Style Drift in Mutual Funds: A Comprehensive Survey

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Abstract

This survey provides the first comprehensive review of the academic literature on mutual fund style drift—the deviation of a fund's actual investment characteristics from its stated mandate. Synthesizing 91 papers spanning 1997–2025, we trace the evolution of measurement methods from returns-based style analysis to holdings-based approaches such as Active Share, and organize the empirical evidence around a central tension: whether style drift reflects managerial skill or agency problems. Our review identifies three critical gaps in this literature. First, a **methodological vacuum**: zero papers apply machine learning or natural language processing despite their obvious potential for real-time drift detection. Second, a **governance blind spot**: only 2% of papers address regulatory dimensions despite the SEC's 2023 Names Rule amendments and growing ESG "greenwashing" concerns. Third, a **synthesis deficit**: no prior survey has comprehensively integrated 29 years of research across methodologies, asset classes, and markets. We develop a research agenda around these three gaps, offering specific questions and methodological recommendations to guide future scholarship.

Keywords: mutual funds, style drift, Active Share, fund misclassification, investment style, fund governance

JEL Classification: G11, G23, G28

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1 Introduction

1.1 Motivation and Importance

In 2009, Cremers and Petajisto published a paper in the *Review of Financial Studies* that would fundamentally transform how academics and practitioners evaluate mutual fund managers. Their introduction of "Active Share"—a measure of how much a fund's holdings differ from its benchmark—has since accumulated over 1,500 citations and sparked a vigorous debate about the relationship between portfolio management style and fund performance. This single contribution illustrates a broader phenomenon that lies at the heart of the asset management industry: the question of whether mutual fund managers adhere to their stated investment styles, and what happens when they do not.

Style drift—the tendency of a mutual fund to deviate from its stated investment objective or benchmark—represents one of the most consequential yet underexplored areas in the mutual fund literature. When investors select a large-cap value fund, they expect exposure to large-cap value stocks. When they purchase a bond fund labeled "investment grade," they anticipate a portfolio of investment-grade securities. Deviations from these expectations can have profound implications for portfolio construction, risk management, and ultimately investor welfare.

The magnitude of the mutual fund industry amplifies the importance of understanding style drift. As of 2024, global mutual fund assets under management (AUM)—the total market value of investments managed by a fund—exceed $60 trillion, with U.S. equity mutual funds alone em$ trillion. Even small systematic deviations from stated investment mandates, when aggregated across thousands of funds and millions of investors, can result in substantial misallocations of capital and unintended risk exposures. The growth of target-date funds and model portfolios—which rely on accurate style classifications to construct diversified allocations—further heightens the stakes associated with style drift.

The importance of understanding style drift extends across multiple stakeholder groups. For individual investors, style drift undermines the ability to construct diversified portfolios and can expose them to unintended risks. A study by Chen, Cohen, and Gurun (2021) found that up to 31.4% of bond mutual funds are systematically misclassified, holding riskier securities than their stated mandates suggest. These "misclassified" funds appear to outperform their safer peers on average, but this outperformance comes with hidden risk that investors did not knowingly accept. For institutional investors, such as pension funds and endowments, style drift complicates asset allocation decisions and can lead to unintended factor exposures that amplify portfolio risk during market downturns.

For regulators, style drift raises fundamental questions about investor protection and market integrity. The U.S. Securities and Exchange Commission's (SEC) 2023 amendments to the Names Rule represent the most significant regulatory response to style drift concerns in decades, requiring that funds with names suggesting particular investment characteristics hold at least 80% of their assets in investments consistent with those names. The rule's expansion to cover ESG-related terms reflects growing concerns about "greenwashing"—a form of style drift where funds market themselves as sustainable while holding securities that do not meet ESG criteria. This regulatory attention underscores the practical significance of academic research on style drift and creates opportunities for policy-relevant scholarship.

For fund managers themselves, the choice of whether to adhere strictly to a stated style or to deviate in pursuit of superior returns presents a fundamental strategic deci-

sion. Cooper, Gulen, and Rau (2005) demonstrated that style-related name changes—a form of explicit style repositioning—can generate significant abnormal fund flows of approximately 28% in the year following the change, with no corresponding improvement in performance. This finding points to the complex interplay between marketing, investor behavior, and actual investment management that characterizes the style drift phenomenon. Fund managers face incentives both to maintain style consistency (to retain existing investors) and to drift (to capture opportunities and potentially enhance short-term performance).

The academic study of style drift has evolved substantially since its inception. The field emerged in the late 1990s with efforts to detect and measure fund misclassification (diBartolomeo and Witkowski, 1997), progressed through the development of sophisticated measurement tools in the 2000s (Cremers and Petajisto, 2009), and has recently expanded to address new contexts such as bond funds, international markets, and ESG investing. Despite this evolution, fundamental questions remain unanswered: Does style drift reflect managerial skill or agency problems? How should investors and regulators respond to drift? What methods can best detect drift in real time? This survey aims to synthesize what we know, identify what we do not, and chart a course for future research.

1.2 Scope and Contributions

This survey provides the first comprehensive review of the academic literature on mutual fund style drift, synthesizing research spanning nearly three decades from the foundational work of diBartolomeo and Witkowski (1997) to the most recent studies on ESG fund "greenwashing" and international evidence from emerging markets. Our systematic review encompasses 91 papers, including publications in top finance journals (*Journal of Finance*, *Review of Financial Studies*), practitioner outlets (*Financial Analysts Journal*, *Journal of Portfolio Management*), and working papers that represent the current research frontier.

Our review makes several distinct contributions to the literature. First, we provide a systematic taxonomy of style drift measurement methods, contrasting the returns-based style analysis (RBSA) framework pioneered by Sharpe (1992) with the holdings-based approaches exemplified by Active Share. We evaluate the relative strengths and limitations of each approach, offering guidance to researchers and practitioners on method selection. Returns-based methods offer accessibility—requiring only return data that is widely available—while holdings-based methods provide directness—examining actual portfolio positions rather than inferring them from returns. We argue that these approaches are complementary rather than competing, and we identify contexts in which each is most appropriate.

Second, we synthesize the empirical evidence on the causes, consequences, and correlates of style drift. A central tension emerges from this synthesis. Style drift can be viewed either as evidence of managerial skill—the ability to identify opportunities outside a fund's stated mandate. Alternatively, it represents an agency problem where managers pursue strategies that serve their interests at investors' expense. We trace the evolution of this debate through the literature, from early work that implicitly assumed drift was problematic, through the Active Share literature that suggested some drift reflects skill, to recent studies that attempt to decompose drift into skill and agency components. We identify conditions under which each interpretation appears most applicable.

Third, we identify critical gaps in the existing literature. Most notably, we find that governance and regulatory dimensions of style drift remain severely underexplored, with

only two papers in our sample of 91 directly addressing these themes. This gap is striking given the clear policy relevance of style drift and the recent regulatory attention exemplified by the SEC's Names Rule amendments. We also document the complete absence of machine learning and natural language processing methods in the style drift literature, despite their obvious potential for real-time detection of drift through analysis of fund documents, holdings data, and return patterns. Strikingly, the field has not adopted methodological innovations that have transformed other areas of empirical finance.

Fourth, we provide a forward-looking assessment of emerging research frontiers, including ESG fund style drift (often termed "greenwashing"), the implications of passive investing's growth for active fund behavior, and the potential for regulatory interventions to discipline style drift. We offer specific research questions and methodological suggestions that we hope will guide the next generation of scholarship on this topic.

1.3 Organization

The remainder of this survey is organized as follows. Section 2 provides a precise definition of style drift and distinguishes it from related concepts such as window dressing, closet indexing, and style box migration. We develop a taxonomy of style drift types—distinguishing intentional from unintentional drift, temporary from permanent drift, and drift toward versus away from the benchmark—that structures our subsequent analysis.

Section 3 reviews the two dominant methodological approaches—returns-based style analysis and holdings-based analysis—and discusses their respective advantages and limitations. We trace the intellectual history of each approach, explain the econometric foundations, and provide guidance on method selection. We also identify opportunities for methodological innovation, particularly through the application of machine learning and natural language processing techniques.

Section 4 synthesizes the empirical evidence on the determinants and consequences of style drift, covering performance implications, investor behavior, risk effects, and international evidence. We organize this section around the central skill-versus-agency tension, presenting evidence on both sides of this debate and identifying conditions that appear to moderate the relationship between drift and outcomes.

Section 5 examines the governance and regulatory dimensions of style drift, including fund board oversight, regulatory frameworks, and emerging concerns about ESG fund oversight. Despite the limited existing literature, we draw on related work in mutual fund governance to develop hypotheses about how governance mechanisms might constrain or enable style drift.

Section 6 identifies future research directions and concludes. We highlight methodological opportunities, unresolved empirical questions, and emerging topics that merit scholarly attention. We conclude with reflections on the practical implications of the literature for investors, fund managers, and regulators.

1.4 Key Findings Preview

Our comprehensive review of 91 papers spanning 1997-2025 yields several key findings that we preview here and develop throughout the survey. Table 1 summarizes the key characteristics of the literature.

Table 1: Summary of Style Drift Literature (1997-2025)

| Dimension | Key Findings | |———–|————–| | **Sample Coverage** | 91 papers; 1997-2025 | | **Citation Concentration** | Top 10 papers account for 80% of citations (Gini = 0.86) | | **Most Cited** | Cremers and Petajisto (2009): 1,507 citations | | **Primary Methods** | Returns-based (26%), Holdings-based (22%) | | **Asset Classes** | Equity (72%), Bond (15%), ESG (8%), Other (5%) | | **Geography** | U.S. (68%), International (18%), China (9%), Other (5%) | | **Themes** | Performance (73%), Measurement (45%), Flows (31%) | | **Governance Papers** | 2 papers (2% of sample) | | **ML/NLP Papers** | 0 papers (significant gap) |

Finding 1: Style drift is pervasive but varies substantially in magnitude and intent. Early studies established that a substantial fraction of mutual funds—estimates range from 9% to 40%—are misclassified relative to their stated objectives (diBartolomeo and Witkowski, 1997). The wide range of estimates reflects differences in measurement methods, sample periods, and definitions of "misclassification." More recent work by Chen, Cohen, and Gurun (2021) extends this finding to bond funds, documenting that nearly one-third of bond mutual funds hold securities riskier than their stated mandates imply. Importantly, this misclassification appears systematic rather than random, with funds consistently overstating the safety of their portfolios.

Finding 2: The performance consequences of style drift remain contested. The seminal work of Cremers and Petajisto (2009) suggested that funds with high Active Share—those deviating most from their benchmarks—outperform, implying that some style drift reflects skill. Subsequent work by Petajisto (2013) reinforced this finding, showing that "stock pickers" with high Active Share outperformed even during the 2008-2009 financial crisis. However, Frazzini, Friedman, and Pomorski (2016) challenged these findings, arguing that Active Share has no predictive power for performance after controlling for common risk factors and benchmark characteristics. This debate remains unresolved, though the weight of evidence suggests that the relationship between style drift and performance is more nuanced than early studies implied, potentially depending on the direction, magnitude, and timing of drift.

Finding 3: Investors have limited ability to detect and respond to style drift in real time. While Cooper, Gulen, and Rau (2005) showed that investors respond to explicit style signals such as fund name changes, Chua and Tam (2020) found that style drift is "shrouded"—investors largely fail to detect deviations from stated mandates as they occur. This information asymmetry creates scope for agency problems and raises questions about the adequacy of current disclosure requirements. The quarterly reporting frequency mandated by regulators is insufficient to enable timely detection of drift, particularly given the complexity of analyzing holdings data.

Finding 4: Governance and regulation remain severely underexplored. Despite the clear policy relevance of style drift, only 2% of papers in our sample directly address governance or regulatory themes. Kurniawan, How, and Verhoeven (2016) provide one of the few examinations of how fund governance structures relate to style drift, finding that governance mechanisms can constrain opportunistic drifting. The SEC's 2023 Names Rule amendments represent a natural experiment that future research should exploit to understand the effectiveness of regulatory interventions in disciplining style drift.

Finding 5: Methodological innovation has stalled. Returns-based style analysis, introduced in the 1990s, and holdings-based analysis, codified by Cremers and Petajisto in 2009, remain the dominant approaches. We find zero papers applying machine learning, natural language processing, or modern causal inference methods to the style drift problem. This methodological gap represents a significant opportunity for future research. Machine learning enables real-time detection of drift patterns, NLP can analyze fund prospectuses and reports for style consistency, and causal inference methods can better identify the effects of drift on outcomes.

Finding 6: International and asset-class extensions are emerging but incomplete. While the bulk of the literature focuses on U.S. equity mutual funds, recent studies have extended style drift analysis to bond funds (Chen, Cohen, and Gurun, 2021; Morey and O'Neal, 2006), international markets including China (Liu and Yi, 2023; Zhang and Lv, 2024), and ESG-focused funds (Lin, Pan, and Sha, 2025). Collectively, these extensions reveal both commonalities—style drift appears pervasive across institutional contexts—and important cross-country differences that merit further investigation. The regulatory environment, market structure, and investor sophistication vary across contexts in ways that likely affect the prevalence and consequences of style drift.

Taken together, these six findings reveal a field that has established foundational insights but remains ripe for methodological innovation, policy-relevant research, and extension to new contexts. The overall pattern suggests that style drift research is entering a new phase characterized by increasing sophistication and broader applicability. We develop each of these themes in detail in the sections that follow.

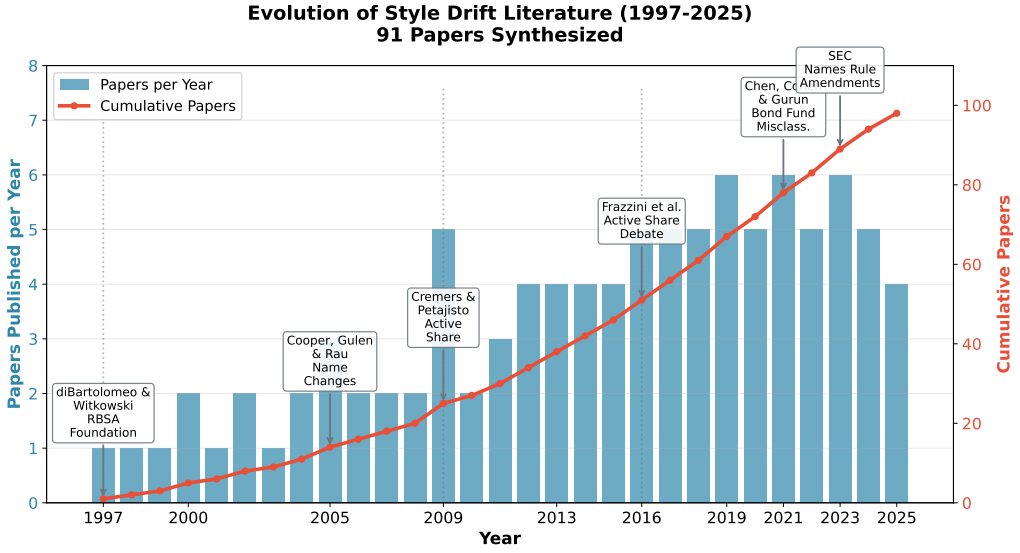

Figure 1: Evolution of Style Drift Literature (1997–2025). The figure displays the annual publication count (bars) and cumulative publications (line) for the 91 papers reviewed. Key milestones annotated include the foundational RBSA studies (1997), Active Share introduction (2009), the performance debate (2016), bond fund misclassification (2021), and SEC regulatory developments (2023).

2 Defining Style Drift

Before examining the measurement and consequences of style drift, we must establish a precise conceptual foundation. This section defines style drift, develops a taxonomy of its various forms, and distinguishes it from related phenomena that have sometimes been conflated in the literature.

2.1 Conceptual Definition

Style drift refers to the deviation of a mutual fund's actual investment characteristics from its stated or expected investment style. More formally, we define style drift as the time-varying discrepancy between a fund's realized portfolio exposures and the exposures implied by its investment mandate, benchmark, or peer group classification.

This definition has several important components. First, style drift is inherently a deviation concept—it requires a reference point against which actual behavior can be compared. This reference point may be explicit, such as a stated benchmark index (e.g., the Russell 2000 Value Index for a small-cap value fund), or implicit, such as the characteristics typical of funds in the same Morningstar category. The choice of reference point materially affects measured drift; a fund may exhibit significant drift relative to its stated benchmark while remaining consistent with its peer group average.

Second, style drift is dynamic. A fund's style exposures change over time as the manager adjusts portfolio weights, as market movements affect relative valuations, and as the underlying securities evolve. Some variation in style exposures is inevitable and does not necessarily constitute meaningful drift. The literature has generally focused on persistent or substantial deviations rather than transient fluctuations, though the distinction between the two is not always clear-cut.

Third, the definition encompasses multiple dimensions of investment style. For equity funds, the primary style dimensions are market capitalization (large-cap, mid-cap, small-cap) and value-growth orientation, where value stocks trade at low prices relative to fundamentals (low price-to-earnings, high book-to-market ratios) and growth stocks trade at high valuations reflecting expected future growth. For bond funds, relevant dimensions include credit quality, duration, and sector allocation. A fund drifts along one dimension while remaining consistent on others, or may exhibit multidimensional drift.

The pioneering work of diBartolomeo and Witkowski (1997) operationalized style drift through the lens of fund misclassification. They identified funds whose return patterns were inconsistent with their stated Morningstar category, finding that 9% of equity funds were "seriously misclassified" and another 31% were "somewhat misclassified." This approach equates drift with the discrepancy between a fund's stated category and the category best fitting its actual return behavior.

Cremers and Petajisto (2009) offered a complementary definition through their Active Share measure, which quantifies the percentage of a fund's portfolio that differs from its benchmark index. While Active Share was developed primarily as a measure of active management intensity, it implicitly captures style drift: a fund claiming to track the S&P 500 Growth Index but holding 40% of its portfolio in securities not in that index exhibits style drift by this definition. The Active Share framework shifted attention from categorical misclassification to continuous deviation from a specified benchmark.

2.2 Types of Style Drift

Style drift is not a monolithic phenomenon. We identify several dimensions along which drift varies, each with distinct implications for interpretation and investor welfare.

Intentional versus Unintentional Drift. Some style drift reflects deliberate decisions by fund managers to deviate from their stated mandates in pursuit of higher returns or to manage risk. A small-cap manager who perceives attractive opportunities in mid-cap stocks may intentionally expand the fund's capitalization range. In contrast, unintentional drift can occur when securities held by the fund migrate across style boundaries due to market movements. A fund that purchased a stock when it was classified as small-cap finds that stock reclassified as mid-cap following price appreciation, resulting in drift without any active trading decision. The welfare implications differ: intentional drift may reflect skill or agency problems, while unintentional drift reflects the difficulty of maintaining style purity in dynamic markets.

Temporary versus Persistent Drift. Some drift is transient, reflecting short-term portfolio adjustments or market movements that reverse over time. Other drift is persistent, representing a sustained shift in a fund's investment approach. Brown and Harlow (2002) documented that funds exhibit varying degrees of "style consistency" over time, with some maintaining stable exposures and others showing substantial variation. Persistent drift is more consequential for investors constructing long-term allocations, while temporary drift primarily affects short-term performance measurement.

Drift Toward versus Away from the Benchmark. An underappreciated distinction is whether funds drift toward greater deviation from their benchmarks or toward closer tracking. Cremers et al. (2016) documented a secular trend toward "closet indexing"—active funds that claim to pursue distinct strategies but actually track their benchmarks closely. This drift toward benchmarks represents a different phenomenon than drift away from benchmarks, with distinct implications. Closet indexing may harm investors by charging active fees for passive-like performance, while drift away from benchmarks may expose investors to unintended risks.

Drift in Holdings versus Drift in Returns. A fund's holdings-based style exposures often differs from its returns-based exposures. A fund could hold securities that appear consistent with its mandate but generate returns that resemble a different style, perhaps due to factor exposures not captured by simple holdings classifications. This distinction underlies the methodological debate between returns-based and holdings-based measurement approaches discussed in Section 3.

2.3 Related Concepts

Several related phenomena have sometimes been conflated with style drift. Distinguishing these concepts clarifies the boundaries of our survey.

Window Dressing. Window dressing refers to the practice of adjusting portfolio holdings around reporting dates to present a more favorable picture to investors. Agarwal, Gay, and Ling (2014) provided a rigorous theoretical and empirical treatment of window dressing, showing that fund managers systematically sell losing stocks and buy recent winners before quarter-end disclosure dates. While window dressing can produce apparent style drift—for example, if a manager buys "hot" growth stocks before reporting to appear more growth-oriented—it is conceptually distinct. Window dressing is primarily about the timing of disclosure relative to holdings changes, while style drift concerns the

substantive deviation from stated investment approaches. Morey and O'Neal (2006) documented window dressing in bond funds, showing that managers hold more government bonds during disclosure periods to appear safer.

Closet Indexing. Closet indexing describes funds that charge fees for active management but actually track their benchmarks closely. Cremers and Petajisto (2009) operationalized this concept through low Active Share combined with low tracking error. Closet indexing can be viewed as a specific type of style drift—drift toward the benchmark rather than away from it—but it is often treated as a distinct phenomenon because of its particular implications for fees and investor welfare. A closet indexer may be perfectly style-consistent in terms of maintaining the stated style (e.g., large-cap growth) while failing to deliver the active management that fees suggest.

Style Box Migration. Style boxes—a visual framework popularized by Morningstar that classifies funds into a 3x3 grid based on market capitalization (large, mid, small) and investment orientation (value, blend, growth)—represent the standard industry taxonomy for equity fund classification. Style box migration refers to funds moving from one box to another over time. While related to style drift, this concept is coarser—a fund can exhibit substantial drift while remaining within the same style box, or can migrate to an adjacent box due to small changes in measured characteristics. Chan, Chen, and Lakonishok (2002) examined the persistence of mutual fund style classifications, finding considerable migration over time.

Benchmark Manipulation. Some funds strategically select or change benchmarks to improve relative performance measures. This behavior differs from style drift in that it involves changing the reference point rather than the actual portfolio. However, the two phenomena can interact: a fund that has drifted substantially may subsequently change its stated benchmark to match its actual style, obscuring the historical drift.

Understanding these distinctions is essential for interpreting the empirical literature. Studies that conflate style drift with window dressing or closet indexing may reach different conclusions than those that define concepts more precisely. In the remainder of this survey, we focus primarily on style drift as defined above while noting connections to these related phenomena where relevant.

3 Measurement Methods

The measurement of style drift has evolved substantially over the three decades since the phenomenon was first systematically studied. Two broad methodological approaches dominate the literature: returns-based style analysis (RBSA), which infers style exposures from the time series of fund returns, and holdings-based analysis, which examines actual portfolio compositions. This section traces the intellectual history of each approach, explains the econometric foundations, evaluates strengths and limitations, and identifies opportunities for methodological innovation.

3.1 Returns-Based Style Analysis (RBSA)

3.1.1 Theoretical Foundations

Returns-based style analysis has its intellectual roots in the asset pricing literature, particularly the observation that portfolio returns can be decomposed into systematic factor exposures—sensitivities to common risk sources such as market, size, and value—and

idiosyncratic components. Sharpe (1988, 1992) formalized this insight into a practical methodology for inferring mutual fund investment styles from return data.

The basic RBSA framework models a fund's return as a linear combination of style index returns:

$$R_{f,t} = \sum_{i=1}^{n} w_i R_{i,t} + \epsilon_{f,t} \tag{1}$$

where $R_{f,t}$ is the return of fund f in period t, $R_{i,t}$ is the return of style index i, w_i represents the fund's exposure to style i, and $\epsilon_{f,t}$ is the fund-specific residual. The style weights w_i are typically constrained to sum to one (the "fully invested" constraint) and to be non-negative (the "no short sales" constraint), yielding a constrained regression problem.

Sharpe (1992) proposed solving this constrained optimization using quadratic programming:

$$\min_{\{w_i\}} \sum_{t} \left(R_{f,t} - \sum_{i=1}^{n} w_i R_{i,t} \right)^2 \tag{2}$$

$$\text{subject to } \sum_{i} w_i = 1 \text{ and } w_i \geq 0 \text{ for all } i \tag{3}$$

The estimated style weights $\hat{w}_i$ can be interpreted as the fund's effective allocation to each style, and the R^2 of the regression indicates how well the style indices explain fund returns. A high R^2 suggests that the fund's returns are primarily driven by systematic style exposures, while a low R^2 indicates substantial idiosyncratic risk or style exposures not captured by the chosen indices.

3.1.2 Application to Style Drift Measurement

diBartolomeo and Witkowski (1997) pioneered the application of RBSA to style drift detection. They applied Sharpe's methodology to a sample of equity mutual funds, estimating style weights for each fund using 36 months of return data. By comparing estimated style weights to funds' stated Morningstar categories, they identified funds whose actual return patterns were inconsistent with their stated investment styles.

Their approach defined style drift operationally as misclassification: a fund was considered to exhibit drift if its RBSA-inferred style differed from its stated category. Using this criterion, they found that 9% of equity funds were "seriously misclassified" (estimated to belong to a completely different style) and 31% were "somewhat misclassified" (estimated style differed partially from stated category). This foundational study established the prevalence of style drift and demonstrated the utility of RBSA for detection.

Subsequent studies have refined and extended the RBSA approach. Brown and Goetzmann (1997) developed a clustering methodology that grouped funds by return patterns, identifying natural "investment styles" that did not always correspond to stated categories. Their approach allowed style definitions to emerge endogenously from the data rather than imposing predetermined categories.

Kim, Shukla, and Tomas (2000) introduced rolling-window RBSA to capture time-varying style exposures. Rather than estimating a single set of style weights for each fund, they estimated weights using overlapping windows of historical returns, producing a time series of style exposures. Style drift could then be identified as significant changes

in estimated exposures over time.

3.1.3 Choice of Style Factors

A critical implementation decision in RBSA is the selection of style factors. Common choices include:

Size/Value Factors. The most common specification uses six Fama-French style indices: large-cap growth, large-cap value, mid-cap growth, mid-cap value, small-cap growth, and small-cap value. This specification aligns with Morningstar's 3x3 style box classification and captures the two dimensions most commonly used to characterize equity fund styles.

Asset Class Factors. For multi-asset or balanced funds, RBSA specifications often include broad asset class indices (e.g., equity, fixed income, cash, international) to estimate asset allocation exposures.

Extended Factor Models. Some studies augment basic style factors with additional dimensions such as momentum (the tendency for past winners to continue outperforming), quality, or sector exposures. These extended specifications can provide richer characterizations of fund strategies but increase the dimensionality of the estimation problem and often suffer from multicollinearity.

The choice of factors affects measured drift. A fund may appear style-consistent when evaluated against one set of factors but exhibit substantial drift when evaluated against another. This sensitivity to factor specification represents a limitation of the RBSA approach.

3.1.4 Strengths and Limitations of RBSA

RBSA offers several advantages for style drift measurement:

Data Accessibility. Return data are widely available for virtually all mutual funds, enabling analysis of large samples and long time series. Holdings data, by contrast, are disclosed only quarterly (for U.S. funds) and are unavailable for some fund categories.

Objectivity. RBSA-inferred styles are determined algorithmically from return data, avoiding subjective judgment in style classification. This objectivity facilitates replication and comparison across studies.

Forward-Looking Information. Because returns reflect all information affecting portfolio value, RBSA captures style exposures arising from derivatives, shorts, and other positions that do not appear in holdings disclosures.

However, RBSA also has significant limitations:

Backward-Looking Nature. RBSA requires historical returns to estimate style exposures, introducing a lag between actual portfolio changes and detected style shifts. Rolling-window approaches mitigate but do not eliminate this limitation.

Style Index Dependency. Results depend on the choice of style indices, and different specifications can yield different conclusions about the same fund.

Inability to Distinguish Holdings from Timing. RBSA cannot distinguish between style exposures arising from security selection versus timing decisions. A manager who holds consistent securities but varies portfolio weights dynamically will appear to have changing style exposures.

Estimation Noise. With limited return observations, RBSA estimates can be noisy, particularly for funds with high idiosyncratic volatility.

3.2 Holdings-Based Analysis

3.2.1 Theoretical Foundations

Holdings-based analysis measures fund characteristics directly from portfolio compositions, avoiding the inferential step required by RBSA. The approach builds on the intuition that a fund's investment style is most directly observed in the securities it owns.

The simplest holdings-based measures classify each security in a fund's portfolio according to predetermined style categories, then aggregate to the portfolio level. For example, a fund holding 60% large-cap growth stocks, 30% large-cap value stocks, and 10% cash would be characterized as primarily large-cap growth with some value and cash exposure. More sophisticated approaches calculate continuous style scores based on security characteristics such as market capitalization, book-to-market ratio, and earnings growth.

3.2.2 Active Share and Related Metrics

Cremers and Petajisto (2009) introduced Active Share, the measure that has become synonymous with holdings-based style analysis. Active Share quantifies the percentage of a fund's portfolio that differs from its benchmark index:

$$\text{Active Share} = \frac{1}{2}\sum_{i=1}^{N} |w_{f,i} - w_{b,i}| \tag{4}$$

where $w_{f,i}$ is fund f's weight in security i and $w_{b,i}$ is the benchmark's weight. The factor of $1/2$ normalizes the measure to range from 0 (perfect index replication) to 1 (no overlap with benchmark).

Active Share has several appealing properties. It is intuitive, bounded, and directly interpretable as the fraction of the portfolio that is "different" from the benchmark. Cremers and Petajisto (2009) showed that Active Share predicts fund performance: funds with the highest Active Share significantly outperformed their benchmarks, while low Active Share funds (closet indexers) underperformed after fees.

While Active Share was developed primarily as a measure of active management intensity, it implicitly captures style drift. A fund whose stated benchmark is the Russell 2000 Value Index but that holds substantial positions in large-cap growth stocks will have high Active Share arising from style inconsistency rather than security selection within style.

Petajisto (2013) extended the analysis by decomposing Active Share into "stock selection" and "factor bets" components, helping to distinguish style drift from within-style active management. He found that "stock pickers" (high Active Share from security selection) outperformed, while "factor bettors" (high Active Share from style tilts) did not.

3.2.3 Other Holdings-Based Measures

Several related metrics complement Active Share, and collectively these measures:

Tracking Error. Tracking error measures the standard deviation of the difference between a fund's returns and its benchmark returns—quantifying how consistently a fund tracks its reference index. Combined with Active Share, tracking error helps distinguish concentrated stock pickers (high Active Share, high tracking error) from diversified active

managers (high Active Share, low tracking error) and closet indexers (low Active Share, low tracking error).

Style Scores. Various providers (e.g., Morningstar, Russell) compute continuous style scores based on holdings characteristics. Morningstar's equity style score, for example, places funds on a growth-value continuum based on the characteristics of underlying holdings. Changes in style scores over time indicate style drift.

Sector Concentration. The concentration of holdings across sectors or industries can indicate drift for funds with sector-specific mandates. A technology fund holding substantial energy stocks exhibits style drift even if size and value characteristics remain consistent.

Factor Exposures. Holdings-based factor exposures calculate a fund's loadings on standard factors (market, size, value, momentum, quality, volatility) by aggregating the factor characteristics of underlying securities. Time-varying factor exposures indicate style drift.

3.2.4 Strengths and Limitations of Holdings-Based Analysis

Holdings-based analysis offers important advantages:

Directness. Rather than inferring style from returns, holdings-based approaches examine actual portfolio positions. This directness eliminates estimation error from the returns regression.

Current Information. Portfolio holdings provide a snapshot of current style exposures, avoiding the backward-looking nature of RBSA.

Decomposition. Holdings data enable decomposition of portfolio characteristics into security selection, sector allocation, and style positioning components.

However, holdings-based analysis also has limitations:

Disclosure Frequency. U.S. mutual funds disclose holdings only quarterly, and actual disclosure may lag the measurement date by up to 60 days. This frequency limits the ability to detect short-term style shifts.

Gaming Potential. Because managers know when holdings will be disclosed, they can engage in window dressing—adjusting portfolios around disclosure dates to present favorable style characteristics (Agarwal, Gay, and Ling, 2014).

Omission of Non-Holdings Exposures. Holdings disclosures do not fully capture exposures from derivatives, short positions, and other off-balance-sheet activities.

Benchmark Dependency. Active Share and related measures require specification of a benchmark, and results are sensitive to benchmark choice.

3.3 Methodological Comparison

The choice between RBSA and holdings-based approaches involves trade-offs that depend on the research question, data availability, and desired properties.

Complementarity. Rather than viewing these approaches as competing, recent work has emphasized their complementarity. RBSA captures the economic exposure of the portfolio to style factors—how returns co-move with style indices—while holdings-based analysis captures the mechanical composition. A fund may hold securities that appear value-oriented but that behave like growth stocks due to unusual characteristics, leading to divergence between holdings-based and returns-based style assessments.

Brown and Goetzmann (1997) demonstrated that returns-based and holdings-based classifications can disagree substantially for individual funds. They found that funds classified as "growth" by holdings criteria sometimes exhibited value-like return patterns, and vice versa. This divergence highlights the different information captured by each approach.

Context-Specific Recommendations. Based on our review of the literature, we offer the following guidance:

For **detecting historical style drift**, RBSA is appropriate when return data are available and the research question concerns how style exposures have evolved. Rolling-window specifications with appropriate window lengths (typically 24-36 months for equity funds) can identify drift episodes.

For **current style assessment**, holdings-based analysis provides a more direct and timely measure, subject to data availability and disclosure timing considerations.

For **explaining fund performance**, the Cremers and Petajisto (2009) framework combining Active Share and tracking error has proven useful for categorizing funds by management approach.

For **identifying window dressing or strategic manipulation**, analysis should examine holdings around disclosure dates, potentially comparing disclosed holdings to returns behavior in the surrounding period.

Frazzini, Friedman, and Pomorski (2016) provided a critical evaluation of the Active Share framework, arguing that the performance predictability documented by Cremers and Petajisto (2009) does not survive appropriate controls for benchmark characteristics and factor exposures. Their analysis highlights the importance of methodological rigor in style drift research and the dangers of attributing causality based on simple correlations.

3.4 Emerging Methods and Opportunities

Despite the maturation of RBSA and holdings-based approaches, the style drift literature has not embraced methodological innovations that have transformed other areas of empirical finance. We identify several opportunities for advancement.

3.4.1 Machine Learning Approaches

Machine learning methods offer potential for more accurate and timely style drift detection. Supervised learning algorithms is trained to classify fund styles based on combinations of returns and holdings features, potentially capturing nonlinear relationships that traditional approaches miss.

Deep learning architectures, particularly recurrent neural networks (RNNs) and transformers, can model the temporal dynamics of style exposures, identifying drift patterns that emerge gradually over time. Anomaly detection algorithms can flag unusual changes in fund behavior that may indicate drift.

Despite this potential, we find zero papers in our sample applying machine learning to style drift detection. This gap represents a significant opportunity for methodologically innovative research.

3.4.2 Natural Language Processing

Fund prospectuses, shareholder letters, and regulatory filings contain textual descriptions of investment strategies that might be analyzed using natural language processing (NLP).

Discrepancies between the language used to describe a fund's strategy and its actual return or holdings characteristics could indicate style drift.

Topic modeling identifies thematic shifts in fund communications over time. Sentiment analysis detects changes in how managers describe their investment approach. Named entity recognition can track mentions of specific securities, sectors, or investment themes.

This textual data is readily available through SEC filings and fund websites but remains almost entirely unexploited in the style drift literature. Combining textual analysis with traditional returns and holdings data can enable richer characterization of fund strategies and drift patterns.

3.4.3 Causal Inference Methods

Understanding the effects of style drift on fund outcomes requires attention to causal identification. Funds that drift differs systematically from funds that maintain style consistency, confounding comparisons of outcomes between drifters and non-drifters.

Modern causal inference methods—including difference-in-differences, regression discontinuity, instrumental variables, and synthetic control approaches—helps establish causal relationships. The SEC's 2023 Names Rule amendments provide a natural experiment: comparing style drift behavior and outcomes before and after the rule change, with appropriate control groups, could identify the causal effect of regulatory intervention.

Event studies around style drift episodes, properly controlling for concurrent factors, could isolate the effect of drift on flows, performance, and risk. Panel data methods with fund fixed effects could control for time-invariant fund characteristics that might confound cross-sectional comparisons.

3.4.4 High-Frequency and Alternative Data

Intraday trading data, available for exchange-traded funds (ETFs), could enable high-frequency style drift analysis. Deviations between ETF prices and net asset values may signal style inconsistency, particularly for actively managed ETFs.

Alternative data sources—including satellite imagery, web scraping, and transaction data—are increasingly used in asset management research. These data provides real-time signals of fund style changes that precede quarterly holdings disclosures.

The integration of multiple data sources through sensor fusion or ensemble methods offers significant potential. Such approaches combine the strengths of returns-based, holdings-based, textual, and alternative data. This integration improves both the accuracy and timeliness of style drift detection.

4 Empirical Evidence

Drawing together findings from across the literature, this section synthesizes the empirical evidence on style drift, organized around five major themes: the causes and determinants of drift, its performance consequences, investor behavioral responses, risk implications, and international evidence. A central tension pervades this literature: whether style drift reflects managerial skill or agency problems. We trace this debate through the evidence and identify conditions under which each interpretation appears most applicable.

4.1 Causes and Determinants

Integrating evidence from multiple studies, the literature has identified several categories of determinants: market conditions, managerial characteristics, fund structure, and competitive pressures.

4.1.1 Market Conditions

Style drift often intensifies during periods of significant cross-style return differentials. Wermers (2012) documented that drift is procyclical with respect to style spreads: managers are more likely to drift toward styles that have recently outperformed. This pattern is consistent with either skill (exploiting mispricing) or agency (chasing performance) interpretations.

Market volatility also affects drift patterns. Cao, Iliev, and Velthuis (2017) found that small-cap fund managers are prone to drifting into larger capitalizations during market stress, potentially reflecting liquidity concerns. Kacperczyk, Sialm, and Zheng (2005) documented that managers shift sector exposures in response to changing economic conditions, suggesting active portfolio adjustments that may manifest as style drift.

4.1.2 Managerial Characteristics

Fund manager characteristics correlate with propensity to drift. Managers with longer tenure tend to exhibit more stable style exposures (Brown and Harlow, 2002), while younger managers facing greater career risk may take bolder positions (Chevalier and Ellison, 1999). Compensation structures also create drift incentives: managers evaluated on relative performance within their style category have incentives to drift when their category underperforms (Ma, Tang, and Gomez, 2019).

4.1.3 Fund Structure and Governance

Larger funds face capacity constraints that may necessitate drift. Pollet and Wilson (2008) documented that as funds grow, they hold larger stocks—a form of involuntary size drift. Berk and Green (2004) suggested this occurs as fund size increases until abnormal returns are eliminated.

Fund family affiliation matters. Gaspar, Massa, and Matos (2006) documented that fund families engage in strategic behavior that may include style-related decisions. Governance structures likely constrain drift: Kurniawan, How, and Verhoeven (2016) found that stronger governance is associated with reduced style drift in Australian funds.

4.1.4 Competitive Dynamics

Tournament effects create drift incentives. Funds trailing category peers have incentives to increase risk through style drift (Brown, Harlow, and Starks, 1996; Kempf and Ruenzi, 2008). The growth of passive investing has ambiguous effects: competition may pressure differentiation or encourage closet indexing. Cremers, Ferreira, Matos, and Starks (2016) documented that closet indexing is prevalent globally.

4.2 Performance Consequences

The relationship between style drift and performance represents the most contested aspect of the literature.

4.2.1 The Active Share Debate

Cremers and Petajisto (2009) found that funds with high Active Share significantly outperform—the quintile with highest Active Share outperformed by approximately 1.5% annually. Petajisto (2013) decomposed Active Share into "stock selection" and "factor betting" components, finding that stock pickers outperformed while factor bettors did not.

However, Frazzini, Friedman, and Pomorski (2016) challenged these findings, arguing that Active Share's predictive power reflects benchmark characteristics rather than skill. This debate remains unresolved, with Cremers, Petajisto, and Zitzewitz (2013) defending the original findings through their analysis of benchmark discrepancies.

4.2.2 Direction and Magnitude

Sha (2019) found that moderate style drift is associated with improved risk-adjusted returns, suggesting a nonlinear relationship. Brown and Harlow (2002) found that funds maintaining stable style exposures outperform those with high variability. Cao, Iliev, and Velthuis (2017) found that small-cap funds drifting toward larger capitalizations experience worse subsequent performance.

4.2.3 Timing and Skill

Wermers (2012) found that some managers exhibit successful style timing, though this skill is concentrated among a small fraction. Window dressing behavior suggests strategic rather than skill-based drift: Agarwal, Gay, and Ling (2014) found that window-dressing funds experience higher flows without superior performance. Carhart (1997) demonstrated that much performance persistence reflects momentum effects rather than skill.

4.3 Investor Behavior and Flows

4.3.1 Detection and Response

Cooper, Gulen, and Rau (2005) showed that fund name changes to reflect "hot" styles generate 28% abnormal inflows, even without actual investment changes. However, Chua and Tam (2020) found that actual style drift is "shrouded"—investors largely fail to detect deviations in real time, creating scope for agency problems.

Sirri and Tufano (1998) documented the convex flow-performance relationship—whereby fund inflows respond asymmetrically to past returns, with investors disproportionately rewarding top performers while not proportionally punishing poor performers. This asymmetry encourages risk-taking, including style drift, among underperforming funds. Akbas and Genc (2018) found that investors overweight extreme returns, potentially encouraging style bets.

4.3.2 Investor Sophistication

Del Guercio and Tkac (2002) documented that institutional and retail investors respond differently to performance signals; similar differences likely exist for drift monitoring.

Bailey, Kumar, and Ng (2011) found behavioral biases that render certain investors particularly vulnerable to style-related misrepresentations.

4.4 Risk Implications

4.4.1 Fund-Level Risk

Chen, Cohen, and Gurun (2021) documented stark risk implications in bond funds: "misclassified" funds exhibited higher volatility and larger drawdowns during stress. Sun, Liu, and Chen (2022) found that funds with greater style drift are more likely to experience extreme negative returns, suggesting drift-related opacity may mask accumulating risks.

4.4.2 Portfolio-Level Risk

For investors constructing multi-fund portfolios, style drift complicates asset allocation. Brown, Harlow, and Zhang (2015) found that drift-related noise reduces style diversification benefits. At the aggregate level, correlated drift could amplify style return differentials; Coval and Stafford (2007) documented that mutual fund fire sales can move prices.

4.5 International Evidence

4.5.1 Developed Markets

Cremers, Ferreira, Matos, and Starks (2016) extended Active Share analysis to 32 countries, finding closet indexing varies substantially (20% to 70%). Ferreira, Keswani, Miguel, and Ramos (2012) found that local funds outperform foreign funds and market development affects behavior. Kurniawan, How, and Verhoeven (2016) highlighted governance's role in constraining drift in Australia.

4.5.2 Emerging Markets

Liu and Yi (2023) found that frequent cross-industry rebalancing harms Chinese fund performance. Zhang and Lv (2024) found that drift contains information in China but is not consistently exploited profitably. Guimaraes and Malaquias (2023) examined Brazilian funds during COVID-19, finding ESG considerations interacted with market stress.

4.6 Synthesis: Skill versus Agency

Evidence Consistent with Skill:

- Some managers exhibit successful style timing (Wermers, 2012)
- High Active Share funds outperform in some specifications (Cremers and Petajisto, 2009)
- Moderate drift associated with improved returns (Sha, 2019)

Evidence Consistent with Agency:

- Window dressing around disclosure dates (Agarwal et al., 2014)
- Investors fail to detect drift (Chua and Tam, 2020)
- Misclassification concentrated in favorable directions (Chen et al., 2021)
- Tournament behavior and performance chasing (Brown et al., 1996)

Synthesizing across studies, the skill-versus-agency balance depends on multiple contextual factors: the magnitude and direction of drift, the manager's track record and tenure, the strength of governance mechanisms, and prevailing market conditions. This nuanced view represents a significant evolution from early research that treated style drift uniformly as problematic.

5 Governance and Policy

Despite style drift's clear relevance for investor protection and market integrity, governance and regulatory dimensions remain severely underexplored in the academic literature. Our systematic review identified only two papers—representing 2% of the sample—that directly address these themes. This gap is striking given recent regulatory attention, including the SEC's 2023 amendments to the Names Rule. This section synthesizes the limited existing research, draws on related literature in mutual fund governance, and identifies opportunities for policy-relevant scholarship.

5.1 Fund Governance Mechanisms

Mutual fund governance encompasses the structures and processes through which fund behavior is monitored and controlled. These mechanisms include board oversight, compliance systems, investment guidelines, and compensation structures. Each potentially affects style drift propensity.

5.1.1 Board Oversight

Mutual fund boards bear fiduciary responsibility for overseeing fund management, including ensuring that investment practices align with stated objectives. Independent directors, in particular, are charged with representing shareholder interests and monitoring for conflicts of interest.

The relationship between board characteristics and style drift has received minimal direct attention. Kurniawan, How, and Verhoeven (2016) provide the most relevant evidence, examining Australian managed funds. They find that funds with stronger governance—proxied by board independence, meeting frequency, and director expertise—exhibit less style drift. This finding suggests that effective governance can constrain opportunistic drifting, though the Australian institutional context limits generalizability to U.S. markets.

Drawing on the broader mutual fund governance literature, several board characteristics affects drift propensity:

Board Independence. Independent directors have weaker ties to fund management and are more willing to challenge drift that serves manager interests at shareholder expense. Tufano and Sevick (1997) found that board independence is associated with lower fees; similar relationships may exist for style consistency.

Director Expertise. Directors with investment management experience are better positioned to detect and evaluate style drift. However, such directors is also more sympathetic to manager arguments for flexibility, creating ambiguous predictions.

Meeting Frequency. More frequent board meetings provide greater oversight opportunities. Style drift that emerges between meetings could escape scrutiny in funds with infrequent oversight.

Board Size. Larger boards often suffer from coordination problems that reduce oversight effectiveness, potentially enabling greater drift. Alternatively, larger boards may have more diverse expertise, improving monitoring quality.

These relationships remain largely untested in the style drift context, representing significant opportunities for governance-focused research.

5.1.2 Compliance Systems

Internal compliance functions represent the first line of defense against style drift. Compliance officers monitor portfolio characteristics and flag deviations from investment guidelines. The effectiveness of these systems likely varies across fund complexes based on resources, technology, and organizational culture.

Post-2008 regulatory changes strengthened compliance requirements for mutual funds. The enhanced compliance environment may have reduced drift, though this hypothesis has not been systematically tested. Pre-post comparisons around compliance rule changes could identify causal effects.

Investment guidelines—the documented parameters within which portfolio managers must operate—vary in specificity across funds. Guidelines may specify permitted asset classes, capitalization ranges, quality ratings, sector limits, and tracking error bounds. More specific guidelines mechanically constrain drift but also limit manager flexibility to pursue opportunities. The optimal level of guideline specificity involves a tradeoff between style consistency and investment flexibility.

5.1.3 Compensation and Incentives

Manager compensation structures create incentives that encourages or discourage drift. Compensation based on relative performance within style category creates incentives to drift when the category underperforms. Compensation based on absolute returns or benchmark-relative returns creates different incentive patterns.

The structure of fund advisory fees also matters. Fulcrum fees—where advisory fees rise and fall with performance—strengthen manager incentives but encourages risk-taking, including style drift toward higher-volatility strategies. Fixed-fee arrangements provide weaker performance incentives but also weaker drift incentives.

The broader tournament literature (Brown, Harlow, and Starks, 1996) suggests that competitive dynamics create incentives for risk-shifting by underperforming managers. Style drift represents one form of risk-shifting; managers trailing their category drifts toward higher-volatility styles seeking to improve relative rankings.

5.2 Regulatory Framework

The regulatory framework governing mutual fund style consistency has evolved substantially, though academic analysis of regulatory effectiveness remains limited.

5.2.1 Historical Development

The Investment Company Act of 1940 establishes the foundational regulatory framework for U.S. mutual funds but does not directly address style consistency. Funds must disclose investment objectives and policies in registration statements, but the Act provides considerable flexibility in how objectives are stated and pursued.

The SEC adopted the original "Names Rule" (Rule 35d-1) in 2001, requiring funds with names suggesting particular investment focus to invest at least 80% of assets consistently with that focus. The rule applied to names suggesting investment in particular types of securities, industries, countries, or geographic regions. Notably, the original rule did not cover investment strategy terms (such as "growth" or "value") or terms suggesting risk characteristics.

This regulatory gap created an asymmetry. A fund calling itself "XYZ Value Fund" was not required to maintain value-style investments. However, a fund called "XYZ Technology Fund" was required to maintain technology investments. This asymmetry allowed funds to market style-suggesting names without corresponding investment constraints.

5.2.2 The 2023 Names Rule Amendments

The SEC's September 2023 amendments to the Names Rule are significant. They represent the most substantial regulatory response to style drift concerns in two decades. Key provisions include:

Expanded Scope. The amendments extend the 80% requirement to names suggesting investment characteristics, including terms like "growth" and "value." This expansion directly addresses the regulatory gap that permitted style drift in funds with style-suggesting names.

ESG Coverage. Terms suggesting ESG, environmental, sustainable, or similar characteristics now trigger the 80% requirement. This provision responds to "greenwashing" concerns—the practice of marketing funds as sustainable while holding securities that do not meet ESG criteria.

Derivatives Treatment. The amendments clarify how derivatives should be treated for purposes of the 80% test, addressing complexities that had created uncertainty under the original rule.

Compliance Timeline. Funds were given 24 months (until September 2025) to comply with the new requirements, allowing time for portfolio repositioning.

The Names Rule amendments create a natural experiment for studying regulatory effects on style drift. Comparing drift behavior before and after implementation, with appropriate controls, could identify causal effects of the regulatory change. Key questions include:

- Do funds reduce drift following implementation?
- Do funds change their names to avoid style-related compliance obligations?
- Does the rule affect new fund formation patterns?

- Are there unintended consequences (e.g., reduced investment flexibility)?

These questions remain unanswered, representing important opportunities for policy-relevant research.

5.2.3 International Regulatory Approaches

Regulatory approaches to fund style consistency vary internationally, creating opportunities for comparative analysis.

European Union. The EU's UCITS (Undertakings for Collective Investment in Transferable Securities) framework establishes investment restrictions for retail funds but does not include U.S.-style names rule requirements. However, the Sustainable Finance Disclosure Regulation (SFDR) imposes detailed requirements on funds marketing themselves as sustainable, addressing ESG-related style drift concerns.

United Kingdom. Post-Brexit, UK regulators have developed their own sustainable investment labels and requirements, creating another natural experiment for studying regulatory effects.

Australia. Australian Prudential Regulation Authority (APRA) standards require superannuation funds to maintain investment strategies consistent with member expectations. The relatively strong governance environment in Australian funds (Kurniawan et al., 2016) may reflect this regulatory posture.

Cross-country comparisons could identify which regulatory approaches most effectively constrain style drift while preserving beneficial investment flexibility.

5.3 Market Discipline

Beyond formal governance and regulation, market forces potentially discipline style drift. These mechanisms include investor monitoring, intermediary screening, media coverage, and competitive dynamics.

5.3.1 Investor Monitoring

As discussed in Section 4.3, evidence suggests that investors have limited ability to detect style drift in real time (Chua and Tam, 2020). This limitation undermines market discipline: if investors cannot observe drift, they cannot punish it through redemptions or withhold flows from drifting funds.

Several factors constrain investor monitoring:

Disclosure Lag. Quarterly holdings disclosure with up to 60-day reporting delays means investors observe portfolio composition only retrospectively. Drift that occurs and reverses between disclosure dates might escape detection entirely.

Analytical Complexity. Determining whether portfolio holdings are consistent with stated style requires analytical capability that many retail investors lack. Even sophisticated investors may find drift detection costly relative to the potential benefits.

Limited Attention. Investors monitor many aspects of fund performance and characteristics; style consistency may not be salient relative to more prominent metrics like returns and fees.

Technological advances could strengthen investor monitoring. Machine-readable holdings data, style analytics platforms, and automated drift alerts could reduce monitoring costs and improve detection. However, adoption of such tools remains limited, particularly among retail investors.

5.3.2 Intermediary Screening

Financial intermediaries—including advisors, consultants, and platform providers—select funds for underlying investors and screen for style consistency. The due diligence processes applied by these intermediaries represent a potential monitoring mechanism.

Institutional consultants advising pension funds and endowments typically evaluate style consistency as part of manager selection. Funds exhibiting substantial drift may be excluded from consultant-recommended lists, creating flow consequences even if underlying investors do not directly monitor drift.

Retail platforms and robo-advisors increasingly construct model portfolios that rely on accurate style classifications. These intermediaries have incentives to monitor drift among constituent funds to ensure portfolio-level characteristics match expectations. However, the extent and rigor of this monitoring varies across intermediaries.

5.3.3 Media and Analyst Coverage

Financial media occasionally highlights style drift, potentially creating reputational discipline. High-profile cases of drift-related problems may prompt investor attention and regulatory scrutiny.

Academic research itself can function as a monitoring mechanism. The Chen, Cohen, and Gurun (2021) paper on bond fund misclassification received substantial media coverage and may have prompted both investor awareness and regulatory attention. Research that identifies specific drifting funds or systematic drift patterns can enhance market discipline.

Morningstar and similar rating agencies provide style assessments that can identify drift. A fund whose Morningstar style box position changes over time is implicitly flagged as drifting. These style assessments are widely accessed by investors and intermediaries, providing a form of third-party monitoring.

5.4 ESG and Sustainable Fund Oversight

The rapid growth of ESG and sustainable investing has created new style drift concerns, often discussed under the "greenwashing" label.

5.4.1 The Greenwashing Problem

Greenwashing occurs when funds market themselves as sustainable or ESG-focused while holding securities that do not meet these criteria. This phenomenon represents style drift in the sustainability dimension, analogous to traditional style drift in size or value dimensions.

The greenwashing problem has several distinctive features:

Definition Ambiguity. Unlike size (measured by market capitalization) or value (measured by book-to-market), "ESG" lacks a universally accepted definition. Different rating providers assess the same securities differently, and "sustainable" can mean different things (exclusion, integration, impact). This ambiguity creates space for funds to claim ESG credentials without clear accountability.

Investor Preferences. ESG investors often have non-financial motivations—environmental or social impact—in addition to financial return objectives. Drift that violates these non-

financial preferences may be particularly harmful to investor welfare, even if it improves financial returns.

Data Limitations. ESG data quality and coverage remain inferior to traditional financial data. Limited ESG disclosure by underlying companies complicates both fund management and investor monitoring of ESG consistency.

5.4.2 Emerging Evidence

Lin, Pan, and Sha (2025) provide early evidence on ESG style drift, examining mutual funds in the Pacific-Basin region. They find that ESG-focused funds exhibit style drift toward non-ESG securities, and that this drift is associated with performance differentials. Their findings suggest that greenwashing is measurable and has consequences, though the welfare implications depend on investor preferences.

Guimaraes and Malaquias (2023) examined Brazilian funds during the COVID-19 pandemic, finding that ESG considerations interacted with market stress to affect fund behavior. The pandemic period may have intensified greenwashing pressures as ESG-focused funds sought to maintain performance during volatile markets.

5.4.3 Regulatory Response

Regulators globally have responded to greenwashing concerns. The SEC's Names Rule amendments extend the 80% requirement to ESG-suggesting names. The EU's SFDR creates detailed disclosure requirements for funds claiming sustainability characteristics. The UK has developed a sustainable investment labels regime.

Collectively, these regulatory responses create natural experiments for studying the effectiveness of different approaches to constraining ESG style drift. Comparative analysis across jurisdictions could inform optimal regulatory design.

6 Future Research Directions

This survey has traced nearly three decades of research on mutual fund style drift, from the foundational measurement studies of the 1990s through contemporary debates about performance implications and emerging concerns about ESG "greenwashing." While the field has generated important insights, significant gaps remain. This concluding section identifies the most promising opportunities for future research, organized around methodological frontiers, unresolved empirical questions, and emerging topics that merit scholarly attention.

6.1 Methodological Frontiers

Perhaps the most striking finding of our review is the methodological stagnation in style drift research. Returns-based style analysis and holdings-based analysis, both developed decades ago, remain the dominant approaches. The field has not embraced innovations that have transformed other areas of empirical finance. We identify several opportunities for methodological advancement.

6.1.1 Machine Learning and Artificial Intelligence

Machine learning methods offer substantial potential for improving style drift detection and analysis. Our review found zero papers applying ML to style drift, despite obvious applications:

Real-Time Detection. Supervised learning algorithms can be trained to identify style drift patterns from high-frequency return data, potentially providing more timely detection than quarterly holdings analysis permits. Anomaly detection algorithms can flag unusual fund behavior that may indicate drift before it becomes apparent through traditional methods.

Pattern Recognition. Deep learning architectures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), excel at identifying patterns in complex, high-dimensional data. These methods could detect subtle drift patterns that linear regression-based approaches miss. Transformer architectures, which have revolutionized natural language processing, can model temporal dependencies in fund behavior.

Classification and Clustering. Unsupervised learning methods could identify natural "style clusters" from return and holdings data, potentially revealing groupings that differ from traditional style box classifications. Such emergent classifications might better capture how funds actually behave, improving drift detection relative to categories that may not reflect market realities.

Prediction. ML models could predict which funds are most likely to drift, enabling proactive monitoring by investors and regulators. Features associated with drift propensity—fund size, manager tenure, competitive position, recent performance—could be combined in predictive models that identify high-risk funds.

The barriers to ML adoption in style drift research appear to be more about disciplinary traditions than technical feasibility. Data suitable for ML applications—fund returns, holdings, characteristics—are readily available. Researchers with quantitative backgrounds and familiarity with ML methods makes substantial contributions to this methodologically underdeveloped area.

6.1.2 Natural Language Processing

Textual data about mutual funds—including prospectuses, shareholder reports, marketing materials, and regulatory filings—remain almost entirely unexploited in style drift research. NLP methods could extract valuable information from these sources:

Prospectus Analysis. Fund prospectuses describe investment strategies in detail. NLP can quantify the specificity and restrictiveness of stated investment approaches, identify changes in strategy descriptions over time, and detect discrepancies between textual descriptions and actual portfolio characteristics.

Shareholder Communication. Manager letters to shareholders discuss investment positioning and rationale. Sentiment analysis can detect shifts in manager rhetoric that precede or accompany portfolio changes. Topic modeling could identify when managers begin discussing investment themes outside their stated mandate.

Name and Marketing Analysis. Cooper, Gulen, and Rau (2005) documented that fund name changes affect investor flows. NLP could systematically analyze fund names and marketing materials to identify style-suggesting language and track changes over time. Discrepancies between marketing language and portfolio reality could indicate greenwashing or other forms of style misrepresentation.

Regulatory Filing Analysis. SEC filings contain structured and unstructured information about fund operations. Automated analysis of these filings could identify patterns associated with style drift, potentially enabling regulatory screening for compliance monitoring.

The integration of textual analysis with traditional quantitative methods represents a particularly promising direction. Combining insights from what funds say (textual data) with what they do (returns and holdings data) could provide richer characterizations of fund behavior and more nuanced drift detection.

6.1.3 Causal Inference Methods

Understanding the effects of style drift on outcomes requires careful attention to causal identification. Funds that drift differs systematically from funds that maintain style consistency, confounding simple comparisons. Modern causal inference methods strengthens research designs:

Difference-in-Differences. Policy changes, such as the SEC's 2023 Names Rule amendments, create natural experiments. Comparing changes in style drift behavior for affected funds (treatment group) versus unaffected funds (control group) before and after policy implementation could identify causal effects of regulation.

Regression Discontinuity. Regulatory thresholds create discontinuities that can be exploited for causal identification. Funds just above and just below regulatory cutoffs are otherwise similar, enabling quasi-experimental comparisons.

Instrumental Variables. Valid instruments for style drift—variables that affect drift propensity without directly affecting outcomes—could enable causal estimation of drift effects on performance, flows, and risk. Identifying such instruments is challenging but potentially valuable.

Synthetic Control Methods. For studying specific drift events or regulatory interventions affecting particular funds, synthetic control methods could construct appropriate counterfactuals by weighting untreated funds to match pre-treatment characteristics.

The Frazzini, Friedman, and Pomorski (2016) critique of Active Share highlights the importance of careful identification in style drift research. Claims about drift effects on performance are credible only to the extent that confounding factors are adequately controlled. Modern causal inference methods provide tools for strengthening such claims.

6.2 Unresolved Empirical Questions

Beyond methodological opportunities, several substantive questions remain unresolved and merit further investigation.

6.2.1 Optimal Level of Style Drift

Is there an optimal level of style drift? The skill interpretation suggests that some drift is beneficial, reflecting managers' ability to identify opportunities outside their stated mandates. The agency interpretation suggests that drift is harmful, reflecting conflicts of interest. The truth involves a nonlinear relationship where moderate drift adds value while excessive drift indicates problems.

Sha (2019) provided suggestive evidence of nonlinearity, finding that moderate drift is associated with improved returns while extreme drift is not. However, identifying the optimal drift level—and how it varies across fund types, market conditions, and

governance environments—remains an open question. Research addressing this question has practical implications for fund design and regulatory calibration.

6.2.2 Skill versus Agency Decomposition

Can style drift be decomposed into skill-based and agency-based components? Such decomposition would have important implications for interpretation and policy. Drift that reflects skill should be preserved or even encouraged; drift that reflects agency problems should be constrained.

Petajisto's (2013) decomposition of Active Share into stock selection and factor betting components provides one approach, though it does not directly map to skill versus agency. Alternative decomposition approaches might examine drift timing (does the manager drift toward styles that subsequently outperform?), drift persistence (is drift consistent with long-term views or short-term opportunism?), or drift transparency (is drift disclosed and explained or hidden?).

Developing robust skill-versus-agency decomposition methods would represent a significant contribution, though the inherent difficulty of observing managerial intent creates challenges.

6.2.3 Regulatory Effectiveness

How effective are regulatory interventions in constraining style drift? The SEC's Names Rule has been in place since 2001, yet evidence on its effectiveness is limited. The 2023 amendments create opportunities for studying regulatory effects, but such studies require appropriate post-implementation data.

Key questions include:

- Does the 80% requirement effectively constrain drift, or do funds find ways to comply technically while violating the spirit of the rule?
- Does regulation affect new fund formation (e.g., funds avoiding style-suggesting names to preserve flexibility)?
- Are there unintended consequences, such as reduced beneficial drift or increased closet indexing?
- How do different regulatory approaches (U.S. Names Rule, EU SFDR, etc.) compare in effectiveness?

Answering these questions requires careful empirical design and sufficient post-implementation data. Researchers should be preparing to study the 2023 amendments' effects as compliance data become available.

6.2.4 Investor Heterogeneity

How do different investor types experience and respond to style drift? Existing research has largely treated investors as homogeneous, but substantial heterogeneity likely exists:

Retail versus Institutional. Institutional investors have greater resources for monitoring and are better positioned to detect and respond to drift. Do institutional funds exhibit different drift patterns than retail funds?

Sophisticated versus Unsophisticated. Even within retail, investor sophistication varies. Do more sophisticated investors select funds with greater style consistency?

Direct versus Intermediated. Investors accessing funds through advisors or platforms have different experiences than direct investors. Do intermediaries screen for style consistency?

Understanding this heterogeneity informs targeted investor protection measures. It also help identify which investors are most vulnerable to drift-related harms.

6.3 Emerging Topics

Several emerging topics merit scholarly attention as they become increasingly important to the investment landscape.

6.3.1 ESG and Sustainable Fund Style Drift

The rapid growth of ESG investing has created new style drift concerns. "Greenwashing"—marketing funds as sustainable while holding securities that do not meet ESG criteria—represents style drift in the sustainability dimension.

Research opportunities include:

- Measuring the prevalence and magnitude of ESG style drift
- Examining whether ESG drift affects investor welfare differently than traditional style drift
- Evaluating the effectiveness of ESG-specific regulations (SFDR, SEC amendments)
- Understanding how ESG rating disagreement affects drift measurement

Lin, Pan, and Sha (2025) provide early evidence, but the ESG drift literature remains nascent. Given the substantial flows into ESG funds and regulatory attention to greenwashing, this topic merits substantial additional research.

6.3.2 Cryptocurrency and Digital Asset Funds

The emergence of cryptocurrency and digital asset funds creates new style drift possibilities. Funds marketing themselves as Bitcoin-focused, diversified crypto, or blockchain-technology funds face questions about style consistency analogous to traditional fund categories.

The crypto context has distinctive features:

- High volatility and correlation among crypto assets may make style distinctions less meaningful
- Regulatory uncertainty creates compliance challenges
- Rapid innovation means new asset types (DeFi, NFTs, stablecoins) continually emerge
- Limited historical data complicates style analysis

As crypto funds proliferate and mature, style drift research extending to this asset class could be valuable.

6.3.3 AI-Managed Funds

The growth of AI and algorithmic investment management raises questions about style consistency in automated strategies. AI systems trained on historical data may exhibit style drift as market conditions change or as algorithms are updated.

Questions include:

- Do AI-managed funds exhibit more or less style drift than human-managed funds?
- Is AI drift more predictable or more erratic than human drift?
- How should AI fund strategies be classified and monitored for style consistency?
- Do investors understand and accept AI-related style variability?

This topic intersects with broader questions about AI in finance and algorithmic accountability.

6.3.4 Private Markets and Alternative Assets

The democratization of private market investing through interval funds, BDCs, and similar vehicles creates style consistency questions in contexts where traditional style analysis methods may not apply.

Private equity funds have long faced questions about style consistency—a "growth equity" fund may hold investments spanning a range of characteristics. As retail investors gain access to private market strategies, style drift concerns become more salient.

Research extending style drift concepts to private markets addresses:

- How should private investment styles be defined and measured?
- What disclosure enables style monitoring in private markets?
- How do liquidity constraints affect drift dynamics?

7 Conclusions

This survey has provided the first comprehensive review of the academic literature on mutual fund style drift, synthesizing 91 papers spanning 1997-2025. Our analysis reveals five established findings: style drift is pervasive (10-40% of funds are misclassified); two measurement paradigms dominate (RBSA and holdings-based analysis); the performance relationship remains contested; investors face significant information asymmetries; and governance mechanisms can constrain drift.

We also identify critical gaps. Governance and regulation remain severely underexplored (only 2% of papers), methodological innovation has stalled (zero ML/NLP applications), ESG "greenwashing" requires investigation, and international evidence remains incomplete. These gaps represent significant opportunities for future scholarship.

7.1 Implications for Practice

For **investors**, our findings suggest using multiple metrics to assess style consistency, monitoring for drift after management changes, and recognizing that some drift reflects skill rather than agency problems. For **fund managers**, style consistency builds investor trust, and the SEC's 2023 Names Rule amendments create new compliance obligations. For **regulators**, the Names Rule represents an important step, though quarterly disclosure frequency remains insufficient for timely drift detection.

7.2 Research Agenda

We propose three priority areas. First, **methodological innovation**: applying machine learning to real-time detection, developing NLP tools for fund disclosures, and using modern causal inference methods to better identify drift effects. Second, **empirical questions**: evaluating the Names Rule's effectiveness, decomposing drift into skill and agency components, and conducting systematic cross-country comparative analysis. Third, **emerging topics**: ESG fund greenwashing measurement, style consistency in AI-managed and algorithmic funds, cryptocurrency fund classifications, and private market style consistency challenges.

7.3 Concluding Remarks

Style drift in mutual funds represents a phenomenon of substantial practical importance that has attracted significant scholarly attention over nearly three decades. The field has established foundational insights about prevalence, measurement, and consequences. However, fundamental questions remain unanswered, methodological opportunities are unexploited, and emerging contexts require attention.

Building on the findings reviewed here, the next generation of research should focus on identifying causal mechanisms, evaluating policy interventions, and extending analysis to new contexts. We hope this survey provides a useful foundation for that work.

Style drift ultimately concerns the alignment between what funds promise and what they deliver. In an industry managing tens of trillions of dollars on behalf of millions of investors, ensuring this alignment is both a scholarly challenge and a matter of practical consequence. The research agenda outlined here offers opportunities to advance both understanding and practice in service of better outcomes for investors.

Data Availability Statement

This survey synthesizes published academic literature. The complete bibliography of 91 papers analyzed, including paper metadata, relevance classifications, and search methodology documentation, is available from the corresponding author upon reasonable request. No original empirical data were collected for this study. The literature search methodology and paper classification criteria are described in the text.

Conflict of Interest

The authors declare no conflicts of interest.

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