Investor Sophistication and Mutual Fund Investment Style Changes

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Abstract

In this paper, we examine different clienteles' reactions to changes in the investment styles of mutual funds. Using the granularity of daily data on mutual funds, we show that the heterogeneity in investors' financial sophistication strongly relates to the heterogeneity in the responses to changes in investment style. The empirical approach that we apply to several proxies for the investors' financial sophistication indicates that while more sophisticated investors leave funds when style changing occurs, less sophisticated investors react to these changes inversely. We also show that the style change has a different impact on various types of fund performance measures. Specifically, a deviation from the stated investment style has a strong positive impact on the performance measures, which are used by less sophisticated investors, while it does not have a significant impact on more advanced performance measures. Overall, we argue that a comparison between the fund flows and style changes that accounts for investor's sophistication level allows for a more complete picture of the fund flow's response to the changes in mutual funds' investment style.

Keywords: Equity mutual funds; investment style analysis; fund flow; fund performance; investor clientele. (*JEL* G11, G12, G23)

1. Introduction

Equity mutual funds often invest in stocks beyond the scope of their prospectus's investment objective that results in a volatile investment style over time. Prior studies find that fund investors need to be aware of changes in the investment style because they can expose investors to unexpected risk.[1] On the other hand, some studies show that investors vary with regards to their financial sophistication and that better-informed investors use more sophisticated tools to monitor the investment strategies of fund managers.[2] Hence, the assumption that all mutual fund investors are equally aware of changes in investment styles and are likely to react equally to these changes is very debateable. Therefore, the central question in this paper is whether the responses of investors to changes in the funds' investment styles vary due to the differences in their financial sophistication. We use fund flows to empirically examine this question. We show that larger outflows are associated with highly sophisticated investors with respect to punishing the changes in investment style, while less sophisticated investors react to this change differently. We argue this mechanism can be plausible for two reasons. First, the heterogeneity in the investors' reactions to the funds' style changes can relate to the different impact they have on different fund performance measures.[3] Second, informed investors play a major role in monitoring mutual funds and in disciplining fund managers with respect to changes in investment style. Therefore, a strong relationship between the presence of sophisticated investors and the subsequent fund's changes in investment style may explain the heterogeneity in fund flows.

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[1] See diBartolomeo and Wikowski (1997), Brown and Goetzmann (1997), Kim, Shukla and Tomas (2000), Kim, White and Stone (2005), Cremers and Petajisto (2007), Sensoy (2009), Mason et al. (2012), Bams, Otten and Ramezanifar (2016), and Cao, Iliev and Velthuis (2017) among others.
[2] See Barber, Huang and Odean (2016) and Berk and Van Binsbergen (2016) among others.
[3] For example, if style changes have a positive impact on a specific performance measure that is used by an investor, it is possible that not only might the investor not penalize this behavior but may even reward it.

Although a large body of literature has identified the sensitivity of fund flows to performance, a topic that has attracted much less attention is the sensitivity of fund flows to changes in investment style.[4] Previous findings are mixed; for example, Cooper, Huseyin and Rau (2005) find that a change in a mutual fund's stated investment objective, on average, causes a stronger positive abnormal fund flow. They show that a simple timed name change can trick fund participants. Cremers, Fulkerson and Riley (2018) and Sensoy (2009) show that a deviation from the stated benchmarks matters to fund investors and causes an increase in fund flows.[5] Barber, Huang and Odean (2016) find that investors, on average, are more sensitive to the factor-related returns associated with the Morningstar-style categories. In contrast, Barberis and Shleifer (2003) infer that investors categorize assets with respect to style category and they do not distinguish between assets within a style. Del Guercio and Tkac (2002) also show that the sponsors of money market pension funds punish a high deviation from the benchmark as measured by the tracking error.[6] However they do not find the same relationship in mutual funds. Holmes and Faff (2007) show that for Australian mutual funds the level of style drift is not related to fund flows.

Our study contributes to the literature in three distinct ways. First, while prior studies on fund flows' reactions to style changes treat all different types of investors equally, we extend this literature by highlighting and considering the heterogeneity of investors' flows with respect to their sophistication level. We argue that taking the average of fund flows means treating all investors as a homogenous group, which may ignore investor class-specific effects. Hence, previous findings could lead to undesirable conclusions.

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[4] For the relationship between fund flow and fund performance, see Ippolito (1992); Chevalier and Ellison (1997); Sirri and Tufano (1998); Brown, Harlow and Starks (1996), and Clifford (2013) among others.
[5] Sensoy (2009) mentions that the mismatched self-designed benchmarks are not typically a result of style drift or a change in fund styles and so do not appear incidental.
[6] The tracking error is the standard deviation in the return difference between the fund and its benchmark.

Second, we expect that investors who use simple fund performance measures, like the benchmark-adjusted return, may interpret the changes in investment style as the manger's skill. Prior studies show that the average investor assesses fund performance without adjusting for different risk exposures that result in over or underestimation of the alpha.[7] Therefore, we expect funds to respond strategically when constructing the portfolio. For example, a fund manager who follows an investment strategy that is riskier than the mandated investment objective may outperform his or her peers before a risk adjustment but underperform after adjustment that can attract additional fund flows. Thus, an understanding of how changes in investment style affect different performance metrics is relevant. By grouping performance measures as either simple or advanced, we test whether style changes have an equal impact on different measures.

Third, we investigate the relationship between the style discipline of fund managers and the fund participant's sophistication level. For example, Egan, Matvos and Seru (2016) show that the misconduct of financial advisers in the US is concentrated in firms with retail customers and argue that this misconduct may be targeted at customers who are less financially sophisticated. Therefore, when highly sophisticated investors represent a larger proportion of fund investors, the fund manager may be restricted to engage in more strategic behavior such as style volatility or style deviation. To test whether informed investors can effectively discipline fund managers with respect to style changes, we examine the relationship between the sophistication level of fund participants and the subsequent deviation or volatility in the fund's investment style.

Using US equity mutual fund data, we use two different proxies to identify an investor's financial sophistication. The first proxy distinguishes between retail and institutional funds at the share-class level. We expect institutional investors to be

[7] Berk and Van Binsbergen (2016) and Barber, Huang and Odean (2016)

better equipped to monitor managers than their smaller counterparts. Evans and Fahlenbrach (2012) use this proxy and show that institutional investors are more sensitive to high fees and poor risk-adjusted performance. Del Guercio and Tkac (2002) and Goyal and Waha (2008) show that institutional investors severely punish funds that perform poorly by redeeming their shares. James and Karceski (2006) report that institutional fund flows are significantly less sensitive to past fund net returns and more sensitive to risk-adjusted measures of performance than retail fund flows. Moreover, for money market mutual funds, Christoffersen and Musto (2002) show that the performance sensitivity of institutional investors is in strong contrast to retail funds. They argue that funds with a worse performance history will have a clientele that is less performance-sensitive. Schmidt, Timmermann and Wermers (2016) find that prime institutional holdings in money market mutual funds, over the financial crisis, have a much higher persistence in run-like behavior than retail share classes. Therefore, we divide our sample into two parts: institutional funds that represent sophisticated investors and retail funds that represent unsophisticated investors.

The second proxy for the investor's financial sophistication distinguishes between a direct-sold versus a broker-sold distribution channel. Buying mutual funds through a broker or an investment company usually means choosing among different mutual fund share classes. Chalmers and Reuter (2013) show that investors who purchase mutual funds through a broker tend to be less well educated than investors who buy funds directly from fund companies. Del Guercio and Reuter (2013) find that flows are more sensitive to risk-adjusted returns for direct-sold funds than for broker-sold funds, while broker-sold funds respond more to market-adjusted returns. Barber, Huang and Odean (2016) find that direct-sold fund investors use more sophisticated models to assess the fund manager's skill than broker-sold fund investors. They infer that direct-sold fund investors consider a fund's exposure to factors such as size and value rather than attributing the excess returns to the manager's skill. For this reason, following Barber, Huang and Odean (2016) and Evans and Fahlenbrach (2012), we split our sample into: broker-sold funds that represents unsophisticated investors and direct-sold funds that represent sophisticated investors.

To measure the style changes of fund managers over time, we use two different approaches to capture both sides of this behavior: style deviation and style volatility. Style deviation is defined as the difference between the actual investment style and the stated investment style that the fund reports in its prospectus. Style volatility in mutual funds is defined as the volatility in their investment styles' exposures over time that represent the consistency in the investment style. To quantify style deviation and style volatility in mutual funds, prior studies propose several methods. Using the return data for mutual funds, Bams, Otten and Ramezanifar (2017) introduce the Style Deviation Degree (SDD) as a continuous measure of the deviation in investment style. Idzorek and Bertsch (2004) also use fund return data and develop the Style Drift Score (SDS) as a single quantitative measure of style volatility of a fund over time. In our analysis, we adopt the SDD and SDS to rank all funds in our sample in terms of style deviation and style volatility respectively.

The empirical analysis that we apply to the fine granularity of hand-inspected data at the share class-level for US equity mutual funds brings new insights to the literature. First, we find that on average, fund flows are more sensitive to the absolute deviation of a fund from the stated investment style than to the volatility in its investment style's exposures over time. In addition, we show that there is a significantly positive relationship between fund flows and the fund's style deviation, which is in line with Cremers, Fulkerson and Riley (2018), Barber, Huang and Odean (2016), Sensoy (2009), and Cooper, Huseyin and Rau (2005). Surprisingly, when we account for the heterogeneity in investors' financial sophistication, the results change. Our findings indicate that the relation between high sophisticated investors' flows and style deviation is negative. For example, to put the magnitude into context, the effect of a style deviation on the retail investors' fund flows is half the magnitude of the effect of a one standard deviation increase in a fund's prior one-year risk-adjusted return on the fund flows. The results are robust for the alternative sophistication proxy, which is broker-sold versus direct-sold funds. For example, the effect of a style deviation on the average inflow of broker-sold funds exceeds the inflow of direct-sold funds by more than 14% per year. We also find that the aggregate result (i.e., the average reaction of all investors to the funds' style deviation) is driven by less sophisticated fund investors.

Second, by using relatively simple performance measures like the benchmark-adjusted return and using more advanced measures like risk-adjusted returns, we find that the style deviation or volatility has a positive impact on the simple measures and no impact on more sophisticated measures. Therefore, less sophisticated investors may interpret style changes by fund managers as managerial skill. However, sophisticated investors correctly interpret the change and leave the funds with a style deviation.

Third, our results show that there is no relationship between the proportion of less sophisticated investors and the subsequent amount of the fund's style changes. This finding indicates that fund managers do not take advantage of less sophisticated investors by using more style changes in the future.

Overall, we argue that a comparison of the relationship between fund flows and style changes by accounting for investor's sophistication level allows for a more complete picture of an investor's response to the changes in mutual funds' investment style.

The remainder of the paper is organized as follows. In section 2, we describe the data that are used in the empirical application. In section 3, we provide a description of the methodology, section 4 represents empirical findings, and section 5 includes a robustness check. Section 6 concludes the paper.

2. Data

To classify the US equity mutual funds in our sample through stated investment objectives, we first review all their prospectuses to determine the principal investment strategy of each fund.[8] We then employ the Lipper objective codes from the CRSP Survivor-Bias Free database to obtain the historical stated investment style of mutual funds. In the CRSP database only the Lipper objective code is based on a mutual fund's prospectus.[9] We also check the historical stated investment style data with the funds' own websites and the official SEC website.

We obtain daily fund return data and monthly/quarterly fund characteristics data including fund expense ratio, Total Net Asset value (TNA), front-end load, back-end load and 12b-1 fees at the share-class level. Following Sirri and Tufano (1998), we calculate flows for each share-class *i* in year *t*+1 as follows:

$$Fund\ Flow_{i,t+1} = \left[TNA_{i,t+1} - \left(1 + r_{i,t+1}\right)TNA_{it}\right]/TNA_{it} \qquad (1)$$

Where TNA_{it} is the total net asset value of fund *i* at the share class-level at the end of year *t*, and $r_{i,t+1}$ is the fund's return over the year *t*+1. All other fund characteristics such as age and turnover are obtained from the CRSP database.

Since the focus of this paper is on actively managed equity funds, we exclude index funds, fixed income funds, as well as balanced and sector funds. Moreover, we remove all funds from the database which have negative weights to exclude short-selling considerations. Also, funds managing less than $1.5 million are excluded from our database. We then categorize funds as institutional and retail funds when

[8] Each fund's prospectus has a specific section which describes what funds invest primarily.

[9] Lipper is also a global leader in providing mutual fund information and its website mentions that: "Lipper's benchmarking and classifications are widely recognized as the industry standard by asset managers, fund companies and financial intermediaries. Our reliable fund data, fund awards designations and ratings information provide valued insight to advisors, media and individual investors."

CRSP designates them as such at the share-class level.[10] The number of distinct U.S. mutual funds that meet our selection criteria over the sample period from July 2003 through January 2016 is 891 funds with 3,624 different share classes. These funds are classified into three main investment style classes including Growth, Value and Small-cap mutual funds. The data for computing the multi-factor model returns includes the CAPM, the Fama and French (1992) 3-factor model and the Carhart (1997) 4-factor model, retrieved from French's website.

Furthermore, as we only consider U.S. equity funds, the relevant style benchmarks are all U.S. indices which are all daily total returns. We include the U.S. value index (S&P500 Value index), the U.S. growth index (S&P500 Growth index), the U.S. small cap index (S&P600 index) and two fixed income classes: cash (30-day Treasury bill rate) and bonds (30-year bonds). The daily indices return data are obtained from FactSet.

[10] The CRSP classification of funds into institutional or retail starts from the year 1999, which is why we use this year as the starting point in our investigation.

Table 1- Descriptive statistics

	Mean	Std. Dev.	Min	Max
A: Fund characteristics				
TNA ($ million)	1,576	7,281	1.5	189,188
Turnover Ratio	0.79	0.87	0.01	13.30
Fund Flow (%)	0.06	0.45	-2.16	2.98
Fund Age (year)	13.66	10.20	1.0	78.1
B: Fund Fees (Annually)				
Expense Ratio	1.26	0.49	0.04	2.15
12-b fee (%)	0.59	0.35	0.00	1.00
Front-end Load (%)	2.20	1.30	0.00	5.70
Back-end Load (%)	0.70	0.69	0.00	2.61
C: Retail vs. institutional funds				
TNA of retail funds ($ million)	1,403	5,942	0.10	112,035
TNA of institutional funds ($ million)	733	3,514	0.10	77,829
Expense ratio of retail funds (Annually)	1.42	0.49	0.01	4.82
Expense ratio of institutional funds (Annually)	0.97	0.36	0.4	2.99

This table reports descriptive statistics (mean, standard deviation, maximum and minimum) for the mutual fund sample in three different panels. Panel A represents total net assets (TNA), fund turnover ratio, fund flows and fund age. Panel B report the fund expense ratio, 12-b fee, front-end load fee and back-end fund fee. Panel C shows the total net asset (TNA) and expense ratios for retail and institutional funds within share classes respectively.

3. Method

In this section, we show how we quantify investment style changing behavior of mutual funds which includes (i) deviation from the stated investment objective and (ii) investment style volatility over time. Although the Security and Exchange Commission (SEC) mandates all mutual funds to adhere to their self-claimed investment style, previous studies on mutual funds style analysis show that a substantial number of funds deviate from their investment style mandates.[11] To measure the style deviation from the stated investment objective we first categorize all funds in our sample in different style classes based on what they claim in their prospectus. To show the difference between actual investment style and stated investment style, we employ the Style Deviation Degree (SDD), which has been introduced by Bams, Otten & Ramezanifar (2016). Based on this measure, we rank all mutual funds on a continuous scale with respect to the extent of their style deviation.

In addition, we capture style volatility of mutual funds as the second dimension of investment style analysis by using the style drift measure. In particular, we employ the Style Drift Score (SDS) of Idzorek and Bertsch (2004). This measure shows the volatility of the investment style of a fund by calculating the volatility of a fund's investment style over time. The style deviation measure can be different from the style volatility measure. For example, if a fund manager of a growth style mutual fund consistently invests in value stocks over time, the style volatility would be close to zero but the style deviation will be high and close to one. The SDD and SDS are determined within the framework of Return Based Style Analysis (RBSA) which has been introduced by Sharpe (1992). RBSA is generally expressed as follows:

[11] See diBartolomeo & Wikowski (1997), Brown & Goetzmann (1997), Kim, Shukla & Tomas (2000), Kim, White & Stone (2005), Cremers and Petajisto (2007), Sensoy (2009), Mason et al. (2012) and Bams, Otten & Ramezanifar (2016) among others.

$$R_{it} = \sum_{k=1}^{N} \beta_{ik} I_{kt} + u_{it} \qquad t = 1, \ldots, T \tag{2}$$

where R_{it} denotes the return of mutual fund i at time t, N is the number of style classes, β_{ik} is a style parameter that expresses the sensitivity of fund i's return to the factor-mimicking portfolio return of index k; I_{kt} denotes the return of index k at time t and u_{it} is an error term. In our analysis, we employ the strong form of RBSA, in which the style parameters must be positive and sum to 1.

SDD measures the deviation of a fund from the stated investment style and is defined as one minus the α percent quantile of the probability distribution function of the exposure to the stated investment:[12]

$$SDD = 1 - min \ \llbracket\{x: P\{\beta_s \leq x\} \leq \alpha\rrbracket \ \} \tag{3}$$

where P is the asymptotic distribution of style parameter $\beta; 0 \leq x \leq 1$ represents possible values for β. The asymptotic distribution of the style parameters is determined by bootstrapping and is by construction always between zero and one, allowing the measure to be interpreted as a standardized degree. As the SDD gets close to zero, it shows that the fund is highly likely to be a style disciplined fund and clearly, as the SDD gets close to one, it shows that the fund is highly likely to be a style deviated fund.

SDS captures investment style volatility of fund over time; the model will be applied using a 'rolling window' technique over an initial time window, which is 12 months using daily observations and the window will be moved forward by 12 months and new style exposures will be calculated. The SDS is calculated as the square root of the sum of the variances of the asset class coefficients:

[12] This paper focuses on the Lipper objective codes as a proxy for the stated investment style. Lipper's objective codes are assigned based on the language that the fund uses in its prospectus to describe how it intends to invest. Morningstar is a widely-used source for style analysis, but the classification method is not based on the fund's prospectus.

$$SDS = \sqrt{var(\beta_{1t}) + var(\beta_{2t}) + \cdots + var(\beta_{kt})} \quad (4)$$

Where $\beta_{1t}, \beta_{2t} \ldots \beta_{kt}$ represent the time series of style exposure estimates which have been obtained from the style analysis process (Equation 2); k is the number of indices. Idzorek and Bertsch (2004) argue that the SDS is an effective, time-efficient way to compare style consistency and eliminates the need to examine rolling window style graphs. A fund with a high SDS will demonstrate greater style inconsistency than a fund with a low SDS. For the cross-sectional analysis, SDS will be used as a measure of style volatility as it provides a mean value of the variation in style index coefficients for each fund. SDS is the primary test variable in our analysis.

Table 2 reports the value of both measures at the end of each year from 2004 to 2015.

Table 2- Style Deviation Degree (SDD) and Style Drift Score (SDS)

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
SDD	0.52	0.51	0.55	0.53	0.44	0.46	0.48	0.45	0.44	0.47	0.44	0.42
	(0.30)	(0.28)	(0.32)	(0.31)	(0.26)	(0.26)	(0.28)	(0.27)	(0.28)	(0.29)	(0.29)	(0.28)
SDS	0.13	0.17	0.15	0.17	0.15	0.15	0.12	0.13	0.12	0.12	0.13	0.10
	(0.07)	(0.10)	(0.09)	(0.10)	(0.09)	(0.10)	(0.09)	(0.10)	(0.08)	(0.10)	(0.09)	(0.07)

This table reports the mean of the Style Deviation Degree (SDD) and the Style Drift Score (SDS) at the end of each year from 2004 to 2015. Standard deviations are shown within parentheses.

4. Results

In this section, we show the sensitivity of fund investors with differing levels of sophistication to style changes of mutual funds. We believe that high-sophisticated investors respond differently to a fund's style-changing behavior than less-sophisticated investors. We next show how style-changing behavior of funds affects different fund performance measures. Finally, we test whether the high proportion of sophisticated fund's participants, can effectively discipline fund managers with respect to style-changing behavior.[13]

4.1. Institutional investors versus retail investors

Institutional mutual fund investors such as banks, hedge funds, pension funds and insurance companies have more sophisticated systems for monitoring the decisions made by mutual fund managers in comparison with retail investors.

The share classes of mutual funds allow us to split our data into an institutional investor subsample and retail investor subsample. Therefore, we test whether institutional investors and retail investors within the same fund react differently to a change in style. For this, we examine the relationship of investor fund flows at the share-class level to style deviation and style drift of mutual funds. Our tests are based on separate panel data regressions for both subsamples, by considering the fund's degree of style deviation/drift as well as various control variables as follows:

STD: the volatility of past performance measured as the standard deviation of returns over the performance estimation period; *AGE*: fund age measured by the natural logarithm of age; *SIZE*: fund size measured by the natural logarithm of fund TNA in the previous year; *FEE*: lagged total expense ratio, and *FLOW*: aggregate flow into each fund category in the preceding year.

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[13] Evans and Fahlenbrach (2012) show that informed investors can effectively discipline fund managers.

We compute the SDD and SDS measures in year *t* to show the level of style deviation and style volatility of mutual funds respectively. The SDD and SDS employ fund's preceding 1-year daily fund returns data. We then establish the panel data regression for institutional investors and retail investors separately. Table 3 reports the results of these regressions.

Table 3- Institutional investors versus retail investors

	All Funds		Flow- style deviation			Flow- style volatility		
	Flow- style deviation	Flow- style drift	Institutional funds	Retail funds	Diff (Retail - Institutional)	Institutional funds	Retail funds	Diff (Retail - Institutional)
Lagged 4- factor alpha	0.23 (0.00)	0.23 (0.00)	0.26 (0.07)	0.21 (0.00)	-0.05 (0.66)	0.26 (0.07)	0.21 (0.01)	-0.05 (0.70)
Volatility (STD)	-0.03 (0.97)	-0.11 (0.87)	-0.86 (0.32)	-0.16 (0.87)	0.70 (0.14)	-0.94 (0.16)	-0.28 (0.74)	0.66 (0.17)
Style deviation (SDD)	0.11 (0.12)	--	0.04 (0.38)	0.14 (0.08)	0.10 (0.05)	--	--	--
Style volatility (SDS)	--	0.07 (0.34)	--	--	--	-0.25 (0.89)	0.10 (0.55)	0.12 (0.72)
Lagged FLOW	-0.11 (0.61)	-0.13 (0.49)	0.01 (0.95)	-0.21 (0.66)	-0.22 (0.71)	0.01 (0.92)	-0.27 (0.56)	-0.28 (0.61)
FEE	1.11 (0.75)	1.11 (0.43)	-2.70 (0.23)	0.68 (0.30)	-2.02 (0.24)	-2.75 (0.22)	0.71 (0.33)	3.46 (0.23)
TURNOVER	-0.02 (0.51)	-0.02 (0.41)	-0.04 (0.44)	-0.02 (0.46)	0.02 (0.45)	-0.04 (0.41)	-0.02 (0.30)	0.02 (0.70)
Age	-0.61 (0.04)	-0.57 (0.03)	-0.34 (0.12)	-0.76 (0.03)	-0.42 (0.04)	-0.30 (0.09)	-0.73 (0.04)	-0.43 (0.04)
SIZE	-0.57 (0.01)	-0.58 (0.00)	-0.64 (0.02)	-0.54 (0.00)	-0.1 (0.32)	-0.66 (0.02)	0.55 (0.00)	0.11 (0.35)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund family fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,045	15,045			15,045			15,045
Adj. R-square	0.04	0.04			0.04			0.04

This table presents parameter estimates from panel regressions of fund flow (dependent variable) on the style deviation measure (SDD) and style volatility score (SDS). The dummy variable for retail fund is one and it is zero for institutional funds. The interaction term between the dummy variable and SDD/SDS shows the difference between retail funds and institutional funds. Control variables include one year lagged fund flow, lagged values of log fund size, log fund age, expense ratio, and return volatility. P-values are in parentheses.

Table 3 shows that difference between fund flow of retail funds versus institutional funds with respect to the style deviation is positively significant. This table also reports that fund retail investors positively respond to style-changing behavior and they may interpret this behavior as a skill of the fund manager. However, the institutional investors leave funds when style changing occurs, which hence suggests that highly sophisticated investors have better tools and knowledge to monitor fund manager behavior.

To compare the coefficients with each other, in unreported results we calculate the standardized regression coefficients. We find that with one standard deviation increase in the style deviation degree, there is 5% increasing in the retail fund flows and 0.3% increasing in the institutional fund flows.

4.2. Broker-sold funds versus direct-sold funds

As a second proxy for investor sophistication level, we divide our sample into two subsamples (i) direct-sold funds and (ii) the broker-sold funds. Following Barber, Huang and Odean (2016), and Evans, and Fahlenbrach (2012), we classify a fund as a broker-sold if 75% of its TNA meets at least one of the following three criteria: the fund charges a front-end load, a back-end load, or a 12b-1 fee greater than 25 bps.[14] Alternatively, a fund is direct-sold if 75% of its TNA charges no front-end load, no back-end load, and no 12b-1 fee. In the average month during our sample period, 41% of funds are broker-sold, 51% are direct-sold, and the remaining 8% have an indeterminate distribution channel.

We then test the hypothesis of heterogeneity of flow-style deviation/drift relations across distribution channels. We use a dummy variable that is one if the fund is

[14] Bergstresser, Chalmers, and Tufano (2009) show that broker-sold funds tend to charge front-end loads, back-end loads, or 12b-1 fees as a means to provide compensation to brokers who sell funds to investors.

broker-sold and zero otherwise and by multiplying the dummy variable with the style deviation/drift measures, we create interaction terms in the regression.

Table 4 shows the results in two parts; the first three columns analyse flow style-deviation relations and the second three columns focus on flow style-volatility relations. The results are in line with the previous findings of Table 3. and show that investors care more about style deviation than style volatility. Column 1 and 4 present the coefficient estimates for the direct-sold channel. Column 2 and 5 present the corresponding estimates for the broker-sold channel and Column 3 and 6 present the difference between the direct-sold and broker-sold channel (i.e., the estimated interaction terms).

The results show that deviation from the stated investment style potentially trick the broker-sold fund investors and attract more fund flow which is marginally higher than the flow from direct-sold fund investors. For example, column 3 shows that the effect of style deviation on the average inflow of broker-sold funds exceeds the inflows of direct-sold funds by more than 14% per year. The same relationship -yet not significant- exists between the broker-sold fund flow and the style drift score. These results are consistent with the notion that investors in the broker-sold channel are less sophisticated in their assessment of fund performance than are investors in the direct-sold channel.

Table 4- Broker-sold versus direct-sold mutual funds

	Flow- style deviation			Flow- style volatility		
	Direct	Broker	Diff (Broker-Direct)	Direct	Broker	Diff (Broker-Direct)
Lagged 4-factor alpha	0.35	0.28	-0.07	0.35	0.29	-0.06
	(0.00)	(0.00)	(0.26)	(0.00)	(0.00)	(0.29)
Volatility (STD)	2.26	2.31	0.04	2.21	2.15	-0.06
	(0.01)	(0.01)	(0.97)	(0.01)	(0.02)	(0.91)
Style deviation (SDD)	0.10	0.24	0.14	--	--	--
	(0.19)	(0.00)	(0.08)			
Style volatility (SDS)	--	--	--	-0.004	0.21	0.22
				(0.98)	(0.10)	(0.30)
Lagged FLOW	0.11	0.15	0.05	0.11	0.16	0.05
	(0.00)	(0.00)	(0.12)	(0.00)	(0.00)	(0.11)
FEE	8.43	5.93	-2.50	8.34	5.50	-2.83
	(0.34)	(0.24)	(0.80)	(0.93)	(0.27)	(-0.28)
TURNOVER	0.05	0.002	-0.05	0.05	0.00	-0.05
	(0.10)	(0.90)	(0.20)	(0.08)	(0.90)	(0.17)
Age	-0.29	-0.18	0.17	-0.27	-0.12	0.15
	(0.00)	(0.17)	(0.06)	(0.00)	(0.18)	(0.10)
SIZE	-0.35	-0.43	-0.08	-0.34	-0.44	-0.09
	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.02)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations		3,866			3,866	
Adj. R-square		0.04			0.04	

This table presents parameter estimates from panel regressions of fund flow (dependent variable) on the style deviation measure (SDD) and style volatility score (SDS). The dummy variable for broker-sold fund is one when 75% of the underlying assets of the fund is related to share classes that charge front load or rear load or 12b-1 fee more than 25 basis point. The interaction term between the dummy variable and SDD/SDS shows the difference between direct- sold funds and broker-sold funds. Control variables include one year lagged fund flow, lagged values of log fund size, log fund age, expense ratio, and return volatility. P-values are in parentheses.

4.3. Fund performance and Style deviation/ Style volatility

We now depart from the assumption that an investor in an actively managed fund seeks to identify a fund's alpha. The fund's alpha is estimated after removing any fund return that can be drawn from the fund's exposure to factors such as size, value versus growth and momentum. But less-sophisticated investors due to a lack of financial literacy may not be able to identify these factors and therefore may simply rank funds based on raw returns or benchmark-adjusted returns. Berk and Van Binsbergen (2016) and Barber, Huang and Odean (2016) suggest that the average investor is only concerned about market risk when assessing mutual funds, and a large proportion of investors tends to ignore other factors.

Thus, one potential explanation of heterogeneity between fund flow and style changing behavior of fund can be defined as a different impact of style deviation/drift on various fund performance measures which are used by different types of investors. To test this conjecture, we examine the impact of style deviation/drift behavior of funds across different fund performance measures ranging from relatively simple to advanced and run a regression as follows:

$$Alpha_{i,t} = a + \beta_1 \times SDD_{i,t-1} + \beta_2 \times \ Alpha_{t-1} + Controls + \varepsilon_{i,t} \qquad (5)$$

$$Alpha_{i,t} = a + \beta_1 \times SDS_{i,t\,-1} + \beta_2 \times \ Alpha_{t-1} + Controls + \varepsilon_{i,t} \qquad (6)$$

where $Alpha_{i,t}$ includes several fund performance measures such as benchmark-adjusted return, CAPM alpha and Carhart 4-factor model alpha. From Table 5 it follows that there is a significant positive relationship between the SDD and benchmark adjusted-return as the most common measure among naive investors. This relation remains positive (not significant) when we use CAPM alpha as a performance measure. However, when we employ the Carhart 4-factor alpha as a proxy for sophisticated fund performance measurement, the sign turns to negative; however, not significant.

Table 5- Fund performance and style deviation/drift

	Benchmark adj. return	Benchmark adj. return	CAPM Alpha	CAPM Alpha	4-factor Alpha	4-factor Alpha
Lagged benchmark adj. return	0.02 (0.00)	0.02 (0.00)	--	--	--	--
Lagged CAPM	--	--	0.08 (0.00)	0.08 (0.00)	--	--
Lagged 4-factor alpha	--	--	--	--	0.09 (0.00)	0.09 (0.00)
Volatility (STD)	0.10 (0.00)	0.09 (0.00)	-0.00 (0.00)	-0.003 (0.64)	-0.001 (0.00)	-0.001 (0.00)
Style deviation (SDD) bps	1.12 (0.00)	--	0.65 (0.71)	--	-0.81 (0.58)	--
Style volatility (SDS) bps	--	1.11 (0.31)	--	0. 21 (0.64)	--	0.12 (0.62)
Lagged FLOW (%)	-0.20 (0.00)	-0.20 (0.00)	0.00 (0.29)	0.00 (0.30)	0.00 (0.19)	0.00 (0.18)
FEE	-0.07 (0.00)	-0.07 (0.00)	-0.002 (0.00)	-0.003 (0.00)	-0.003 (0.00)	-0.003 (0.00)
TURNOVER	-3.1 (0.00)	-3.1 (0.00)	-0.12 (0.00)	-0.11 (0.00)	-0.11 (0.00)	-0.11 (0.00)
Age (%)	0.06 (0.05)	0.05 (0.09)	0.07 (0.58)	-0.04 (0.55)	0.03 (0.83)	0.04 (0.79)
SIZE	-1.1 (0.28)	-1.1 (0.15)	0.69 (0.18)	0.71 (0.18)	-0.59 (0.16)	-0.56 (0.18)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5493	5493	5198	5198	5473	5473
Adj. R-square	0.23	0.23	0.14	0.14	0.13	0.13

This table presents parameter estimates from panel regressions of fund performance (dependent variable) on the style deviation measure (SDD), style drift score (SDS), the relative fund performance with one year lag and other control variables. Controls include one year lagged fund flow, lagged values of log fund size, log fund age, expense ratio, and return volatility. P-values are in parentheses.

4.4. Shareholder composition and fund manager incentive

Sophisticated fund investors may play the role of shareholder activism in mutual funds and as such they may effectively discipline fund managers with respect to style changing behavior. Thus, the absence of sophisticated investors may create an incentive for a fund manager to employ more strategic behavior like changing the style in the future. To measure the relationship between the proportion of less-sophisticated investors and style-changing behavior, we introduce two different shareholder ratios at the fund's share-class level. The first ratio is the proportion of retail investors in the fund versus institutional investors and the second ratio is high expense funds versus low expense funds.

Based on each ratio, we first split the funds in two parts, sophisticated and unsophisticated investors; we then define the first shareholder ratio as the cumulative TNA of unsophisticated investors divided by the aggregated value of portfolio TNA. The ratio represents the skin of different types of investors in the game. For example, for the first proxy, the ratio is defined as the cumulative TNA of retail investors divided by the aggregated TNA of the portfolio, including TNA of both institutional and retail funds. This ratio varies from 0 to 1, and if the ratio is close to 1, it means retail investors are dominant.

The second ratio of fund activism is defined as a proportion of higher-median expense funds versus lower-median expense funds at the fund's share-class level. Low-expense ratio share classes are related to large-scale and more sophisticated investors. Christoffersen and Musto (2002) show that there is heterogeneity among investors regarding sensitivity to fund fees. They show that there is an adverse relation between fees and performance. Gil-Bazo and Ruiz-Verdu (2009) interpret this negative relation as an agency problem in which high-expense funds target less performance-sensitive investors, also referred to as naive investors that are not responsive to expenses. Viewed through this lens, recent studies show signals of agency issues related to style deviation. For example, Bams, Otten and Ramezanifar (2016) show that high style deviation occurs most likely in poorly performing funds with high expense ratios. Frijns, Gilbert, and Zwinkels (2016) report that funds that switch style more aggressively, have on average higher expense ratios. Sensoy (2009) points out that mismatched self-designed funds are more common among high-fee funds. Huang, Sialm & Zhang (2011) show that funds with higher expense ratios experience more severe performance consequences when they alter the risk profile of the fund. Therefore, we split each fund share class into (i) lower than median and (ii) higher than median expense ratios and refer to them as higher- and lower-sophisticated investors respectively. Thus, the second shareholder ratio is defined as the cumulative TNA of upper-median expense funds divided by the aggregated value of portfolio TNA. To examine the relationship between sophistication level of fund and the fund's style changing behavior, we first rank all funds into five portfolios based on two ratios. We then calculate the average SDD and SDS of funds for the subsequent year.

Fund performance and other control variables in year *t* may be affected by this relationship. The relevant panel regression equations are defined as follows:

$$SDD_{i,t+1} = a + \beta_1 \times Alpha_{i,t} + \beta_2 \times Shareholder\ ratios_{i,t} + Controls + \varepsilon_{i,t+1} \quad (7)$$

$$SDS_{i,t+1} = a + b_1 * Alpha_{i,t} + b_2 * Shareholder\ ratios_{i,t} + Controls + \varepsilon_{i,t+1} \quad (8)$$

where $SDD_{i,t+1}$ and $SDS_{i,t+1}$ represent the style deviation and style volatility of fund i in the next period respectively. The $Shareholder\ ratios_{i,t}$ represent the proportion of unsophisticated fund at the share class-level. We consider time fixed effect and fund fixed effect in the regression.

Table 6 shows that there is a positive relationship between the proportion of retail investors versus institutional investors and style-deviation of fund managers. Although this relationship is not significant, the positive sign is robust among different style-changing behavior and shareholder ratios. Overall, our findings reject the hypothesis that fund managers take advantage of presence of less-sophisticated investors in the fund.

Table 6- Shareholder composition and fund manager incentive

One-year future style deviation (SDD_{t+1}) and style volatility (SDS_{t+1})

	SDD_{t+1}	SDS_{t+1}	SDD_{t+1}	SDS_{t+1}
Lagged 4- factor alpha	0.34	0.29	0.36	0.25
	(0.00)	(0.00)	(0.00)	(0.00)
Volatility (STD)	-0.64	0.07	-0.67	0.03
	(0.05)	(0.63)	(0.02)	(0.83)
Lagged style deviation (SDS)	--	0.58	--	0.49
		(0.00)		(0.00)
Lagged style volatility (SDD)	0.71	--	0.74	--
	(0.00)		(0.00)	
Shareholder ratio 1	0.031	0.24	--	--
	(0.20)	(0.46)		
Shareholder ratio 2	--	--	0.20	0.07
			(0.75)	(0.84)
Lagged FLOW	-0.008	0.001	-0.003	0.003
	(0.14)	(0.49)	(0.51)	(0.18)
FEE	-0.22	0.94	1.21	1.54
	(0.75)	(0.00)	(0.02)	(0.00)
TURNOVER	-0.006	0.003	-0.003	-0.002
	(0.21)	(0.16)	(0.31)	(0.99)
Age	-0.041	-0.009	-0.02	-0.008
	(0.00)	(0.05)	(0.00)	(0.09)
SIZE	-0.004	-0.001	-0.004	-0.002
	(0.30)	(0.39)	(0.26)	(0.32)
Time fixed effect	Yes	Yes	Yes	Yes
Style fixed effect	Yes	Yes	Yes	Yes
Observations	3087	3029	3087	3029
Adj. R-square	0.69	0.42	0.68	0.42

This table presents parameter estimates from panel regressions of the future style deviation measure (SDD) and future style volatility measure (SDS) as dependent variables on the shareholder ratio, which is the total net asset of retail funds divided by the total net asset value of the whole fund. Shareholder ratio 1 is defined as the TNA of retail investors divided by the cumulative TNA of the fund and shareholder ratio 2 is defined as the TNA of higher- median expense funds divided by the cumulative TNA of the fund. We also consider the one-year lag style deviation measure (SDD) and style volatility score (SDS) as independent variables. Controls in this regression include one year lagged fund flow, lagged values of the log fund size, the log fund age, expense ratio, and return volatility. Because the variation of return among the styles is considerable, we use style- fixed effect beside the time- fixed effect in this panel. P-values are in parentheses.

5. Robustness check

Convex relationship between fund flow and fund performance

Prior studies point out an asymmetric (nonlinear) relationship between mutual fund flows and past performance, in which flows are more strongly related to positive market-adjusted performance than to negative performance. The results in section 4.3 are based on the linear relationship between fund flows and fund performance; we test the robustness of our results by considering the convex relationship between fund flow and style-changing behavior. For this purpose, we follow Huang, Wei and Yan (2007), and rank all mutual funds each year based on their Carhart 4-factor alphas; subsequently we classify them into low-, medium-, and high-performance buckets. Funds in the lowest (highest) performance quintile are in the low (high) group. The medium group includes funds with performance ranked in the middle three quintiles. We employ dummy variables for each bucket and by interacting the dummy variables to the alphas in each bucket, we capture the nonlinear relationship between fund flows and fund performance. The model is given by:

$$\begin{aligned} Flow_{i,t} = a + \beta_1 \times Low_{i,t-1} \times D_{1i} + \beta_2 \times D_{1i} + \beta_3 \times High_{i,t-1} \times D_{2i} \\ + \beta_4 \times D_{2i} + \beta_5 \times D_{2i} \times SDD_{i,t-1} \\ + \beta_6 \times D_{2i} \times SDS_{i,t-1} + Controls + \varepsilon_{i,t} \end{aligned} \quad (9)$$

where $Low_{i,t-1}$ represents the fund performance in the lowest quintile, and $High_{i,t-1}$ represents the fund performance ranks in the highest quintile. D_1 is a dummy variable that takes on a value of one for funds in the lowest quintile and D_2 is a dummy variable that takes on a value of one for funds in the highest quintile. We show the results of this regression in Table 7. Consistent with prior studies, there is a nonlinear relationship between fund performance and fund flows. The results show an even a stronger impact of style deviation and style volatility measures on fund flows under the nonlinearity assumption in comparison with prior results.

Table 7- Convexity of the future fund flow and fund performance

	All Funds		Flow- style deviation			Flow- style volatility		
	Flow- style deviation	Flow- style drift	Institutional funds	Retail funds	Diff (Retail - Institutional)	Institutional funds	Retail funds	Diff (Retail - Institutional)
Alpha Low decile	0.30	0.31	0.22	0.26	0.04	0.21	0.27	0.06
	(0.05)	(0.05)	(0.16)	(0.08)	(0.66)	(0.23)	(0.08)	(0.56)
Alpha Med decile	0.20	0.21	0.35	0.20	-0.15	0.35	0.20	-0.15
	(0.00)	(0.00)	(0.00)	(0.02)	(0.05)	(0.00)	(0.02)	(0.05)
Alpha High decile	0.47	0.47	0.43	0.44	0.01	0.43	0.48	0.05
	(0.09)	(0.09)	(0.08)	(0.03)	(0.21)	(0.08)	(0.08)	(0.32)
Volatility (STD)	-0.11	-1.23	-4.13	-1.77	5.90	-4.32	0.79	5.11
	(0.16)	(0.06)	(0.11)	(0.00)	(0.07)	(0.15)	(0.01)	(0.11)
Style deviation (SDD)	0.12	--	-0.15	0.16	0.31	--	--	--
	(0.14)		(0.06)	(0.08)	(0.01)			
Style volatility (SDS)	--	0.07	--	--	--	-0.46	-0.16	0.62
		(0.59)				(0.52)	(0.39)	(0.48)
Lagged FLOW	-0.26	-0.26	-0.71	-0.10	0.61	-0.70	-0.09	0.61
	(0.51)	(0.52)	(0.03)	(0.86)	(0.41)	(0.03)	(0.87)	(0.42)
FEE	-2.93	-2.90	-3.26	-2.87	3.39	-3.39	-3.01	-3.39
	(0.71)	(0.76)	(0.40)	(0.89)	(0.40)	(0.40)	(0.89)	(0.45)
TURNOVER	0.09	0.09	0.01	0.02	0.01	0.01	0.00	0.01
	(0.41)	(0.36)	(0.77)	(0.34)	(0.77)	(0.79)	(0.34)	(0.53)
Age	-0.12	-0.12	1.52	1.75	0.23	1.62	1.78	0.16
	(0.10)	(0.11)	(0.24)	(0.24)	(0.32)	(0.25)	(0.25)	(0.25)
SIZE	-0.70	-0.70	-1.41	-0.60	0.81	-1.41	-0.60	0.81
	(0.00)	(0.00)	(0.03)	(0.00)	(0.07)	(0.03)	(0.00)	(0.07)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund family fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,881	11,881			11,881			11,881
Adj. R-square	0.05	0.05			0.04			0.04

This table presents parameter estimates from panel regressions of the future fund flow (as dependent variable) with respect to the convexity relationship between fund flow and fund performance. We also consider the one-year lag style deviation measure (SDD) and style volatility score (SDS) as independent variables. Controls in this regression include one year lagged fund flows, lagged values of the log fund size, the log fund age, expense ratio, and return volatility. Because the variation of returns among the styles is considerable, we use style- fixed effect beside the time- fixed effect in this panel. P-values are in parentheses.

6. Conclusion

While mutual fund investors share some commonality, previous studies show that they are different with respect to their financial sophistication levels. Given that some investors are better equipped to monitor fund's style-changing behavior, it is natural to ask how different types of investors with various levels of sophistication react to a fund's style changing behavior. We use two different quantitative methods to cover different aspects of style-changing behavior including deviation from the stated investment style and style volatility over time. We find that fund flows are more sensitive to style deviation than style volatility over time and on average investors reward deviation from the stated style. Surprisingly, by explicitly considering the sophistication level of fund investors, we observe that highly sophisticated investors punish this behavior with redemption, while less sophisticated investors appreciate it by investing more money into the style deviated funds. We also demonstrate that the less-sophisticated investors drive aggregate results.

Moreover, because investors with differing sophistication level employ different fund performance tools, one of the explanations of the aforementioned relationship stems from the effect of style-changing behavior on different fund performance measures. By using relevant simple fund performance measures (e.g. benchmark-adjusted return) and more advanced ones (e.g. factor related return), we find that style deviation or volatility positively effects simple measures and negatively affects more sophisticated measures. Thus, some investors may, based on their performance measures, interpret style change as a skill of the fund manager and reward it, while other investors may not.

In addition, it is likely that this relationship works in both directions; for example, sophisticated investors may punish funds that display higher levels of style deviation or volatility with redemption, and at the same time, fund managers with a larger clientele of sophisticated investors are careful to not let their portfolios deviate too far from their stated style. By introducing the ratio of sophisticated versus unsophisticated investors of funds, we show that there is no relationship between the proportion of less sophisticated investors and the subsequent degree of fund's style deviation or style volatility. Overall, our evidence is consistent with sophisticated investors having better abilities to monitor fund managers and extend the conclusions of previous studies which treat all investors as a homogeneous group with regard to the style changing of funds.

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