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A Matter of Style: The Causes and Consequences of Style Drift in Institutional Portfolios

R. Wermers

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Russ Wermers
Department of Finance
Robert H. Smith School of Business
University of Maryland at College Park
College Park, MD 20742-1815
Phone: (301) 405-0572
rwermers@rhsmith.umd.edu

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Abstract

The equity style orientation of an institutional portfolio has a large influence on its yearly returns. This paper analyzes the causes and consequences of portfolio "style drift" among U.S. equity mutual funds by developing new portfolio holdings-based measures of drift. These holdings-based measures allow a decomposition of style drift into components that result from active versus passive portfolio decisions by a fund manager in three different equity style dimensions: size, book-to-market, and price momentum. We find that a significant amount of style drift results from active manager trades, therefore, managers that trade more frequently tend to manage portfolios with greater style drift. In addition, managers of growth-oriented funds and small funds, and managers having good stockpicking track records, tend to have higher levels of style drift than other managers; these managers also deliver better future portfolio performance as a result of their trades, even after accounting for their higher trading costs. Consistent with this superior performance, managers do not seem to be concerned with controlling style drift; indeed, managers tend to be "style chasers" during most years, which appears to benefit their performance. Overall, our findings suggest that controlling the style drift of a fund manager does not necessarily result in higher performance for investors.

Introduction

Do institutional portfolio managers who remain focused on a certain equity style category outperform other managers who allow their portfolios to "drift" from one style category to another? This issue brings two competing viewpoints: the first view is that institutional managers build expertise, and perhaps connections with corporate executives, that create economies-of-style specialization. The second view is that star fund managers are generalists who possess talents in identifying underpriced stocks in several style categories, since the talent in analyzing company fundamentals may apply across different style categories of stocks.[1] It is important to address which of these competing views applies, as the biggest influence on the performance of an equity portfolio is its allocation toward equity style factors, and the resultant relative returns on those factors.

The importance of the style tilt of an equity portfolio has resulted in a greatly increased emphasis over the past few decades, by institutional managers, on marketing themselves as specializing in a certain style category. Indeed, pension fund sponsors and mutual fund shareholders appear to rely on the advertised style of a portfolio manager as a credible signal of that manager's investment strategy. Further, a fund is often explicitly marketed, perhaps through its chosen name, as having a manager who possesses talents in choosing stocks within a very focused style sector.[2] Examples of funds with a focused style concentration include small-capitalization growth funds, large-capitalization value funds, or even momentum funds.

Even with these self-declared, specialized style mandates, a good deal of recent attention has focused on the tendency of managers to stray from their advertised styles.[3] "Style drift," which can more formally be defined as the shift in loadings on priced style factors (e.g., Fama and French (1993)) or style characteristics (e.g., Daniel and Titman (1997)) over time for a portfolio, can be a substantial source of risk for those who invest in the funds. These investors cannot possibly monitor every fund manager trade, especially since trades are usually disclosed with a large lag and with noise. In response, fund managers appear to categorize themselves into style groups partly to

[1]For instance, Sonney (2009) finds that sell-side analysts who are specialized along industry lines exhibit better skills in rating stocks than analysts who specialize along country lines.

[2]This specialization has, in part, been driven by fund rating companies such as Morningstar, who provides peer-ratings of funds according to their style orientation ("style box").

[3]For example, some market observers have criticized U.S. mutual funds for excessively straying from their advertised styles, even calling for preventative SEC regulations. In response, the SEC now requires mutual funds to maintain a minimum of 80 percent of the value of the portfolio in securities that are consistent with the fund's advertised style. However, there is a good deal of latitude in interpreting this rule. For further background on this topic, see the U.S. Securities and Exchange Commission website, www.sec.gov.

provide information on their risk-taking to investors.

Further complicating the picture is that a large body of research (the "tournaments" literature) finds that mutual fund managers modify the style of their portfolios in response to myopic labor market incentives (see, for example, Sias and Starks (1997) and Chevalier and Ellison (1997)). Aside from these labor market incentives, a portfolio manager may be exposed to unintended style drift, since the style characteristics of stocks in the manager's portfolio often change substantially even if the manager passively holds the same stocks over time. To understand the nature and impact of style drift, it is important to precisely measure and separate style drift that results from active manager trades from drift resulting from passively holding a portfolio of stocks with changing styles.

Past academic research has, in general, employed returns-based measures of style investing. Specifically, these studies have extracted style loadings from the net returns of funds using regression-based methods over a return "window" centered at a particular desired date (see, for example, Brown and Goetzmann (1997) and Sharpe (1992)). While relatively easy to apply, these methods are limited in their ability to precisely capture dynamic shifts in style. For instance, regression-based methods would identify a style-switching manager with noise, even if the manager made an abrupt shift, due to the need for sufficient observations in the regression window.

This paper presents a new method of measuring style drift, using the periodic portfolio holdings of fund managers. These new "holdings-based style drift measures" have several advantages over past "returns-based style drift measures," including the ability to track portfolio style drift in each style dimension as frequently as portfolio holdings are reported, as well as allowing the separation of drift that results from active trades and the drift that results from passively holding stocks with changing characteristics.[4]

This study measures both active and passive holdings-based style drift in three distinct style dimensions: changes in the market capitalization of equity (size) of portfolio holdings, changes in the ratio of industry-adjusted book-equity to market-equity (value-growth), and changes in the price momentum (momentum-contrarian) of equity holdings. In doing so, we follow recent research on the cross-sectional influences on equity returns [Fama and French (1992, 1993, 1996), Jegadeesh

[4]Of course, the advantages conferred by measures of holdings-based style drift are only as good as the available portfolio holdings data. Holdings-based measures can precisely track style drift at the same frequency as the available holdings data; in cases where returns data are available at a higher frequency than holdings data, which is often the case, returns-based measures may add further information to the analysis of a manager's tendency to hold a portfolio with style drift.

and Titman (1993), and Daniel and Titman (1997)] as well as research on the influence of industry membership on book-to-market based returns [Cohen and Polk (1998)].

This study finds that both passive and active drift contribute substantially to overall drift, in each style dimension, in the average U.S. mutual fund portfolio. Further, we find that drift in the price momentum dimension is about twice the level of drift in the other two dimensions for the average fund. We also provide a breakdown of this momentum drift, and find that both sources of drift (active and passive) contribute significantly to overall price momentum drift. This finding is consistent with that of Carhart (1997), who finds that cross-sectional differences in the price momentum loading can be explained by funds passively holding winning or losing stocks, and with Grinblatt, Titman, and Wermers (1995) and Wermers (1997), who find that funds actively engage in price momentum strategies.

A further examination reveals that growth-oriented funds have higher levels of style drift than income-oriented funds, and small funds have higher levels than large funds. Also, managers having better career stockpicking track records and higher levels of career portfolio turnover tend to engage in trades that cause more active style drift. These managers are much less likely to use available cash to purchase more shares of stocks that they already own than other managers, indicating either that they are overconfident in their abilities or that they have talents in identifying a broad variety of underpriced stocks. Further analysis shows that high active style-drift managers deliver superior future portfolio performance, which indicates that they are not simply overconfident. Specifically, the value-weighted portfolio of the top decile of funds, ranked by their three-year trailing average active style-drift (ASD), outperforms the bottom decile by about 3 percent per year, before costs, and about 1.6 percent per year, after estimated execution costs and actual fund expense ratios. Most of this outperformance can be traced to the superior performance of the top ASD decile funds, rather than any underperformance of the low ASD funds. This evidence is consistent with the recent "active share" paper by Cremers and Petijisto (2009), who find that fund managers who stray further from their benchmarks provide higher risk-adjusted returns. We show that fund managers who vary their styles, rather than simply holding a portfolio with large tracking error relative to a benchmark are most likely to outperform.

We also find that the average mutual fund manager seems to pay little attention to controlling style drift. That is, we find, on average, that the manager would have had a similar level of style drift had that manager passively held her portfolio through time rather than trading. In the size and book-to-market dimensions, the average manager made trades of equities that pushed the portfolio such that it experienced even higher levels of drift than it would have, had the manager passively held the prior-year's portfolio.

Our study is also related to a recent study that uses returns-based measures of style drift to analyze the style drift-performance relation. Brown and Harlow (2002) find that style-consistent funds outperform other funds, in terms of their stockpicking performance. In contrast, our study finds that the relation between style consistency and stockpicking talent is, at best, tenuous. Moreover, we find evidence that managers with the best stockpicking talents often tend to implement strategies that involve a significant amount of equity style drift. Our new findings are made possible by the precision of our holdings-based style drift measures, and provide an interesting contrast to the Brown and Harlow study. We also believe that holdings-based and returns-based measures can be combined to create a superior measure of style drift when both data sources are available. We leave this promising avenue to future research.

The remainder of this paper is organized in four sections. The construction of the mutual fund and fund manager database is discussed in Section I, while our style drift measurement methodology is discussed in Section II. We present empirical findings in Section III. We present study conclutions in Section IV.

I Data

The first dataset used in this study is an updated version of the merged CDA–CRSP mutual fund database of Wermers (2000). For each U.S. equity mutual fund (defined as having at least 50 percent of assets invested in U.S. equities) that exists anytime between January 1975 and December 1994, CDA–CRSP contains data on various fund attributes, such as the monthly net return, total net assets, annual expense ratio, annual turnover ratio, and quarterly stock holdings of each fund. This database is the longest time-series having both stockholdings and net returns/characteristics information that has been assembled to date. See Wermers (2000) for more information on the construction and limitations of an earlier version of this database–we have extended this merged database to cover all mutual funds existing through December 31, 1999, and we measure the attributes of all funds in our database through December 31, 2000.

Next, we merge the CDA-CRSP database with a newly constructed database of mutual fund managers that covers the 1985 to 2000 (inclusive) time period. In constructing our database of managers, we focus on U.S. equity funds, that is, funds having a self-declared investment objective of aggressive growth (AG), growth (G), growth and income (GI), income or balanced (I or B) at the beginning of a given calendar quarter. The fund manager data is assembled from three separate sources of manager data: the 2001 Morningstar Principia Pro database, the CRSP Survivor-Bias Free Mutual Fund Database, and a database of fund managers that was purchased from Thomson/Wiesenberger in 1999. Further information on the construction of this database is given in Ding and Wermers (2002). As in that paper, we focus our attention on the lead manager of each mutual fund when measuring the characteristics of managers associated with funds with a certain level of style drift. As a proxy to identify the lead manager, we choose the manager with the longest tenure at a given fund (if team managed) to decide on which manager is the lead manager.[5]

Counts of our sample of funds and of fund lead managers over the entire 1985 to 2000 period, as well as counts at the beginning of 1985, 1990, 1995, and 2000 are presented in Table I. There are a total of 2,892 CDA–CRSP funds and 2,670 lead managers in our sample. Growth funds account for the majority of the fund universe, and about 80 percent of the fund managers have experience in managing at least one growth fund during 1985 to 2000. Not surprisingly, the number of funds and fund managers grows rapidly with the expansion of the entire U.S. mutual fund industry during our sample period. The average number of funds lead-managed by a given fund manager also gradually increases from 1.26 at the beginning of 1985 to 1.53 at the beginning of 2000.

To check the completeness of our merged manager/fund database, we further examine the CDA–CRSP funds that fail to be matched with any fund manager, and report the results in panels C and D of Table I. Overall, we are able to identify the lead manager for more than 92 percent of funds in our CDA–CRSP database. In addition, more than 85 percent of all fund-months during 1985 to 2000 in the merged CDA–CRSP database contain information about the lead manager.

A close look at the number of missing managers at four different points in time reveals more detailed information. Thirty-nine percent of the funds that exist at the beginning of 1985 are unable to be matched with a manager during 1985, but this fraction steadily declines over our sample period to 6.3 percent and 6.2 percent during 1995 and 2000, respectively. One reason that post-1995 manager data is noticeably more complete than pre-1995 data is that our data sources, in general, began to formally collect manager data in the first half of the 1990s, and probably backfilled previous manager data.

[5] If there is tie in the start date, we use the total career experience as the tie-breaker, i.e., we pick the currently active fund manager who becomes a fund manager (of any fund) at the earliest date.

In Panel D, a further comparison is provided between funds with complete manager data and funds that have missing manager data. This panel presents data on the total net assets under management and the net return, in excess of the S&P 500 index return, between funds having manager data and funds with missing manager data at the beginning of each five-year period, as well as for the entire sample period of 1985 to 2000. We find that funds with missing manager data tend to be smaller and perform somewhat worse than those with complete manager data.

Since our manager data is obviously less complete than our fund data, we use the complete fund dataset, when possible in this paper (whether we have manager data or not) to minimize survivorship bias. In cases where we report the average characteristics of managers, we report these averages across only funds having information on manager characteristics.

II Methodology

A Style Benchmarks

In this paper, we use non-parametric measures of style to form our style drift statistics. To construct the non-parametric style measure for a given stock during a given year, we characterize that stock over three characteristic dimensions–the size, the ratio of the book value of equity to the market value of equity, and the one-year lagged return of the stock. This method modifies and updates the style benchmarks used by Daniel, Grinblatt, Titman, and Wermers (DGTW; 1997). Specifically, we use a variance-normalized industry adjustment to the book-to-market value for each stock-year in order to create industry-diversified book-to-market control portfolios.[6]

To further explain, all stocks (listed on the NYSE) having book value of equity information in the merged CRSP/Compustat file, as well as stock return and market capitalization of equity data, are ranked, at the end of each June, by their market capitalization. Quintile portfolios are formed (using these NYSE size quintile breakpoints), and each quintile portfolio is further subdivided into book-to-market quintiles (based on their industry-adjusted book-to-market ratio, as of the end of the December immediately prior to the year of the ranking quarter). Then, each of the resulting 25 fractile portfolios are further subdivided into quintiles based on the 12-month past return of stocks

[6]Specifically, we industry-adjust each stock-year's book-to-market ratio by subtracting the industry average book-to-market ratio for that year (for the industry corresponding to that stock), then by normalizing this excess book-to-market ratio by the standard deviation of that industry-year's book-to-market ratio. This procedure ensures that the extreme book-to-market ratio control portfolios are industry-diversified. In contrast, DGTW (1997) simply subtract the industry-year average book-to-market ratio without the normalization.

through the end of May (to avoid the one-month return reversal effect). This three-way ranking procedure results in 125 fractile portfolios, each having a distinct combination of size, book-to-market, and momentum characteristics.[7] All other CRSP-listed stocks (i.e., AMEX and Nasdaq stocks) are placed in the appropriate fractile portfolios, using the constructed NYSE breakpoints. This three-way ranking procedure is repeated at the end of June of each year, and the 125 portfolios are reconstituted at that date.

To measure the style of a certain stock during a certain year, we construct a database that maps each stock-year to the portfolio numbers (one through five) in each style dimension that result from the sorting procedure above. Thus, we can track the style drift, in each of the three dimensions, of each stock contained in the CRSP/Compustat file during two consecutive years by tracking the non-parametric style characteristics of the stock.

We will also use these constructed portfolios to measure the style-adjusted return of each stock during each quarter of our study. This procedure is developed by DGTW, and is briefly described in Section E below.

B Measuring Style Drift

This paper extends the equity style classification technique presented in Section A to develop new measures of style drift that employ the periodic portfolio holdings of fund managers. These new "holdings-based style drift measures" have several advantages over "returns-based style drift measures." Specifically, in contrast to returns-based measures, these new holdings-based measures

- precisely capture portfolio drift in each style dimension at each portfolio reporting date,
- separate style drift, in each of these three dimensions, that results from active trades and style drift that results from passively holding an equity portfolio with changing style characteristics, and
- allow an analysis of the impact on portfolio performance of each type of style drift, in each style dimension for a given fund.

[7] Thus, a stock belonging to size portfolio one, book-to-market portfolio one, and prior return portfolio one is a small, low book-to-market (growth) stock, having a low prior-year return.

B.1 Measuring Total Style Drift

Style drift can be measured in several different dimensions. Fama and French (1992, 1993, 1996) find that the market capitalization (size) and the ratio of book-equity to market-equity of a stock (value-growth) are two dimensions that influence the cross-section of average stock returns. Jegadeesh and Titman (1993) and Chan, Jegadeesh, and Lakonishok (1996) find that "momentum" (6- to 12-month lagged return) is a third important dimension. For style drift in each of these three dimensions, we use portfolio holdings to precisely measure the drift.

Specifically, we measure the total style drift of a managed portfolio during the year prior to June 30th of year t in style dimension l (where l=size, book-to-market, or momentum) as

$$TSD_t^l = \sum_{j=1}^{N} (\widetilde{w}_{j,t}\widetilde{C}_{j,t}^l - \widetilde{w}_{j,t-1}\widetilde{C}_{j,t-1}^l) \ . \tag{1}$$

Here, $\widetilde{w}_{j,t}$ equals the fund's portfolio weight on stock j on June 30th of year t, while $\widetilde{C}_{j,t}^l$ equals the (non-parametric) style characteristic of stock j in style dimension l at the same time, which is constructed as described previously in Section A. Clearly, a non-zero value of TSD can occur for a buy-and-hold portfolio due to the changing characteristics of stockholdings, as well as to the drift in portfolio weights that occurs over time. For example, a manager holding stocks with higher returns during a given year, relative to the median stock during the same year, will tend to have a positive value of TSD in the size and momentum dimensions, as these stocks move from lower to higher non-parametric ranks within these two dimensions, and due to the increasing portfolio weights of the subgroup of stocks with the highest returns in the managed portfolio.[8]

Active changes in the portfolio (through trades of stocks) also contribute to the value of TSD; therefore, it is important to separate the drift that is attributable to each of these two effects. We outline our method of decomposing total style drift into active and passive components in the next section.

B.2 Separating Active from Passive Style Drift

With portfolio holdings information, we can separate portfolio style drift that results from active manager trades from drift that results from the passively holding stocks with changing portfolio

[8]This manager may also have a negative TSD in the book-to-market dimension, depending on the influence of the changing book value of the stocks.

weights and characteristics. We decompose total style drift during year t into passive and active style drift components, respectively,

$$TSD_t^l = PSD_t^l + ASD_t^l \ ,$$

where PSD is measured as the change in style, assuming that the manager passively held a portfolio during year t, or

$$PSD_t^l = \sum_{j=1}^{N} (\widetilde{w}'_{j,t}\widetilde{C}_{j,t}^l - \widetilde{w}_{j,t-1}\widetilde{C}_{j,t-1}^l),$$

where $\widetilde{w}'_{j,t}$ equals the portfolio weight on stock j on June 30th of year t, assuming that the manager employed a buy-and-hold strategy for the entire portfolio over the period $t-1$ to t. PSD measures drift that occurs due to the changing style characteristics of individual stocks, as well as drift due to the changing portfolio weights of a buy-and-hold portfolio.

Style drift attributable to active portfolio trades constitutes the remainder of total style drift, and is measured with

$$ASD_t^l = \sum_{j=1}^{N} (\widetilde{w}_{j,t}\widetilde{C}_{j,t}^l - \widetilde{w}'_{j,t}\widetilde{C}_{j,t}^l),$$

where $\widetilde{w}_{j,t}$ equals the manager's actual portfolio weight on stock j on June 30th of year t.[9]

Separating style drift into PSD and ASD components is useful in characterizing the style risks and rewards associated with a certain fund. PSD, for example, tells us the style risk associated with holding a given fund during a given period, which can partially be controlled by actions of the portfolio manager through the ASD component. A perfectly style-controlled fund would have offsetting PSD and ASD measures, giving a TSD measure of zero in each style dimension.

In reality, some managers may indeed trade to push the portfolio back to a desired style tilt, while other managers may allow the portfolio to drift to avoid incurring transactions or other costs (such as tax realizations). Still other managers may deem it necessary to temporarily shift the

[9]Note that this decomposition assumes that the manager observes the style characteristics of her portfolio during the year preceeding June 30th of year t, then makes portfolio revisions to modify the style characteristics just before June 30th. A more realistic assumption is that the manager trades stocks more evenly throughout the year, for both style management and other reasons. Since our periodic holdings data do not allow us to analyze the exact date of trades, we are limited in this decomposition to making such an assumption. In a future version of this paper, we will investigate the robustness of our results to alternative assumptions on this issue.

style of their portfolios to capture abnormal returns from equities that lie outside their normal style focus. Finally, managers may actively shift the style of their portfolios as a response to labor market pressures that penalize them for falling behind the performance of peer managers. Our decomposition of style drift into active and passive components allows insights into each of these issues.

In presenting cross-sectional average statistics, across funds, we average the absolute value of the style drift in each dimension. For example, in computing the level of TSD in style dimension l during year t, averaged across the M funds with style drift information during that year, we use

$$\overline{TSD}_t^l = \frac{1}{M} \sum_{m=1}^{M} \left| TSD_{m,t}^l \right|, \tag{2}$$

where $TSD_{m,t}^l$ is the total style drift of fund m, as defined by Equation (1). The values of $\overline{PSD}_t^l$ and $\overline{ASD}_t^l$ are computed analogously. By the triangle inequality,

$$\overline{TSD}_t^l \leq \overline{PSD}_t^l + \overline{ASD}_t^l \quad . \tag{3}$$

If, for example, managers primarily trade to control style drift, we will observe a much higher value for $\overline{PSD}_t^l$ (and for $\overline{ASD}_t^l$) than for $\overline{TSD}_t^l$. However, if managers trade with little concern for style drift, then we will observe a value of $\overline{TSD}_t^l$ that is similar in magnitude to the values of $\overline{PSD}_t^l$ and $\overline{ASD}_t^l$.[10]

We also, for certain tests, compute a summary measure of total, active, and passive style drift (across all dimensions) for an institutional portfolio during a given year t with

$$TSD_t = \sum_{l=1}^{L} \left| TSD_t^l \right|, \tag{4}$$

$$PSD_t = \sum_{l=1}^{L} \left| PSD_t^l \right|, \tag{5}$$

[10] For example, suppose that each manager's portfolio passively drifts by one style number in dimension l during year t (i.e., $\overline{PSD}_t^l = 1$). If each manager replaces half of her portfolio holdings with stocks having the same style dimension l characteristics as those of the replaced stocks at the end of year t, and half with stocks having the same style characteristics as those that the replaced stocks had one year earlier, at the end of year $t-1$, then the $\overline{TSD}_t^l$ measure across these managers will be equal to 0.5, and the $\overline{ASD}_t^l$ measure will also equal 0.5.

and

$$ASD_t = \sum_{l=1}^{L} \left| ASD_t^l \right|, \quad (6)$$

respectively. This summary measure is done to characterize a manager's tendency to experience overall style drift.

C Measuring the Impact of Style Drift on Fund Performance

To directly analyze the impact of style drift on fund performance, we measure the correlation between the style changes of a manager and the return of the style. For example, in the book-to-market style dimension, the impact of passive style drift and active style drift on performance, "passive style drift return" ($PSDR$) and "active style drift return" ($ASDR$), is measured as

$$PSDR_{t-k,t}^{BTM} = \sum_{j=1}^{N} (\widetilde{w}'_{j,t} - \widetilde{w}_{j,t-k}) R_{t+1}^{BTM} \quad \text{and} \quad (7)$$

$$ASDR_{t-k,t}^{BTM} = \sum_{j=1}^{N} (\widetilde{w}_{j,t} - \widetilde{w}'_{j,t}) R_{t+1}^{BTM} \ , \quad (8)$$

respectively.[11] Here, R_{t+1}^{BTM} equals the return, during period $t+1$, for a portfolio having the same book-to-market characteristics as stock j at the end of period t, and $\overline{R}^G$ equals the long-term average return to this portfolio.

Similar timing measures for other style dimensions are formed analogously. We sum the PSDR and ASDR components across all three dimensions (size, book-to-market, and momentum) to arrive at summary measures for each fund during each period.

D Measures of Manager Characteristics

This study examines manager characteristics that are correlated with style drift in the manager's portfolio. Therefore, we construct measures that quantify various manager characteristics, such as experience, track record in picking stocks, attitude toward risk-taking, and aggressiveness in trading stocks. In this subsection, we describe these measures.

[11] An alternative approach is to use $PSDR_{t-k,t}^{BTM} = \sum_{j=1}^{N} (\widetilde{w}'_{j,t} - \widetilde{w}_{j,t-k})(R_{t+1}^{BTM} - \overline{R}^{BTM})$ and $ASDR_{t-k,t}^{BTM} = \sum_{j=1}^{N} (\widetilde{w}_{j,t} - \widetilde{w}'_{j,t})(R_{t+1}^{BTM} - \overline{R}^{BTM})$. With a long and stationary time-series of style portfolio returns, R_t^{BTM}, these estimates will converge faster to their true.

The first manager characteristic of interest is experience, which we define as the total number of months that an individual has served as a fund manager over her entire career. To capture the track record of a fund manager, we develop a measure of the stockpicking talent of the fund manager, as defined by the Characteristic Selectivity measure of DGTW. This measure of career performance is defined as the time-series average of a manager's Characteristic Selectivity (CS) measure (henceforth, CS measure), over the entire career of the manager. The CS track record measure (CST) for manager i at month t is given by

$$CST_t^i = \frac{1}{t - t_0^i} \sum_{\tau=t_0^i}^{t} \sum_{j=1}^{J_\tau} w_{j,\tau}(R_{j,\tau} - R_\tau^{b_{j,\tau}}) \tag{9}$$

where $w_{j,\tau}$ is manager i's portfolio weight on stock j at the end of the calendar quarter just preceding month τ; $R_{j,\tau}$ is the month τ return of stock j; $R_\tau^{b_{j,\tau}}$ is the month τ return of stock j's value-weighted characteristic-matched portfolio (matched as described in Section A above); J_τ indicates the number of stocks held in the fund(s) managed by manager i at the end of the quarter preceding month τ. An advantage of the CS measure is that it uses portfolio holdings information, which DGTW argue provides a more precise measurement of performance relative to regression-based methods. Further information on the construction of this measure is given in the next section, when we further describe this measure.

Some managers may be more aggressive in trading stocks than others, perhaps because they have better private information about stock values than others, because they believe they have superior stock-picking skills (perhaps due to overconfidence), or because they are simply less risk-averse than other fund managers in using their private information. We would believe that such aggressiveness would lead to higher trading frequency and volume, and perhaps to greater levels of style drift. As such, a manager's aggressiveness in managing her portfolio is measured as the time-series average turnover ratio of the fund(s) managed by her.[12] The expression for the aggressiveness of manager i through month t is

$$Aggressiveness_t^i = \frac{1}{t - t_0^i} \sum_{\tau=t_0^i}^{t} TURNOVER_\tau^i. \tag{10}$$

[12] The annual turnover ratio of a fund is defined, by CRSP, as the lesser of securities purchased and sold, divided by average monthly total net assets during the year.

E Measures of Mutual Fund Performance

We use the single-period characteristic selectivity measure of Daniel, et al (1997) for fund i during quarter *t+1*,

$$CST_{t+1}^{i} = \sum_{j=1}^{J_t} w_{j,t}(R_{j,t+1} - R_{t+1}^{b_{j,t}}), \tag{11}$$

where the weights for each of J_t stocks held by the fund at the end of quarter t are $w_{j,t}$, and the buy-and-hold return during quarter t+1 is $R_{j,t+1}$. $R_{t+1}^{b_{j,t}}$ is the quarterly buy-and-hold value-weighted return during quarter $t+1$ of the portfolio (out of the 125 style portfolios described in Section II.A.) that contains stock j as of the most recent June 30.

Besides the CS measure described above, we also employ the alpha from a four-factor Carhart (1997) regression. Carhart (1997) develops this four-factor regression method for estimating mutual fund performance from net returns data. This four-factor model is based on an extension of the Fama and French (1993) factor model, and is described as

$$R_{j,t} - R_{F,t} = \alpha_j + b_j \cdot RMRF_t + s_j \cdot SMB_t + h_j \cdot HML_t + p_j \cdot PR1YR_t + e_{j,t} \ . \tag{12}$$

Here, $R_{j,t} - R_{F,t}$ equals the excess net return of fund j during month t (the fund net return minus T-bills); $RMRF_t$ equals the month t return on a value-weighted aggregate market proxy portfolio; and SMB_t, HML_t, and $PR1YR_t$ equal the month t returns on value-weighted, zero-investment factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns. We use the Carhart (1997) regression measure of performance, α, to estimate the performance of mutual funds from their net return time-series data.

III Results

A The Tendency of Mutual Funds to Drift

We begin with an overview of the tendency of U.S. mutual funds to experience style drift over our sample period. To measure the average style drift in each style dimension during each year of our period, for total, passive, and active style drift, we compute the cross-sectional average of the absolute value of the size, book-to-market, and momentum style drift measures, respectively. These cross-sectional averages are described by Equations (4), (5), and (6), respectively, which are discussed in Section IIB. Thus, for example, some funds may drift to larger stocks, while other funds drift to smaller stocks; our average measure captures the tendency to drift on the market capitalization dimension, regardless of the direction of the drift.

Figure 1 presents yearly average cross-sectional measures of passive (PSD), active (ASD), and total style drift (TSD), in each style dimension–these measures represent the potential yearly risk from drift in these dimensions that exist in the average manager portfolio, without regard to whether the manager makes active trades to reduce the drift during the year. Panel A shows results in the market capitalization (size) style dimension; panel B shows results in the value/growth (book-to-market) dimension; panel C shows results in the momentum dimension.

Panels A and B show that, in the size and value/growth dimensions, total style drift initially increased during the late 1970s (following the termination of fixed equity trading commissions in 1975), then decreased through the remaining 30 years (with the exception of a few years with high market volatility). This decrease in TSD has occurred, even though the level of PSD has shown some moderate increases (except for some reduction in drift during the last few years of the sample period). Note, also, that ASD has shown a strong trend downward in these two style dimensions, indicating that fund managers tend to increasingly hold similar portfolios (in terms of their size and value/growth orientation) from one year to the next over the sample period, compared to a buy-and-hold strategy. Also, the gap between TSD and PSD has decreased in both style dimensions, which indicates that fund managers have made active trades to offset PSD to a greater degree during the later years. Apparently, managers are more concerned about staying style consistent during these later years, which is likely due to the industry moving toward style specialization of managers over time.

The average reduction in TSD and ASD over time is relatively small, amounting to a reduction of about 0.05 quintiles from the early 1980s to the mid-2000s. To put this number in perspective, a manager that buys 5% fewer stocks with a size (or value/growth) that is one quintile different from the stocks sold would exhibit an ASD that is lower by 0.05.

Panel C shows that the main risk is in the momentum dimension; the average passive style drift in the size and book-to-market dimensions are roughly 0.1 and 0.15 style quintile numbers per year, respectively, while the average pasive style drift in the momentum dimension is roughly 0.5 quintiles per year. Also, fund managers do not seem to show any more concern over momentum drift over time (as shown by the relatively constant gap between PSD and TSD), probably because controlling yearly momentum drift would require substantial portfolio turnover. It is also interesting that active trades (ASD) are stronger in the momentum dimension than in the size and value/growth dimensions. This confirms that the tendency of fund managers to use momentum as an investment strategy persists during the sample window.[13]

As discussed in Section II.B.2, a manager who trades to maintain a relatively constant style over time will have a very small total style drift value, relative to the passive and active style drift values of that manager. However, a manager who trades with little regard to the consequences for style drift will have a level of total style drift that is closer in magnitude, and perhaps even greater than the levels of passive and of active drift.

In the size and value/growth dimensions, the level of TSD is higher than the level of PSD, indicating that active trades are not, on average, made to reduce the passive drift of funds. Managers clearly do not trade with style consistency in mind: the level of total style drift actually exceeds the drift that would have resulted had the manager not traded (which is measured by passive style drift) in the size and book-to-market dimensions. In the momentum dimension, total style drift is only slightly lower than passive style drift, indicating that some portfolio rebalancing is taking place (selling some winners or buying some losers), but the overall effect on the portfolio's style drift is not large.

Also interesting is that, while there is some variation in the yearly total style drift in the size and book-to-market dimensions, this variation is relatively small. In contrast, the variability in momentum total style drift is much larger. Specifically, the average total size drift is below 0.3 quintiles for both size and value/growth. However, the average TSD ranges from just below 0.4 to almost 1 quintile for the momentum dimension.

In related studies, Grinblatt, Titman, and Wermers (1995) and Wermers (1997) find that many U.S. funds actively buy momentum stocks, while Carhart (1997) finds that some funds passively hold stocks that have increased in price. Our analysis shows that both effects are important in characterizing the tendency of mutual fund portfolios to drift in the momentum style. The PSD in panel C shows the Carhart effect, which is that the average fund experiences a momentum drift of about 0.5 quintile numbers. ASD in panel C shows the Grinblatt, Titman, and Wermers effect, which is that the average fund trades to modify the momentum characteristic by almost 0.4 quintiles. Thus, passive and active momentum affect fund portfolios almost equally.

While it is interesting that funds do not appear to actively control their style drift in any

[13]Grinblatt, Titman, and Wermers (1995) first document that most fund managers actively use momentum in their strategies from 1975 to 1984.

dimension, we are interested in the types of funds, and the types of fund managers, that are associated with mutual funds having varying levels of style drift. Our next section covers this issue.

B Who Drifts?

We next examine the characteristics of mutual funds that are more prone to experience style drift. To do this, we separate funds on two observable characteristics–the stated investment objective of the fund, which indicates whether the fund is a growth-oriented or income-oriented fund, and the size (total net assets) of the fund, which indicates whether the fund generally holds small stocks or large stocks. In this section, we wish to examine a summary measure of the tendency of a fund to drift on all three style dimensions; thus, we measure the total style drift across all three dimensions for a certain fund during year t as

$$TSD_t = \sum_{l=1}^{L} \left| TSD_t^l \right|, \tag{13}$$

where TSD_t^l equals the total style drift in dimension l (size, book-to-market, or momentum) during year t. The cross-sectional average of this summary measure is computed each year, and the time-series average statistic is presented for different fractiles of funds in Panels A and B of Table II. Specifically, Panel A presents this summary measure of total style drift, averaged across all growth-oriented mutual funds in each size category. Growth-oriented funds are defined as funds with a self-declared investment objective of "aggressive growth" or "growth" at the end of a given year, while the fund is ranked on its total net assets at the same date.

The results show that small funds have substantially more style drift than large funds, but there is still a surprising level of drift in large portfolios. For example, the smallest decile of growth-oriented funds have an average total drift level of 1.1, while the largest decile have an average level of 0.63. Style drift is almost monotonically decreasing in the size of a fund.

Panel B repeats the analysis for income-oriented funds: those funds with an investment objective of "growth and income," "income," or "balanced" at the end of a given year. These funds also show a strong inverse relation between style drift and fund size. A comparison of Panels A and B of Table II show that growth-oriented funds have higher levels of drift than income-oriented funds, perhaps due to the more active trading of these fund managers. To some extent, this result is due to the smaller average size of growth-oriented funds during our sample period. However, a comparison of like-sized deciles between the two panels indicates that growth-oriented funds, even adjusted for size, have more total style drift.

In Table III, we present the characteristics of managers who are associated with mutual funds having various levels of active style drift, which is defined across all three style dimensions for a given fund as

$$ASD_t = \sum_{l=1}^{L} \left| ASD_t^l \right| . \tag{14}$$

The table presents several characteristics of the equal-weighted fractile of funds falling within different ranks of this active style drift measure. First, consistent with our prior findings for total style drift (Table II), we find that smaller funds engage in trading that results in higher levels of active style drift than other funds. For example, the top quintile of fund managers oversee portfolios averaging \$421 million (averaged over time from 1985 to 1999), and these managers make trades that push the portfolio, in aggregate across all three style dimensions, by 1.3 style numbers. By comparison, the bottom quintile manage portfolios averaging \$1.3 billion, and these managers make trades that result in an aggregate style shift of only 0.2.

Also presented are the average total style drift figures, aggregated across all three style dimensions (as given by Equation 13). Note that total style drift is highly correlated with active style drift, which is a further indication that managers pay little attention to style drift as they trade, and those managers who trade most aggressively do not pay any more attention than those who trade less aggressively, as shown by the average levels of portfolio turnover in the table.

Also shown for each fractile is the average tendency of fund managers to purchase more shares of the same stocks already owned in their portfolios, which can be a rough indication of a desire to stay style-focused. Note that funds with greater levels of active style drift (and portfolio turnover) tend to use available cash to purchase new stock positions, rather than to increase the positions of their existing stockholdings. In contrast, lower turnover funds tend to purchase more of the same stocks.[14]

Finally, the table presents average manager characteristics associated with funds having various levels of active style drift (aggregated across all three dimensions). Four characteristics are presented: the average aggressiveness (average portfolio turnover) of the manager over her career, the manager's level of experience, the manager's career stockpicking CST record, and the average percentage of mutual fund managers that were replaced during a year.

The results show, not surprisingly, that managers of funds having a large level of active style

[14]The reader should note that the bottom fractiles contain some index funds, which we would expect to exhibit a tendency to engage in "same stock buys."

drift have a career record of being aggressive in their trading activity. In addition, there is no clear relationship between manager experience level and active style drift. Perhaps more interesting is the finding that managers with higher levels of active style drift tend to be managers with a much better career stockpicking record, as measured by CST, than other managers. For example, the top quintile of managers have a career record of picking stocks that beat their style benchmarks by an average of 1.8 percent per year, while the bottom quintile managers beat their benchmarks by only 1 percent per year.

Finally, there is little relation between the tendency of managers to engage in trades that result in active style drift, and the replacement rate of those managers. Both high and low active style drift managers have a replacement rate of two to four percent per year.

C The Consequences of Style Drift: Performance Implications

C.1 The "Style Timing" Returns of Style Drift

Figure 2 shows the style return implications of both passive and active style drift. Here, we compute the passive and active style drift returns for each mutual fund during each quarter in the book-to-market dimension, as shown in Equations (7) and (8), respectively. Weight changes are measured from the end of quarter t-4 to the end of quarter t, and style returns are computed over quarter t+1. Next, we compute similar measures of PSDR and ASDR in the size and momentum dimensions. Finally, we sum, for each fund-quarter, the PSDR (and ASDR) measures across all three style dimensions, then average them over all four quarters and all funds during a particular calendar year. The resulting summary style drift return measures, shown in Figure 2, can be interpreted as the amount of "style timing" return that results from passively holding the prior-year portfolio (PSDR) and actively trading away from that buy-and-hold portfolio (ASDR).

The figure shows that, over the 30 years in our sample, PSDR and ASDR average a very small 2.8 and 3.5 basis points per year, respectively. However, these returns are much larger during some years, especially during market reversals. For instance, during 1999, passively holding the prior-year portfolio resulted in excess style returns that exceeded 40 basis points, while, during 2000, passively holding the prior-year portfolio lost almost 30 basis points. Over time, PSDR and ASDR exhibit a correlation of 0.16, which indicates that mutual funds tend to chase the styles that performed well over the past year. However, it is also interesting to observe that, during 2000, funds actively moved their styles to counteract the poor returns from their passive style drift. ASDR returned almost 20 basis points, while PSDR lost almost 30 basis points. Thus, the industry appears to have correctly forecasted the change in favored styles by the market.

C.2 Do Unconstrained Fund Managers Outperform?

Our final tests examine whether mutual fund managers that engage in high active style-drift trading strategies have higher levels of future stockpicking results than other managers. These tests address a fundamental issue of this paper: do managers have specialized skills that apply only to their specific style categories, or do managers have more general skills that can be used to find underpriced stocks across several different styles? As mentioned previously, Brown and Harlow (2002), using returns-based style analysis, find that style-consistent funds outperform other funds. We wish to test this hypothesis using our new holdings-based style measures.

It is interesting to determine whether differences in active style drift results in differences in fund performance. That question speaks to the central theme of this paper: should we constrain our portfolio managers? To address this question, we repeat the ranking method used in the prior section: funds are ranked by their level of active style drift, aggregated across all three style dimensions as in Equation (14).[15]

Panel A of Table IV measures the average net return and the average CS stockpicking performance measure of DGTW during the year following (Year +1) this ranking. To minimize any biases that might arise from small funds that are missing from our panel, we weight these measures by the total net assets of funds at the beginning of year +1. Panel A of Table V presents the TNA-average net return of funds in each active style-drift fractile, while Panel B shows the TNA-average CS measure. The results show some differences in net returns, across the fractiles, but these differences are concentrated in the extreme top 5 percent and 10 percent of funds. This finding likely reflects that very high turnover fund managers are most likely to hold portfolios of small stocks, which had higher average returns during our period of study.

Further insight is added by Panel B, which examines the level of stockpicking skill exhibited by

[15] An earlier version of this paper showed the difference in active style drift (ASD) between the top and bottom quintiles of mutual funds (ranked by their trailing three-year average ASD) at the beginning of each year from 1979 to 2000. We found that the difference in ASD decreased substantially over this 22-year period, consistent with the reduction in "active share" documented by Cremers and Pettijisto (2009). Active share captures the distance between actual portfolio weights and benchmark portfolio weights, for the best-fit benchmark, of a fund manager. Further, we found that this reduction in ASD difference is mainly due to a reduction by the top quintile active style drift, and not to an increase in ASD by bottom quintile funds. Thus, we find that a substantial reason for the reduction in active share documented by Cremers and Pettijisto (2009) is due to a reduction in active style drift over this time period.

managers with varying levels of active style drift. This panel shows very clear results: managers that actively move their portfolios in the three style dimensions produce substantially higher style-adjusted returns than other managers. For example, the top quintile of managers, ranked by their active style drift, hold stocks that beat their style benchmarks by 1.8 percent per year, while the median quintile exhibits no performance. Even more dramatic is the level of stockpicking skill exhibited by the extreme top 5 percent and 10 percent fractiles: these managers hold stocks that beat their style benchmarks by over three percent per year! In unreported tests, we find that the year +1 total and active style drift measures of the most active managers, ranked by their year 0 active style drift measure, are much higher than the respective total and active measures of other funds. Thus, fund managers who shift their portfolios to a greater degree across the style dimensions also persist in this activity (measured by the active style drift), and they do so with little regard to the overall changing nature of their portfolios (measured by the total style drift).

Panel C shows the estimated execution costs of each value-weighted portfolio of funds, based on the methodology outlined in Wermers (2000). Note that higher ASD funds have substantially higher execution costs. Further, panel D shows the value-weighted expense ratio for each portfolio. Higher ASD funds also have higher expense ratios. In total, the top ASD quintile funds have an estimated execution cost that is 89 bps per year greater than the lowest ASD quintile funds, and an expense ratio that is 39 bps per year greater. The total of these two components, 1.28 percent per year, is roughly equal to the stock-level outperformance prior to costs–1.13 percent per year. This finding indicates that high active style drift managers outperform at a level high enough to compensate investors for their higher trading costs and fees.

However, top ASD decile funds hold stock portfolios that outperform bottom ASD decile funds by almost 3 percent per year, while their estimated execution costs and expenses are about 1.4 percent per year higher. Most of this difference is due to the outperformance of the top decile funds, rather than any underperformance by the bottom decile funds. Thus, extreme ASD funds are able to provide their investors with positive risk-adjusted returns, net of execution costs and fees. This finding suggests that a strategy that selects high active style-drift funds (or the stocks held by these funds) may outperform a naive buy-and-hold strategy.

We, therefore, conclude this section with our summary finding: managers holding portfolios with greater levels of style drift, both active and total, provide higher levels of performance, on average, than their counterparts. There is evidence that the extreme active style drift funds outperform net of all costs (except load fees). Thus, our paper finds results contradictory to the Brown and Harlow (2002) hypothesis that style consistency is an important variable in picking fund managers. The key to our study is that we use detailed portfolio holdings to measure both mutual fund style drift and performance.

IV Conclusion

In this paper, we have provided new holdings-based measures of equity portfolio style drift, and we have applied these new measures to present evidence on the causes and consequences of drift. Other than the recent paper by Brown and Harlow (2002), this topic has received little attention in the academic literature. Our study uses a large cross-sectional database of fund manager information, extending from 1985 to 2000, to investigate the correlation of manager characteristics with portfolio style drift.

We find that both passive and active drift contribute significantly to overall drift in the average U.S. mutual fund portfolio. Drift in the price momentum dimension is the most important contributor to overall style drift, having about twice the level of drift in the other two dimensions for the average fund.

Our study also finds that growth-oriented funds have higher levels of style drift than income-oriented funds, and small funds have higher levels than large funds. Also, managers having better career stockpicking track records and higher levels of career portfolio turnover tend to engage in trades that cause more active style drift. Further analysis shows that these managers deliver superior future portfolio performance, which indicates that they are not simply overconfident.

Our study opens other possible avenues for future research, including a more detailed examination of labor-market pressures on the tendency of managers to engage in strategies that involve active style drift. For example, Chevalier and Ellison (1997) and Sias and Starks (1997) find that managers who fall behind their peers tend to react by engaging in riskier strategies than their peers. Of interest is whether these strategies involve deviations in certain style dimensions, such as a value manager taking "growth bets" or a large-cap manager taking "small-cap bets." In addition, some managers may "herd" or "cascade" on the previous style bets taken by their competitors, once this information becomes known. Our style-drift methodology opens up these areas of research for future study.

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Table I: Summary Statistics of Mutual Funds and Fund Managers

This table presents the summary statistics of mutual funds and fund managers in our fund-manager sample between 1985 and 2000 (inclusive). Our mutual fund data are drawn from the merged CDA–CRSP mutual fund database (CDA–CRSP). An early version of CDA–CRSP is used in **?**, which also contains a detailed description of the construction of CDA–CRSP. The fund manager data are collected from three most used mutual fund data sources: the Morningstar Principia Pro (2000), the CRSP Mutual Fund Data Base (2000Q3), and Wiesenberger. Panel A reports the number of mutual funds at the beginning of 1985, 1990, 1995, and 2000, as well as during the whole sample period, 1985–2000, for the whole fund universe and each of the following four investment objective categories—aggressive growth (AG), growth (G), growth and income (GI), income or balanced (I or B). Self-declared investment objectives are mainly collected from CDA. If CDA fails to report the investment objective for a fund, then we use the objective reported by CRSP as its objective. Panel B presents the counts of lead managers and the average number of funds managed by a lead manager during 1985–2000 as well as at the beginning of 1985, 1990, 1995, and 2000. If a fund is managed by multiple managers, the lead manager is defined as the active manager who starts to manage the fund earliest. To calculate the average number of funds managed by a fund manager up to a point in time, we first compute the time-series average number of funds under lead management for each lead manager and then take the cross-sectional average across all managers in the (sub)group. A fund manager is included in a subgroup of an investment objective (e.g. AG) for one point in time (e.g. the beginning of 2000) if she is the lead manager of at least one fund with that objective at that time. Since some managers may lead-manage several funds with different investment objectives at one point in time, the sum of the number of lead managers in the subgroups may be greater than the total number of lead managers at that time. Panel C reports the number of funds missing managers. The 1985 (1990, 1995, 2000) column in Panel C reports the funds that exist at the beginning of 1985 (1990, 1995, 2000) but do not have managers matched in 1985 (1990, 1995, 2000). The 1985–2000 column in Panel C reports the funds that exist at some time during 1985–2000 but do not have a matched manager throughout the sample period. The percent of funds missing managers is calculated as the the number of funds missing managers to the number of funds existing at the same time. Panel D provides a comparison of median total net assets (TNA) and mean excess returns between the funds that are matched with a manager and the funds that do not have any matched fund manager. The 1985 (1990, 1995, 2000) column in Panel D reports the funds that exist at the beginning of 1985 (1990, 1995, 2000) and have year 1985 (1990, 1995, 2000) as the matching period. The 1985–2000 column in Panel D is for the funds that exist at some time during 1985–2000 and have 1985–2000 as the matching period. A fund's total net assets over 1985–2000 is the time-series average of its monthly total net assets between 1985 and 2000 and is expressed in millions of year 2000 dollars. The excess return of a fund-year is obtained by subtracting the annual S&P 500 return during the year from the fund's raw annual return. The excess return of a fund over 1985–2000 is the time-series average of annual excess return.

Panel A: Counts of Mutual Funds

	1985	1990	1995	2000	1985–2000
All Funds	409	654	1511	2339	2892
AG	96	137	203	276	482
G	160	306	899	1393	2031
GI	103	136	265	459	729
I or B	50	75	144	211	356

Panel B: Counts of Lead Managers of Mutual Funds

	1985		1990		1995		2000		1985–2000	
	N	Avg. No. of Funds	N	Avg. No. of Funds	N	Avg. No. of Funds	N	Avg. No. of Funds	N	Avg. No. of Funds
All Funds	195	1.28	397	1.34	1004	1.46	1453	1.57	2670	1.31
AG	45	1.44	94	1.70	171	1.88	234	2.07	778	1.52
G	86	1.49	211	1.41	659	1.59	962	1.72	2148	1.36
GI	67	1.45	92	1.59	216	1.68	363	1.94	994	1.47
I or B	31	1.61	55	1.63	124	2.05	173	2.18	531	1.60

Panel C: Counts of Mutual Funds Missing Managers

	1985		1990		1995		2000		1985–2000	
	N	Percent	N	Percent	N	Percent	N	Percent	N	Percent
All	158	38.6	109	16.7	95	6.3	146	6.2	216	7.5
AG	45	46.9	16	11.7	7	3.4	8	2.9	32	6.6
G	61	38.1	56	18.3	64	7.1	89	6.4	132	6.5
GI	34	33.0	27	19.9	15	5.7	32	7.0	49	6.7
I or B	18	36.0	10	13.3	3	2.1	17	8.1	32	9.0

Panel D: Comparison of Funds Reporting Lead Managers and Funds Missing Managers

	1985		1990		1995		2000		1985–2000	
	Median TNA	Mean Excess Return	Median TNA	Mean Excess Return	Median TNA	Mean Excess Return	Median TNA	Mean Excess Return	Median TNA	Mean Excess Return
All Funds	134.4	-4.68	120.6	-1.44	113.9	-7.55	184.4	8.85	97.8	-2.42
Funds Reporting Lead Managers	149.6	-3.75	149.1	-2.32	120.8	-7.37	188.3	9.05	105.2	-2.17
Funds Missing Managers	104.7	-6.02	50.8	-3.79	56.8	-9.15	94.1	6.38	26.4	-6.66

Table II
Total Style Drift of Growth-Oriented vs. Income-Oriented Funds, by Size of Fund

Total style drift (TSD) measures are provided below for the merged CDA holdings and CRSP mutual fund characteristics/net returns databases. At the end of each calendar year starting December 31, 1985 and ending December 31, 1999, we rank all mutual funds in the merged database that existed during the entire prior year, and had an investment objective at the end of that year of "aggressive-growth" or "growth," for the growth-oriented funds in Panel A; or, "growth and income," "income," or "balanced," for the income-oriented funds in Panel B; on their total net assets at the end of that prior year (the "ranking period"). Then, fractile portfolios are formed, and we compute the equal–weighted total net assets (TNA) and total style drift (TSD) of each fractile of funds during the following year (the "test period"). The table also shows the time-series average number of funds within each fractile portfolio.

Panel A. Growth-Oriented Funds

Ranking Variable = Total Net Assets Fractile	Number	Total Net Assets ($Millions)	Total Style Drift (Style Number)
Top 10 % (Large Funds)	68	2,708	0.63
10-20 %	68	696	0.74
20-30 %	68	378	0.74
30-40 %	68	227	0.81
40-50 %	68	144	0.80
50-60 %	68	92	0.87
60-70%	68	57	0.89
70-80%	68	33	0.90
80-90%	68	18	1.00
Bottom 10% (Small Funds)	68	14	1.10
Top-Bottom 10%	—	—	-0.47***
All Funds	678	437	0.87

Panel B. Income-Oriented Funds

Ranking Variable = Total Net Assets Fractile	Number	Total Net Assets ($Millions)	Total Style Drift (Style Number)
Top 10 % (Large Funds)	31	5,150	0.51
10-20 %	31	1,389	0.61
20-30 %	31	651	0.70
30-40 %	31	356	0.68
40-50 %	31	212	0.76
50-60 %	31	131	0.76
60-70%	31	83	0.75
70-80%	31	47	0.80
80-90%	31	23	0.86
Bottom 10% (Small Funds)	31	17	0.95
Top-Bottom 10%	—	—	-0.45***
All Funds	308	806	0.75

* Significant at the 90% confidence level.
** Significant at the 95% confidence level.
*** Significant at the 99% confidence level.

Table III
The Characteristics of High vs. Low Style Drift Mutual Funds
(Ranked on Three-Year Active Style Drift)

Selected mutual fund measures are provided below for the merged CDA holdings and CRSP mutual fund characteristics/net returns database. At the end of each calendar year starting December 31, 1987 and ending December 31, 1999, we rank all mutual funds in the merged database that existed during the entire prior three-year period, had an investment objective at the end of that three-year period of "aggressive-growth," "growth," "growth and income," "income," or "balanced," and had complete holdings data during that three-year period, on their average yearly active style drift (ASD) of that three-year period (the "ranking period"). Then, fractile portfolios are formed, and we compute average measures (e.g., manager experience) for each fractile portfolio during that ranking period. Presented in this table are the EW-average annual: active style drift, total style drift, portfolio turnover ratio, the percentage of portfolio purchases (in dollars) that represent purchases of stocks already owned by a fund, career manager aggressiveness (time-series average portfolio turnover ratio of career funds managed), career manager experience, manager career stockpicking record (using the CS performance measure), and the fraction of managers replaced during each year of that ranking period. The table also shows the time-series average number of funds within each fractile portfolio, as well as the EW-average TNA of funds in each fractile.

Average Fractile Characteristics During Three-Year Ranking Period (Equal-Weighted Across Funds)

Ranking Variable = ASD Fractile	Avg No	Avg TNA ($mil)	Active Style Drift (Style #)	Total Style Drift (Style #)	Portfolio Turnover (%/yr)	Same Stock $Buys (% of Buys)	Career Aggress. (%/yr)	Career Experience (Months)	Career CST (%/yr)	Mgr Replace. (%/yr)
Top 5 % (Most Drift)	33	240	1.83	1.49	143	28.2	131	129	2.26	4.1
Top 10 %	66	306	1.59	1.33	143	29.3	129	123	2.21	3.2
Top 20 %	132	421	1.34	1.17	134	30.1	122	118	1.83	1.9
2nd 20 %	132	629	0.82	0.90	101	34.7	100	95	1.13	2.1
3rd 20 %	132	714	0.59	0.75	78	37.5	82	99	0.76	1.9
4th 20 %	132	781	0.41	0.63	55	43.9	58	113	0.92	1.7
Bottom 20 %	132	1,335	0.22	0.53	34	50.9	42	135	0.99	1.7
Bottom 10%	66	1,413	0.16	0.50	27	54.2	33	141	0.87	2.5
Bottom 5% (Least Drift)	33	1,562	0.11	0.47	26	55.8	33	136	0.96	3.4
All Funds	660	776	0.68	0.80	81	39.4	80	112	1.09	1.9

* Significant at the 90% confidence level.
** Significant at the 95% confidence level.
*** Significant at the 99% confidence level.

Table IV
The Performance of High vs. Low Style Drift Mutual Funds
(Ranked on Prior 3-Year Active Style Drift)

Selected mutual fund measures are provided below for the merged CDA holdings and CRSP mutual fund characteristics/net returns databases. At the end of each calendar year starting December 31, 1979 and ending December 31, 1999, we rank all mutual funds in the merged database that existed during the entire prior three-year period, had an investment objective at the end of that three-year period of "aggressive-growth," "growth," "growth and income," "income," or "balanced," and had complete holdings data during that three-year period, on their average yearly active style drift (ASD) of that period (the "ranking period"). Then, fractile portfolios are formed, and we compute average measures (e.g., net returns) for each fractile portfolio during the following year (the "test period"). In computing the average measure for a given test period, we first compute the quarterly buy-and-hold measure for each fund that exists during each quarter of the test period, regardless of whether the fund survives past the end of that quarter. Then, we compute the total net asset-weighted (TNA) cross-sectional average quarterly buy-and-hold measure across all funds for each quarter of the test period. Finally, we compound the net return and characteristic selectivity measures into an annual measure that is rebalanced quarterly, and we compute the average estimated quarterly execution cost (annualized, in percent per year) and average annual expense ratio. Presented in this table are the TNA-average annual: net return (Panel A), characteristic-selectivity measure (Panel B), estimated execution cost (Panel C), and expense ratio (Panel D). The table presents test year statistics over the year following the formation year, averaged over all event dates. The table also shows the time-series average number of funds within each fractile portfolio. Significance levels, based on time-series t-statistics, are denoted with asterisks.

Panel A. Net Return (percent per year)

Ranking Variable = Active Style Drift Fractile	Avg No	Avg TNA	Year +1
Top 5 %	33	240	18.0
Top 10 %	66	306	17.3
Top 20 %	132	421	16.1
2nd 20 %	132	629	16.1
3rd 20 %	132	714	14.4
4th 20 %	132	781	15.2
Bottom 20 %	132	1,335	15.6
Bottom 10%	66	1,413	15.2
Bottom 5%	33	1,562	16.2
Top-Bottom 5%	33	—	1.8
Top-Bottom 10%	66	—	2.0
Top-Bottom 20%	132	—	0.4
All Funds	660	776	15.8

Panel B. Characteristic-Selectivity Measure (percent per year)

Ranking Variable = Active Style Drift Fractile	Avg No	Avg TNA	Year +1
Top 5 %	33	240	3.43**
Top 10 %	66	306	3.23**
Top 20 %	132	421	1.80**
2nd 20 %	132	629	0.71
3rd 20 %	132	714	-0.07
4th 20 %	132	781	0.99
Bottom 20 %	132	1,335	0.67
Bottom 10%	66	1,413	0.27
Bottom 5%	33	1,562	0.50
Top-Bottom 5%	33	—	2.93**
Top-Bottom 10%	66	—	2.97**
Top-Bottom 20%	132	—	1.13**
All Funds	660	776	0.75*

* Significant at the 90% confidence level.

** Significant at the 95% confidence level.

*** Significant at the 99% confidence level.

Table IV (continued)

Panel C. Estimated Execution Costs (percent per year)

Ranking Variable = Active Style Drift Fractile	Avg No	Avg TNA	Year +1
Top 5 %	33	240	0.97
Top 10 %	66	306	0.90
Top 20 %	132	421	1.18
2nd 20 %	132	629	0.86
3rd 20 %	132	714	0.65
4th 20 %	132	781	0.53
Bottom 20 %	132	1,335	0.29
Bottom 10%	66	1,413	0.12
Bottom 5%	33	1,562	0.09
Top-Bottom 5%	33	—	0.87***
Top-Bottom 10%	66	—	0.78***
Top-Bottom 20%	132	—	0.89***
All Funds	660	776	0.70

Panel D. Expense Ratio (percent per year)

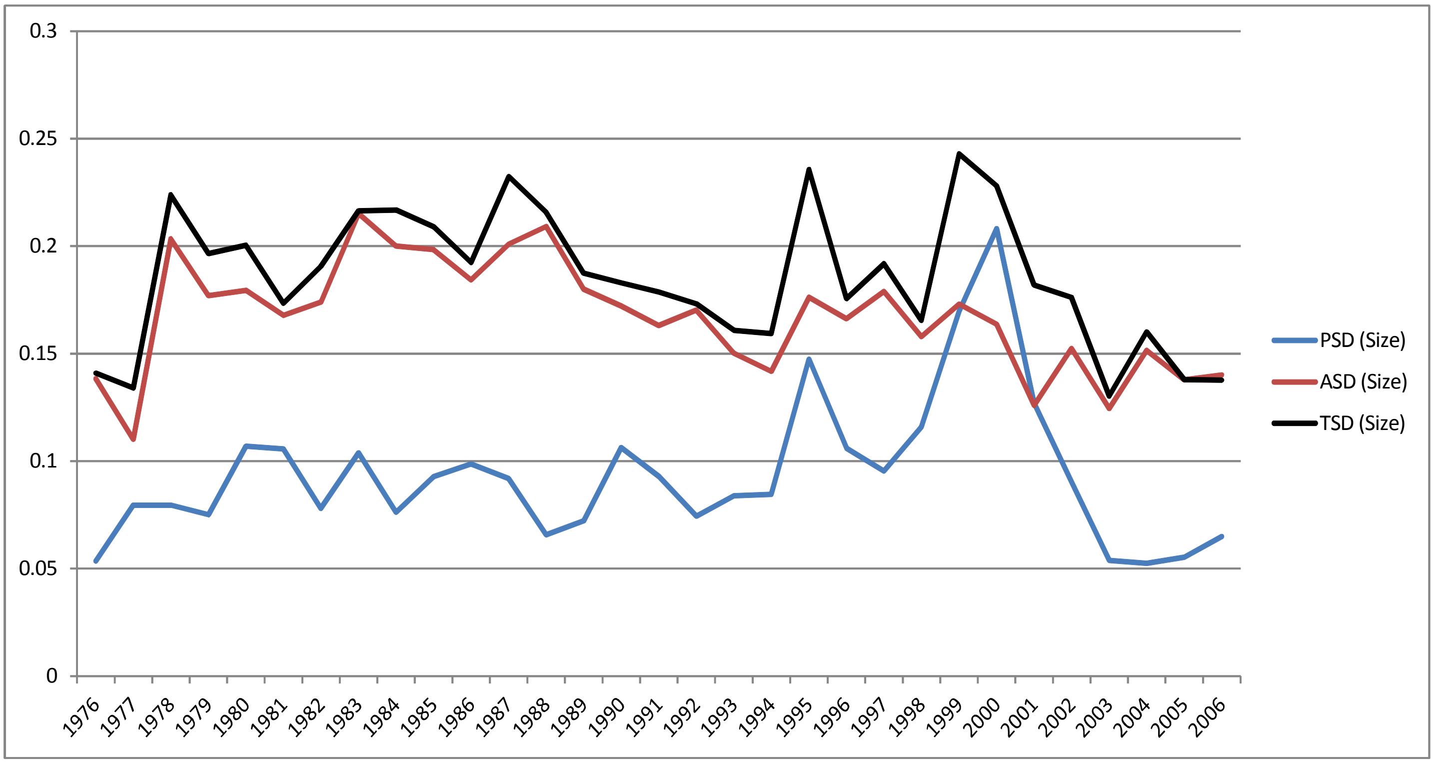
Ranking Variable = Active Style Drift Fractile	Avg No	Avg TNA	Year +1
Top 5 %	33	240	1.29
Top 10 %	66	306	1.22
Top 20 %	132	421	1.06
2nd 20 %	132	629	0.92
3rd 20 %	132	714	0.86
4th 20 %	132	781	0.82
Bottom 20 %	132	1,335	0.67
Bottom 10%	66	1,413	0.64
Bottom 5%	33	1,562	0.59
Top-Bottom 5%	33	—	0.71***
Top-Bottom 10%	66	—	0.58***
Top-Bottom 20%	132	—	0.39***
All Funds	660	776	0.87

* Significant at the 90% confidence level.
** Significant at the 95% confidence level.
*** Significant at the 99% confidence level.

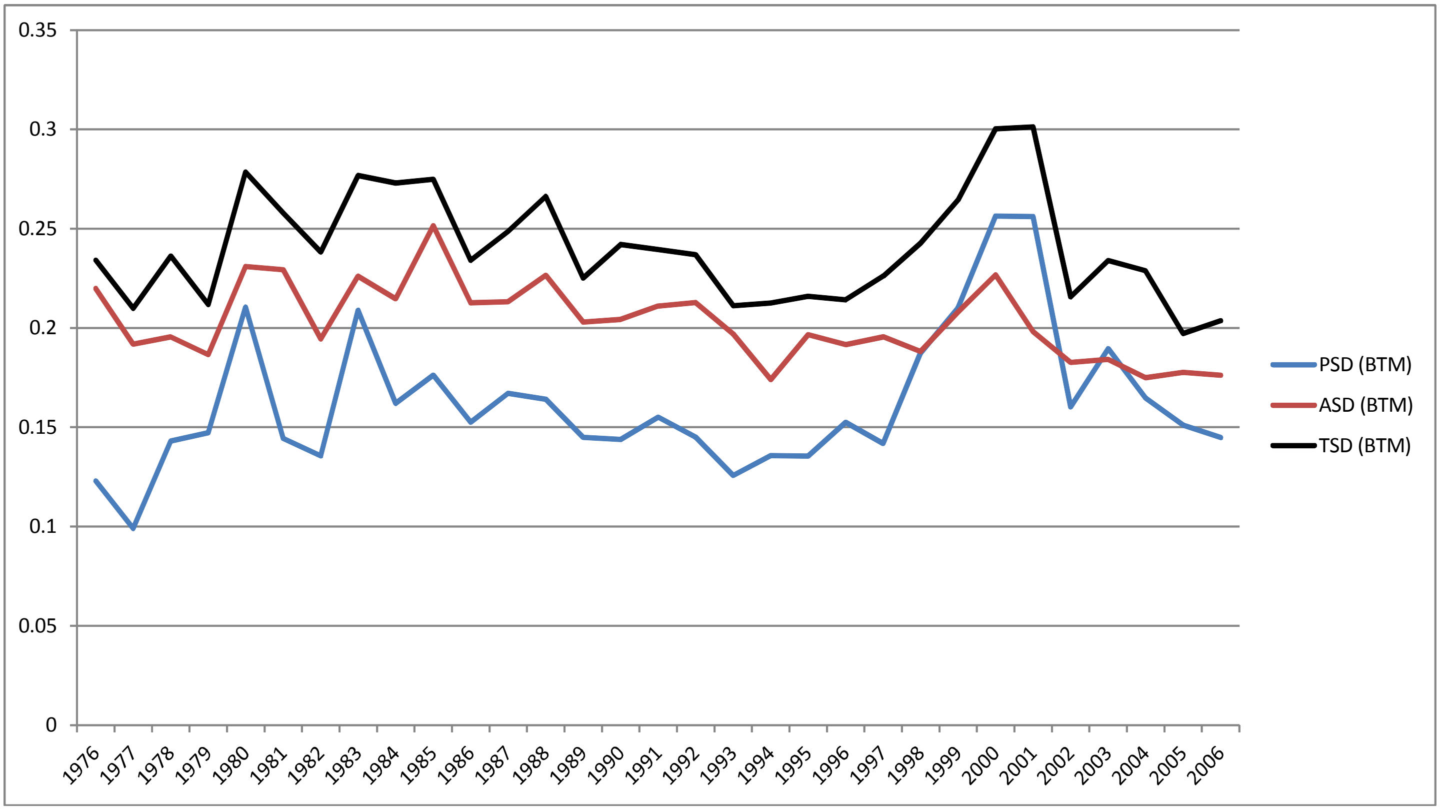
Figure 1
The Time Trend in Style Drift

This figure shows the yearly style drift in each dimension from June 30 of year t-1 to June 30 of year t (year t is shown on the x-axis labels). The average (absolute value of) style drift in each dimension, across all mutual funds existing during that entire year and having an investment objective at June 30 of year t of "aggressive-growth," "growth," "growth and income," "income," or "balanced," and having complete holdings data at June 30 of years t-1 and t, is presented.

Panel A. Average Style Drift [Style Quintile Numbers per Year, Market Capitalization (Size) Dimension]



Panel B. Average Style Drift [Style Quintile Numbers per Year, Value/Growth (Book-to-Market) Dimension]



Panel C. Average Style Drift [Style Quintile Numbers per Year, Momentum Dimension]

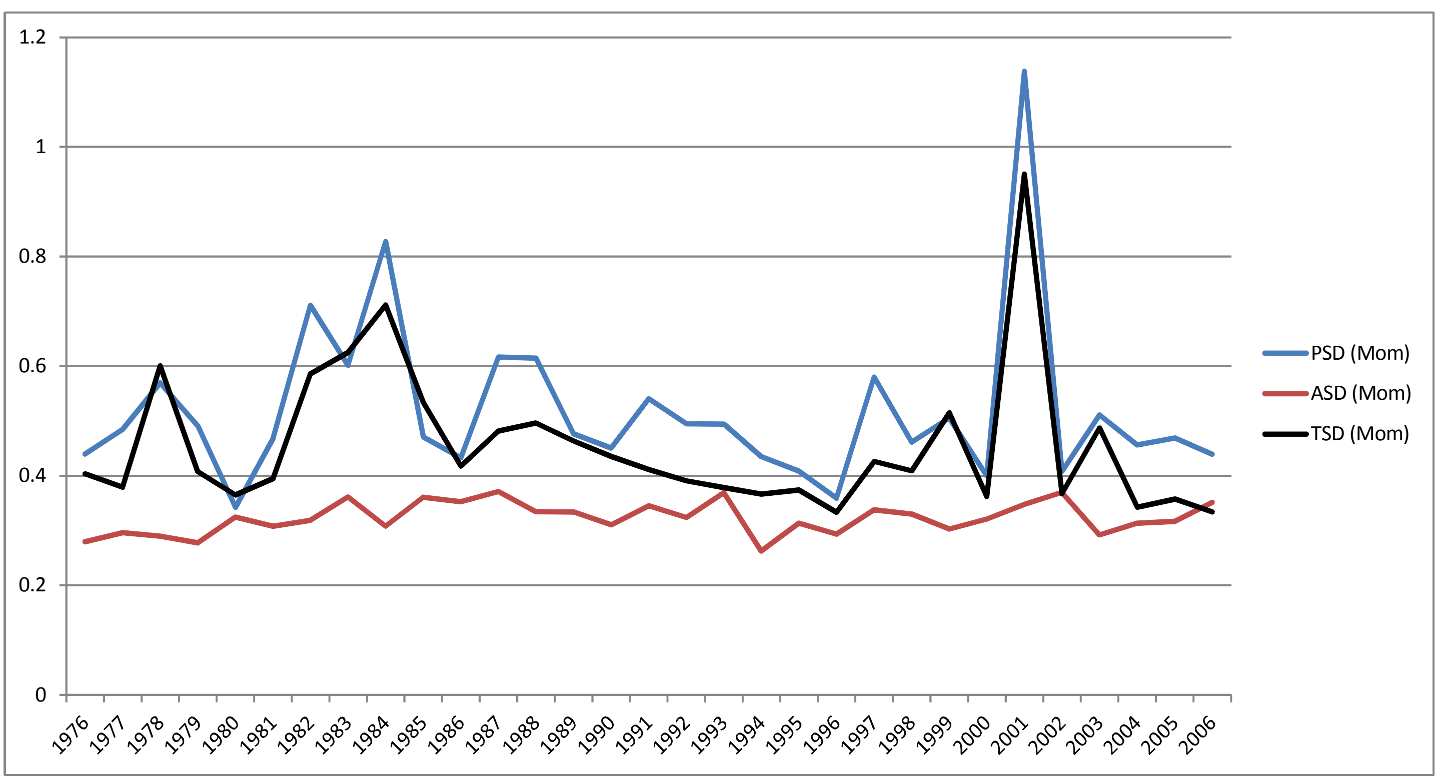
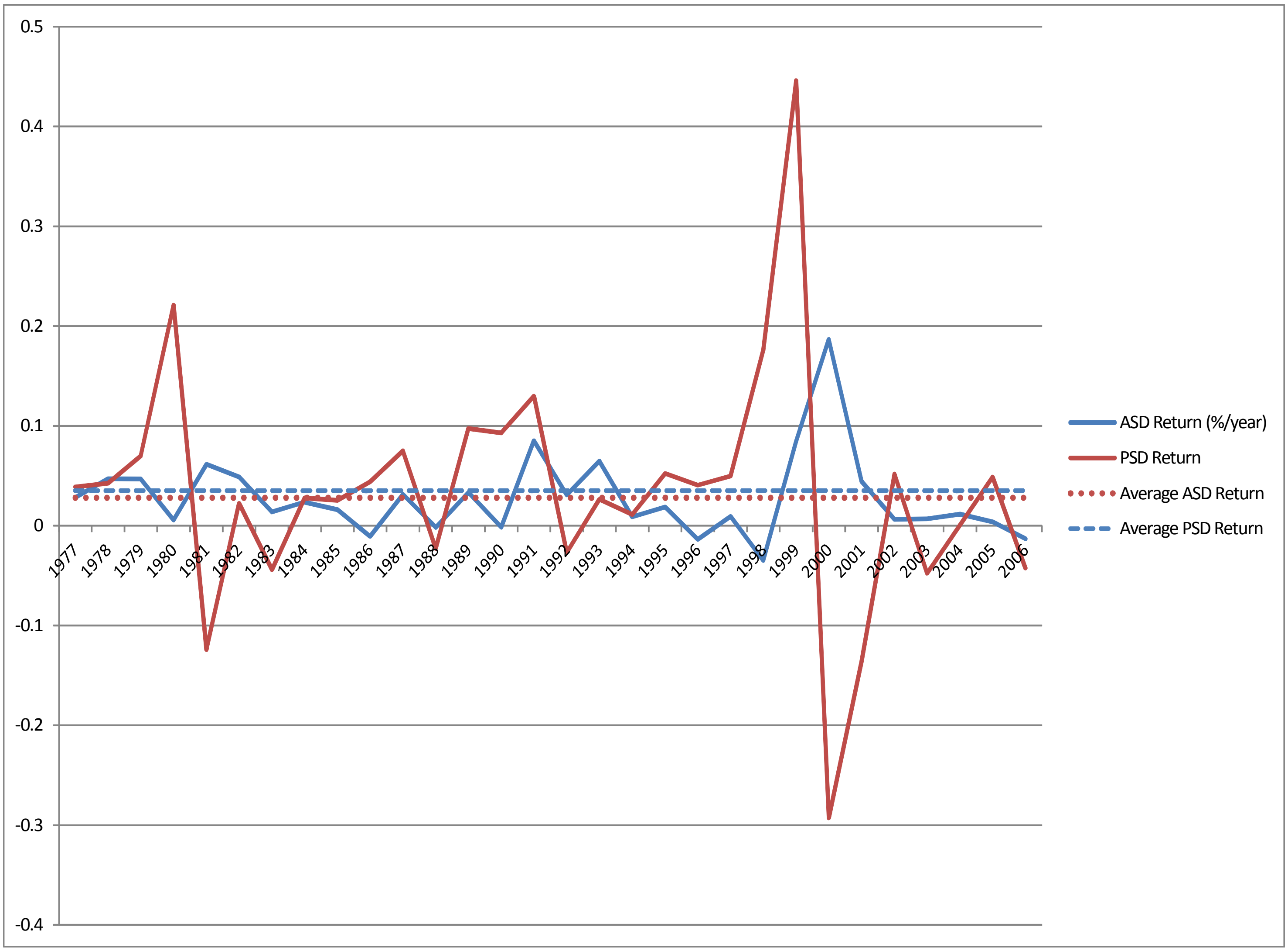


Figure 2
The Style Returns of Active and Passive Style Drift

This figure shows the yearly style drift returns (PSDR and ASDR) based on the change in portfolio weights for a given stock during a particular 4-quarter period, and the return of the style benchmark for that stock during the following calendar quarter. For example, the style drift return accruing to passive (buy-and-hold) style movement in the value/growth (book-to-market) dimension equals (for quarter t+1, where k=4 quarters) $PSDR^{BTM}_{t-k,t} = \sum_{j=1}^{N}(\widetilde{w}'_{j,t} - \widetilde{w}_{j,t-k})R^{BTM}_{t+1}$, while the active style drift return equals $ASDR^{BTM}_{t-k,t} = \sum_{j=1}^{N}(\widetilde{w}_{j,t} - \widetilde{w}'_{j,t})R^{BTM}_{t+1}$. The graph sums PSDR and ASDR across the size, book-to-market, and momentum dimensions to arrive at a total style drift return for each fund, then presents the average PSDR and ASDR (across funds) for each year.

Active Style Drift Return (ASDR) and Passive Style Drift Return (PSDR) (%/year)



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cfr/university of cologne
Albertus-Magnus-Platz
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fax +49(0)221-470-3992
kempf@cfr-cologne.de
www.cfr-cologne.de