclosing quarterly before 2019, but were forced to disclose monthly subsequently. We can consider this group of funds as our treatment group. Some funds had been voluntarily disclosing monthly before the 2019 regulation change. Thus, the change in the regulation will not affect the style drift of this group of funds. Therefore, we treat this group of funds as our control group.

Table 4.8 presents our regression results. Again, we find α_3 to be negative and sig nificant in all model specifications at a 1% level of significance. For instance, when considering the model specification, including the time and fund fixed effects, we find the coefficient for α_3 to be -0.51, which is both negative and significant. This suggests that style drift has declined for previously quarterly disclosing funds by 0.51 points per month when compared to the monthly disclosing funds. This finding again supports our hypothesis that an increase in the disclosure frequency limits style drift within mutual funds. However, we do note that the 2019 policy shows a milder effect on the reduction in style drift scores as compared to the 2004 policy change. This may be because the monthly disclosure is only available to the SEC on monthly basis and not to the general public

Table 4.8: Difference-in-Difference Test for Sample Period (2009-2021)

This table inspects the impact of change in disclosure frequency on mutual fund style drift using a difference-in-difference test. The dependent variable is style drift score. $Quar_i$ is a dummy variable that takes a value of one if fund *i* is quarterly from 2009-2018 and zero if it is monthly. POST2019 is an indicator variable taking a value of one if *t* is later than 2019 and zero otherwise. We control for expense ratio, turnover ratio, the natural logarithm of total net assets, the natural logarithm of age, and fund flow. We further use month dummies in the regression. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

$$Drift_{it}=\alpha_1 Quar_i+\alpha_2 POST2019+ \alpha_3 Quar_i*POST2019+\alpha_4 RETURNRANK_{it}+\alpha_5 EXP_{it}+\alpha_6 TURN_{it}+\alpha_7 LogTNA_{it}+\alpha_8 LogAGE_{it}+\alpha_9 FLOW_{it}+TIME_t+FUND_t+e_{it}$$

Quar	1.58***	1.54***	15.34***	14.99***
	(41.65)	(43.32)	(17.62)	(18.99)
POST2019	-1.01***	7.40***	-1.29***	-5.55***
	(-14.50)	(24.02)	(-19.31)	(-22.47)
Quar*POST2019	-0.62***	-0.48***	-0.50***	-0.51***
	(-6.53)	(-5.34)	(-6.02)	(-6.97)
Return Rank	0.08***	-0.18***	0.06***	-0.09***
	(6.49)	(-7.92)	(5.43)	(-4.39)
Expense Ratio	5.73***	4.41***	-0.08	-0.20*
	(123.34)	(84.69)	(-0.68)	(-1.66)
Turnover Ratio	0.00***	0.00**	0.01***	0.01***
	(6.25)	(-2.10)	(12.45)	(12.41)
Log (TNA)	0.47***	0.01	0.01	0.03
	(103.45)	(0.63)	(0.52)	(1.26)
Log (Age)	-0.80***	-0.67***	-1.34***	0.20*
	(-28.20)	(-25.03)	(18.65)	(1.96)
Fund Flow	-0.02***	-0.02***	-0.00	0.00
	(-4.17)	(-4.05)	(-1.07)	(-0.73)
Time Fixed Effects	No	Yes	No	Yes
Fund Fixed Effects	No	No	Yes	Yes
Observations	200,728	200,728	200,728	200,728
R-Sq	0.7677	0.1728	0.3563	0.8682

4.5.3. Robustness Tests

In this section, we test for the robustness of our main results by considering several alternatives for the main tests. In all of the cases, we find that the main results are unchanged for all of the alternatives under consideration.

4.5.3.1. The Difference-in-difference Test for Small and Large Funds

In this section, we run a difference-in-difference test for small and large funds for the 2004 policy change. We split the funds based on the sample median of the size (i.e., total net assets) of funds to partition funds each month. We then define funds below the median size (i.e., total net assets) as small funds and funds above the median size (i.e., total net assets) as large funds.

In Chapter 2, we determine that smaller funds are likely to exhibit more style deviation than larger funds. Wermers (2012) and Brown, Harlow, and Zhang (2015) suggest larger funds are less exposed to style drifting activities as they have greater investment opportunities in their pronounced style universe than smaller funds. Our conjecture predicts that the change in disclosure frequency will have a greater negative impact on the style drift of small funds compared to large funds.

We conduct tests similar on these funds as we did in the previous section. Table 4.9 presents the results of our tests. In line with our hypothesis, the results suggest a greater impact of the regulatory change on the style drift of smaller funds. The style drift of previously semi-annually disclosing small funds has declined by around 2.41 points per month after 2004 and is statistically significant. There is only a small impact of the change in disclosure frequency on the style drift of previously semi-annual large funds as the style drift of previously semi-annual large funds has dropped by around 0.22 points per month after 2004 and is statistically insignificant.

Table 4.9: Difference-in-Difference Test for Small and Large Funds (1995-2010)

This table reports the impact of change in disclosure frequency on mutual fund style drift for small and large funds using a difference-in-difference test. The dependent variable is style drift score. $Semi_i$ is a dummy variable that takes a value of one if fund i is semi-annual from 1995-2003 and zero if it is quarterly. POST2004 is also an indicator variable taking a value of one if *t* is later than 2004 and zero otherwise. We control for expense ratio, turnover ratio, the natural logarithm of total net assets, the natural logarithm of age, and fund flow. We further use month dummies in the regression. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

$$Drift_{it}=\beta_1 Semi_i+\beta_2 POST2004+ \beta_3 Semi_i*POST2004+\beta_4 RETURNRANK_{it}+\beta_5 EXP_{it}+\beta_6 TURN_{it}+\beta_7 LogTNA_{it}+\beta_8 LogAGE_{it}+\beta_9 FLOW_{it}+TIME_t+FUND_t+e_{it}$$

	Small Funds		Large Funds	
Semi	15.96***	8.58***	15.05***	-5.22**
	(23.37)	(5.11)	(17.40)	(-2.18)
POST2019	-6.41***	-6.77***	-5.14***	-6.06***
	(-8.84)	(-8.47)	(-7.89)	(-8.58)
Semi*POST2019	-2.17***	-2.41***	-0.48**	-0.22
	(-5.99)	(-6.60)	(-2.09)	(-0.98)
Return Rank		-0.02		-0.15***
		(-0.32)		(-2.34)
Expense Ratio		0.81***		1.83***
		(3.25)		((3.52)
Turnover Ratio		0.01***		0.02***
		(5.96)		(13.18)
Log (TNA)		0.25***		0.70***
		(2.78)		(7.09)
Log (Age)		0.53*		1.79***
		(1.83)		(6.99)
Fund Flow		0.04***		-0.06***
		(3.72)		(-3.88)
Time Fixed Effects	Yes	Yes	Yes	Yes
Fund Fixed Effects	Yes	Yes	Yes	Yes
Observations	353,749	353,749	353,749	353,749
R-Squared	0.8552	0.8558	0.8588	0.8610

4.5.3.2. The Difference-in-difference Test for Growth and Value Funds

We run a difference-in-difference test for growth and value funds for the 2004 regulation change. We follow Wermers (2012) and categorize a fund as a growth fund if its self-declared investment objective is either “aggressive growth” or “growth.” Whereas we categorize a fund as a value fund if its self-declared investment objective is either “growth and income” or “income.”

In Chapter 2, we find that growth funds are more likely to style deviate than value funds. Wermers (2012) also suggests growth funds have higher levels of style drift when compared to value funds. Our hypothesis predicts that the change in disclosure frequency will have a greater negative impact on the style drift of growth funds compared to value funds.

We conduct similar tests on these funds as we did in the previous section. Table 4.10 shows the results of our tests. In line with our hypothesis, the results suggest a greater impact on the style drift of growth funds. The style drift of previously semi-annual growth funds has declined by around 0.93 points per month after 2004 and is statistically significant. There is only a small impact of the change in disclosure frequency on the style drift of previously semi-annual large funds as the style drift of previously semi-annual large funds has dropped by around 0.44 points per month after 2004 and is statistically insignificant.

Table 4.10: Difference-in-Difference Test for Growth and Value Funds (1995-2010)

This table reports the impact of change in disclosure frequency on mutual fund style drift for value and growth funds using a difference-in-difference test. The dependent variable is style drift score. $Semi_i$ is a dummy variable that takes the value of one if fund *i* is semi-annual from 1995- 2003 and zero if it is quarterly. POST2004 is also an indicator variable taking a value of one if *t* is later than 2004 and zero otherwise. We control for expense ratio, turnover ratio, the natural logarithm of total net assets, the natural logarithm of age, and fund flow. We further use month dummies in the regression. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

$$Drift_{it}=\beta_1 Semi_i+\beta_2 POST2004+ \beta_3 Semi_i*POST2004+\beta_4 RETURNRANK_{it}+\beta_5 EXP_{it}+\beta_6 TURN_{it}+\beta_7 LogTNA_{it}+\beta_8 LogAGE_{it}+\beta_9 FLOW_{it}+TIME_t+FUND_t+e_{it}$$

	Growth Funds		Value Funds	
Semi	15.55***	9.01***	10.78***	13.60***
	(24.13)	(6.24)	(11.52)	(5.18)
POST2004	-6.98***	-6.96***	-3.46***	-4.20***
	(-10.98)	(-10.15)	(-3.05)	(-3.28)
Semi*POST2004	-0.87***	-0.93***	-0.35	-0.44
	(3.82)	(-4.13)	(0.96)	(-1.17)
Return Rank		-0.12*		-0.18
		(-1.94)		(-1.22)
Expense Ratio		1.46***		-1.51**
		(5.36)		(2.26)
Turnover Ratio		0.01***		0.00
		(13.54)		(0.55)
Log (TNA)		0.08		-0.25*
		(1.05)		(1.78)
Log (Age)		0.38*		2.11***
		(1.71)		(4.41)
Fund Flow		0.05***		0.00
		(4.49)		(0.12)
Time Fixed Effects	Yes	Yes	Yes	Yes
Fund Fixed Effects	Yes	Yes	Yes	Yes
Observations	29,663	29,663	6,590	6,590
R-Squared	0.8513	0.8529	0.8498	0.8505

4.5.3.3. The Difference-in-difference Test Using Style Drift Scores from Morningstar Style Indices

To test the robustness of our results regarding the impact of 2019 policy changes on the style drift of a fund, we calculate the style drift score using the Morningstar style indexes in contrast to the Russell style indexes used previously and re-run our analysis. Table 4.11 provides the results of this analysis. Again, the results are consistent with our hypothesis and previous results (though the impact is much milder) and suggest that the style drift of previously quarterly disclosing funds declined by 0.26 points per month after the 2019 change in disclosure requirements from quarterly to monthly and is statistically significant.

4.6. Conclusion

To our knowledge, this is the first paper that explores the style drift of mutual funds before and after the regulatory transformation in the disclosure frequency in 2004 and 2019. We find that the style drift in semi-annual funds drops after the regulatory change in 2004. Our results are economically significant and remain robust under different settings. These results suggest that funds disclosing less frequently are more exposed to style drifting activities than those disclosing more often are. Further analysis of the funds after the 2019 regulatory change also suggests a decrease in style drift for the previously quarterly disclosing funds after they moved to a more frequent (i.e., monthly) disclosure regime.

Our results offer implications for regulatory authorities around the globe for changes in the disclosure frequency in the future. Before the regulatory authorities mandate any further increase or decrease in the disclosure frequency, it may be wise to consider the optimal frequency of disclosure given its benefits and costs.

Table 4.11: Difference-in-Difference Test for the Sample Period Using Style Drift Scores From Morningstar Style Indices (2009-2021)

This table reports the impact of change in disclosure frequency on mutual fund style drift using a difference-in-difference test. The dependent variable is style drift scores. $Quar_i$ is a dummy variable that takes the value of one if fund *i* is quarterly from 2009-2018 and zero if it is monthly. POST2019 is an indicator variable taking a value of one if *t* is later than 2019 and zero otherwise. We control for expense ratio, turnover ratio, the natural logarithm of total net assets, the natural logarithm of age, and fund flow. We further use month dummies in the regression. *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

$$Drift_{it}=\alpha_1 Quar_i+\alpha_2 POST2019+\alpha_3 Quar_i{*}POST2019+\alpha_4 RETURNRANK_{it}+\alpha_5 EXP_{it}+\alpha_6 TURN_{it}+\alpha_7 LogTNA_{it}+\alpha_8 LogAGE_{it}+\alpha_9 FLOW_{it}+TIME_t+FUND_t+e_{it}$$

Quar	19.05***	1.29***	16.13***	15.43***
	(22.79)	(34.90)	(18.18)	(15.71)
POST2019	-3.81***	14.25***	-0.81***	-4.05***
	(-15.19)	(45.62)	(-13.23)	(-15.97)
Quar*POST2019	-0.21***	-0.12	-0.23***	-0.26***
	(-2.66)	(-1.39)	(-2.95)	(-3.41)
Return Rank		-0.24***	0.07***	-0.06**
		(-9.72)	(6.43)	(-2.69)
Expense Ratio		4.34***	-0.01	-0.19
		(74.06)	(-0.10)	(-1.53)
Turnover Ratio		-0.00***	0.01***	0.01***
		(-6.86)	(9.49)	(10.45)
Log (TNA)		-0.11***	0.13***	0.09***
		(-9.40)	(5.36)	(3.64)
Log (Age)		-0.63***	-1.38***	1.03***
		(-23.03)	(-18.08)	(9.52)
Fund Flow		-0.01	0.01**	0.01**
		(-1.02)	(2.22)	(2.14)
Time Fixed Effects	No	Yes	No	Yes
Fund Fixed Effects	No	No	Yes	Yes
Observations	200,728	200,728	200,728	200,728
R-Sq	0.8948	0.8402	0.8819	0.8950

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Appendix B

Table B.1:Description of Variables
This table describes all of the main variables of this study.

Variable	Description
Drift	Measure of the style drift score of a fund.
Semi	Dummy variable that takes a value of one if the fund is semi-annual between 1995 and 2003 and zero if it is quarterly.
POST2004	Indicator variable taking a value of one if time *t* is later than 2004 and zero otherwise.
Quar	Dummy variable that takes a value of one if the fund is quarterly between 2009 and 2018 and zero if it is monthly.
POST2019	Indicator variable taking a value of one if time *t* is later than 2019 and zero otherwise.
RETURNRANK	The average mid-year performance of the fund relative to its peers.
EXP	The percentage of fund assets paid for management fees and operating expenses.
TURN	The lesser of sales or purchases divided by the average monthly net assets of a fund.
Log (TNA)	The natural logarithm of the total net assets under management of a fund.
Log (AGE)	The natural logarithm of the number of years from the inception date of a fund.
FLOW	The percentage growth of the total net assets of a fund due to additional investments.

Chapter 5: Conclusion

This chapter concludes this dissertation by summarizing the main findings of the three essays in Section 5.1 and documenting possible directions for future research in Section 5.2.

5.1. Major Findings and Conclusions

In the first essay, we do a critical evaluation of the current literature with regards to the style deviating practices of the fund managers to develop a better understanding of the concept. For this purpose, we first analyze the U.S. mutual fund industry from 1990-2019. We then demonstrate the key differences between active and passive managers, establish that not all deviations from the indicated investment style of the fund are alike, and present a conceptual framework for better understanding of the style deviating phenomenon. This framework introduces style enhancement, presents a newer way of viewing style drift, and uses style misclassification already present within the literature.

The second essay of this thesis uses a sample of U.S. active equity mutual funds from 1995-2019 and attempts to determine the presence of a threshold level of deviation from where we can classify a fund as a misclassified one. To do this, we use tracking errors as a proxy to measure the level of style deviations of a fund and examine its association with various performance metrics. We do this by fitting the quadratic regression equation of a parabola and assuming a concave relationship between fund performance and tracking errors. We then consider this threshold level of deviation an inflection point from where the relationship between performance and tracking error changes from positive to negative. Our findings suggest such a threshold level exists and indicate a concave relationship between fund performance and style deviations.

Our final essay, Essay 3, explores the relationship between the frequency of mutual fund holdings disclosure and the style drift of a fund. It uses a difference-in-difference test and examines the 2004 and 2019 policy changes relating to mutual fund holdings disclosure. It considers previously semi-annual funds that had to disclose every quarter after 2004 as the treatment group and funds that disclosed quarterly throughout as the control group. The findings indicate that the style drift of previously semi-annual funds has declined by about 0.79 points per month after 2004. Our findings remain robust while analyzing the 2019 regulatory change when the mandatory disclosure frequency was changed again from quarterly to monthly and utilizing data from January 2009-December 2021. We find our results to be robust in the recent framework suggesting style drift to decrease by 0.51 points with an increase in the disclosure frequency.

5.2. Future Research

We have completed three research studies in detail within this dissertation. However, the inaccessibility of some of the databases and the time frame for completion of the degree have put some limitations on our thesis. Therefore, some areas of our research could be addressed in possible future studies. Our first study provides a critical evaluation of the existing literature regarding the style deviating practices of fund managers and introduces a conceptual framework to present a fuller picture of the phenomenon. As such, this is a critical review and we do not have any further recommendations for its future study.

Focusing on the results of our second study, analyzing the presence of the threshold level from where a fund starts exhibiting the properties of a misclassified fund in other variations of asset allocations, such as hedge funds, would be an interesting topic to study. Additionally, it would also be interesting to check for the existence of this threshold level of deviation in jurisdictions other than the U.S.

In the third study, we measure style drift using the style drift score from return based style analysis to examine the impact of more frequent portfolio disclosure in limiting style drift within mutual funds. However, it can be even more insightful to use a holding-based measure. In addition, endogeneity is another issue in this study. This is because the farther a fund is from its prospectus benchmark (more deviation), the greater the incentive to disclose less frequently. We do address endogeneity by using a difference-in-difference approach and studying the change in mandatory portfolio disclosure requirements in 2004 and 2019 as a natural experiment. However, other factors, such as reverse causality, omitted variables, and selection bias, may also cause endogeneity. Although, it is impossible to resolve endogeneity in full, the finance literature does present several other techniques in addition to the difference-in-difference approach to deal with endogeneity issues, such as the instrumental variable approach, and future studies may test for it.