Sharpening the Sharpe Style Analysis with Machine-Learning

— Evidence from Mutual Fund Style-Shifting

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Abstract

We investigate the factors driving mutual funds to alter their investment styles and examine the consequences of such style shifts within a multi-style framework. Our approach involves a two-step machine-learning-based procedure for identifying tradable style sets, which we integrate with the Sharpe (1992) style analysis. Our findings reveal that over 95% of mutual funds exhibit multi-dimensional investment styles. We develop a novel method for detecting style shifts and find that mutual funds actively engage in adjusting their investment styles. Notably, these style-shifting funds not only display the capability to identify superior new styles but also outperform the benchmarks associated with their newly adopted styles. In essence, this suggests that fund managers engaging in style shifting possess both the ability to time style changes effectively and expertise in managing these styles, thereby supporting the hypothesis of style-shifting skills.

Keywords: Mutual fund style-shifting; Machine learning; LASSO; Sharpe style analysis; Style-timing; Style expertise

JEL classifications: G10, G11, G23

1. Introduction

It is well-known that active mutual funds are categorized by investment styles, which are used as benchmarks for fund performance evaluation and guidance for investor fund selection (Brown and Goetzmann, 1997). One important research question is whether mutual funds resort to style-shifting as an active strategy. Several studies have investigated mutual fund investment style and document evidence of style-shifting over time (Chan, Chen and Lakonishok, 2002; Cooper, Gulen and Rau, 2005; Annert and Campenhout, 2007; Cao, Iliev and Velthuis, 2017). However, the literature finds that in contrast to hedge funds, mutual fund managers do not possess style-shifting skills and style-shifting is mostly driven by poor past performance (*e.g.*, Chan, Chen and Lakonishok, 2002; Barberis and Shleifer, 2003; Cici and Gisbon, 2012).[1] It is noted that most existing studies have based on a single style framework with a small number of benchmarks, namely size, value or momentum styles under the Carhart (1997) model and the *DGTW* framework. We argue that such a broad classification of styles may not be effective to identify mutual fund style-shifting activities and to understand the motivations as well as economic consequences of style-shifting.[2] In this study, we fill this gap by examining whether mutual funds actively shift investment styles under a multi-style setting. More importantly, we investigate whether fund managers possess style-shifting skills, namely style-timing ability and style expertise.

As pointed out by Barberis and Shleifer (2003, P.164), to conduct style analysis '…, it is important to have a concrete way of identifying styles.' There are two major challenges to study mutual fund style-shifting under a multi-style setting. First, it is critical to identify

[1] For instance, Sun, Wang and Zheng (2012) show that hedge fund managers with skills strategically shift investment styles; Jiang, Liang and Zhang (2021) document evidence that style-shifting hedge funds exhibit both style-selection expertise and style-timing ability.

[2] Based on all active funds in the CRSP database, we show that the CAPM, Fama-French (1993) three-factor and Carhart (1997) four-factor models explain, on average, 78.93%, 84.54%, and 85.27% of individual fund returns, respectively, over the period from January 1984 to December 2020. The combined incremental power of size, value and momentum factors is only about 6%.

a sufficient and yet parsimonious set of active benchmarks in the mutual fund industry. Such benchmark set is essential to correctly identify individual fund's styles. In practice, Lipper and Morningstar propose very broad style categories based on fund holdings or prospectus. The literature suggests a set of rank combinations of size-value or size-value-momentum exposure sorts (*e.g.*, Cao, Iliev and Velthusi, 2017). However, Cremers, Petajisto and Zitzewitz (2012), and Berk and Binsbergen (2015) argue that conventional risk factors used as artificial benchmarks do not effectively represent the actual investable and marketed-at-time styles. In our study, we follow Hunter, Kandel, Kandel and Wermers (*HKKW* thereafter, 2014) and employ a broader set of investable styles in stock markets as the candidate styles in the mutual fund industry. However, one challenge is that the number of styles is not only large but also increasing over time.[3] The increasing dimension of styles and the fact that many styles are highly correlated present statistical issues in style analysis, such as redundancy, inefficiency, and statistical invalidity. In this study, we propose a dimension-reduction approach using a two-step machine learning procedure to select a parsimonious set of investable style benchmarks in the mutual fund industry. The dimension reduction procedure is based on the least absolute shrinkage and selection operator (*LASSO*) procedure, which is flexible to deal with the increasing-in-time high-dimension styles and can identify the parsimonious yet efficient set of styles in mutual fund industry without subjective discretion. Moreover, our two-step procedure is able to fix the potential reliability issue in the standard *LASSO* procedure because of the curse of dimensionality.[4] Our machine learning-based style selection approach is different from the manual approach employed in the literature (Brown and Goetzmann, 1997; Hunter, Kandel, Kandel and Wermers, 2014; Berk and

[3] Hunter, Kandel, Kandel and Wermers (2014) provide a survey on the investable benchmarks of open-end equity mutual funds.

[4] Chernozhukov, Hansen and Spindler (2015) show that simple application of the standard *LASSO* procedure or other dimension reduction methods may produce poor approximation of low-dimension style set because the estimation equations in the high-dimensional style set are locally insensitive to small mistakes.

Binsbergen, 2015). Using this procedure, we find that 9, out of existing 32 tradable styles, can be used as a sufficient set of active style benchmarks over the period from January 1996 through December 2020. This *LASSO*-selected style set includes the *NYSE* composite Index, the *NASDAQ* composite index, Russell Midcap index, Russell Midcap Growth Index, Russell 2000 Growth Index, the S&P400 Midcap Growth Index, the S&P 600 Small Cap Growth Index, *NYSE* Amex Index, and the *NYSE* 100 International Leaders.

The second challenge is to identify styles of individual mutual funds. It is well-known that self-disclosed styles are not informative (Brown and Goetzmann, 1997; DiBartolomeo and Witkowski, 1997). The literature proposes two approaches to identify individual fund styles. The most common ones are based on fund return loadings on either styles or risk factors in linear regressions, and the other approach is based on the characteristics of fund holdings. However, none of these approaches can precisely identify fund portfolio allocations among styles (Hunter, Kandel, Kandel and Wermers, 2014). In this study, we propose a new style identification approach by taking advantage of the nonlinear regression proposed by Sharpe (1992). Fung and Hsieh (1997) show that the Sharpe approach is appropriate in identifying mutual fund styles but not sufficient in identifying hedge fund styles. This nonlinear approach has several advantages. First, this approach allows us to identify styles under a multi-style setting, which is statistically robust and has direct economic interpretations on portfolio allocation (Buetow, Johnson and Runkle, 2000; Annaert and Campenhout 2007; Dor, Budinger, Dynkin and Leech, 2008). The style identification allows us to examine mutual fund style-shifting under a multi-style setting. Second, this approach allows us to define and compute precisely the benchmark returns and style-adjusted returns for multiple-style funds. The benchmark portfolio return is the exact weighted sum of investment style returns. Finally, this approach allows us to identify fund styles at a monthly frequency based on monthly returns, which contains more style information relatively to quarterly fund holdings given the intra-quarter trading by mutual funds (Kacperczyk, Sialm, and Zheng, 2008). Overall, the style identification procedure proposed in this study is clean and does not suffer the statistical issues in conventional factor-model regressions (Goetzmann, Ingersoll, Spiegel and Welch, 2007). Applying the procedure to the US active mutual funds in the *CRSP* database, we find that fewer than 3% funds are single-style funds, and most (around 90%) funds have exposure to three to six styles. Single-style funds, relative to multi-style funds, are small and old with high turnover and expense ratios, and volatile returns.

To investigate whether individual funds shift styles over time, we adopt a two-rolling-window approach to overcome the overlapping issue in the conventional approach in the literature (*e.g.*, Jiang, Liang and Zhang, 2021).[5] We use quarterly style weight changes between two rolling windows, a 36-month rolling window [*t*-35, *t*] and a 48-month rolling window [*t*-35, *t*+12]. Given the fact that most mutual funds invest in multiple styles, style shifts in a multi-style setting can be detected by either maximum or average changes of the same-style weights estimated over the two rolling windows, respectively. Specifically, we define style shifting using the max weight change cutoffs of 30%, 40% or 50% or the average weight change cutoffs of 20%, 25% or 30%. With these cutoffs, there are 1.6% – 6% mutual funds in each quarter shifting investment styles. Style-sifting funds shift styles around three times over the sample period, and they hold the new styles for about one year and one quarter. As we will show below, these findings are quite robust.

The key research questions of this study are what motivates mutual funds to shift styles and what are the consequences of style-shifting on fund performance. The literature proposes several arguments for why mutual fund managers shift investment styles. On the one hand, Banerjee (1992), and Bikhchandani, Hirshleifer and Welch (1992) argue that skilled fund managers can infer information and profit from trading strategies of other funds. Pastor, Stambaugh and Taylor

[5] Annaert and Campenhout (2007) examine mutual fund style-shifting using a structural change approach proposed by Bai and Perron (1998, 2003).

(2017) argue that active fund managers possess skills to profit time-varying investment opportunities. Empirically, the findings on active asset management by *DGTW*, Wermers (2000), Kacperczyk, Sialm and Zheng (2005, 2008), Cremers and Petajisto (2009), Ferson and Mo (2016), and Jiang and Zheng (2018), among others, show that active fund managers can deliver abnormal returns to investors using their portfolio skills, suggesting that style-shifting may be driven by manager skills. We categorize and formalize these motivations as ***style-shifting skill*** hypothesis, in which style-shifting fund managers are skilled and can generate abnormal returns by shifting styles. On the other hand, the findings in Chan, Chen and Lakonishok (2002), Cooper, Gulen and Rau (2005), and Cao, Iliev and Velthuis (2017) suggest that mutual fund managers do not have the ability to forecast and shift accordingly to outperforming styles. Instead, they shift styles when they experienced bad performance, or when fund investors' style preferences change. Wermers (1999) finds that unskilled mutual fund managers may herd with other fund managers and shift to hot styles. Barberis and Shleifer (2003), and Lynch and Musto (2003) further argue that style-shifting may be driven by ill-performed fund or style performance in the past or by agency concerns. We categorize and formalize these motivations as ***style-chasing*** hypothesis, in which style-shifting fund managers chase hot styles in current market but are not able to generate profits from style shifting.

To investigate the shifting motivations, we first conduct determinant analyses of style-shifting by regressing the style-shifting decision dummy variable, which equals one if the fund shifts its style and zero otherwise, on (lagged) fund characteristics, and fund as well as style returns using a *Probit* model. The results show that (*i*) the coefficient of past shifting dummy is positive and significant, suggesting that shifting funds are more likely to shift in future periods and consistent with the argument that style-shifting can be an active trading strategy adopted by skilled fund managers; (*ii*) the coefficients of past style performance and fund flows are negative but insignificant, suggesting that bad performance or fund outflow may drive funds to shift styles but these factors do not play important roles in funds' style-shifting decisions; (*iii*) the coefficients of volatilities of fund return and flow are positive and the former is significant, suggesting that funds experienced high performance uncertainty are more likely to shift investment styles. Overall, these results are more consistent with the style-shifting skill hypothesis and less consistent with the style-chasing hypothesis.

We further differentiate the two competing hypotheses by comparing the performance of style-shifting funds in quarters before and after the shifts with that of all active equity funds. First, style-shifting funds outperform peer funds in both pre- and post-shifting periods while the pre-shifting outperformance is small and insignificant. Second, shifting funds perform better in the post-shifting quarter than in the pre-shifting quarter in terms of both total returns and style-adjusted returns, but we do not find performance improvement among non-shifting funds in the same periods. Specifically, the average return of style-shifting funds in the subsequent quarter (between 3% to 11%, depending on the cutoffs of style-shifting identification) is much higher than that of all funds, which is 1.6%. The average style-adjusted returns of shifting funds are both statistically and economically large but the average style-adjusted return of all funds is close to zero. Third, we regress the style-adjusted fund returns in the subsequent quarter on a shifting dummy variable, which equals one if a fund shifts its style(s) in the current quarter and zero otherwise. We find that style-shifting decision is positively significantly related to future fund returns. The results remain consistent after controlling fund performance and characteristics. Taking together, we conclude that style-shifting decisions in the mutual fund industry should be largely attributed to fund manager skills.

Finally, we investigate what skills fund managers possess to profit from style shifts. We link shifting funds' abnormal returns to two manager skills, *i.e.*, style timing ability and style expertise, based on a performance decomposition in the spirit of Brinson, Hood and Beebower (1995) and Jiang, Liang and Zhang (2021). Overall, the contribution of style-shifting to fund net returns, depending on the style-shifting cutoffs, ranges from 50% to 90%. We further find that shifting-related returns are mostly (more than 80%) attributed to managers' style expertise. That is, style-shifting in the mutual fund industry is mostly driven by fund managers' expertise in the new style. We find that style-shifting fund managers are able to exploit time-varying style profitability and exhibit style expertise in up-market and style-timing in down-market, consistent with the literature that fund manager skills is related to economic state (*e.g.* Kacperczyk, Nieuwerburgh and Veldkamp, 2014; Jiang, Zaynutdinovo and Zhang, 2021),

We perform additional analyses and find that our results are robust after controlling for the impacts of spurious style-shifts and fund manager turnovers. The spurious shift concern is raised when the new styles are very similar to (hence highly correlated with) the current style. In this analysis, we employ a variance-inflation-factor (VIF) suggested in Belsley, Kuh and Welsch (2004) and Kutner, Neter and Nachtsheim (2004) to identify the spurious new styles and exclude them in our style-shifting analysis. To control the impact of fund manager turnover, we remove all manager turnover events from our sample and reexamine style shifts in the mutual fund industry. Our findings quantitatively remain in both cases. Finally, we employ our two-step *LASSO* procedure to identify the style set using all out-of-sample investable styles. Specifically, we split the whole sample into four subsamples by decade. The current low-dimension style set is selected out of the high-dimension style set investable in the last decade by the *LASSO* procedure. We repeat the analyses of individual fund's style selection, style shifting, and manager skills with the out-of-sample style set. The findings remain quantitatively and consistently support the style-shifting skill hypothesis.

The paper contributes to the following sets of literature. First, we add to the literature of mutual fund manager skills.[6] In closely related studies, *DGTW* propose skill measures of stock selection and characteristic-timing based on funds' stock holdings. Ferson and Mo (2016) further extend the DGTW decomposition to measure fund managers' market volatility timing ability. We introduce a new dimension of fund manager skill, *i.e.*, style-shifting skill. We show that mutual fund managers possess style expertise and style-timing ability and investigate the economic channels of these skills. Second, our study highlights the fact that most mutual funds have multiple styles. We identify an efficient set of styles in the mutual fund industry by taking advantage of machine-learning technology. The style set is much more complex than the Lipper or Morningstar style classification. Moreover, our study provides an approach to capture the dynamic multi-style selections of active mutual funds based on the nonlinear regression in Sharpe (1992). This feature is important because it allows us to directly examine the exact style shifts for multi-style funds, an important extension of existing style-shifting studies (Chan, Chen and Lakonishok, 2002; Lynch and Musto, 2002; Kumar, 2009). We further employ the VIF approach in a multi-style setting to address the concern that some style shifts may be spurious. Third, to our best knowledge, this study is the first paper to introduce dimension reduction to the literature of mutual fund style analysis. Dimension reduction is important to efficient benchmark identification under the high dimensionality context and has attracted a great amount of attention in the finance

[6] Existing literature has mostly focused on stock-picking and market-timing skills by mutual fund managers (Daniel, Grinblatt, Titman and Wermers, 1997; Wermers, 2000; Kacperczyk, Sialm and Zheng, 2005, 2008; Berk and Binsbergen, 2015; Ferson and Mo, 2016; Pastor, Stambaugh and Taylor, 2017). For instance, Daniel, Grinblatt, Titman and Wermers (*DGTW* thereafter, 1997), Wermers (2000), and Ferson and Mo (2016) document evidence of stock-picking ability by fund managers, *i.e.*, stocks held by mutual funds outperform other stocks of similar characteristics. While early studies document insignificant or even negative market timing skills for mutual funds (Treynor and Mazuy, 1966; Henriksson and Merton, 1981), more recent studies find positive market-timing by mutual funds (Bollen and Busse, 2001; Jiang, Yao and Yu, 2007; and Kacperczyk, Nieuwerburgh, and Veldkamp, 2014). Recent studies further investigate whether mutual fund managers have the ability of timing stock market volatility and liquidity conditions (Busse, 1999; Cao, Simin and Wang, 2013).

area. Conventional principal component analysis (*e.g.*, Kelly, Pruitt and Su, 2019) and Bayesian shrinkage (*e.g.*, Kozak, Nagel and Santosh, 2020) approaches are used in existing literature. Machine-learning has been recently introduced in asset pricing studies.[7] Our new dimension reduction framework adds the application of machine-learning technology in finance. Our approach is flexible in dealing with the large dimension of investable styles in practice, which increases over time and calls for style dimension reductions. Our two-step *LASSO* procedure is in the spirit of Feng, Giglio and Xiu (2020) but more intuitive and simpler to minimize the possible selection failure in the standard *LASSO* procedure documented in Chernozhukov, Hansen and Spindler (2015). Empirically, the two-step *LASSO* selected style set is different from the existing studies (*e.g.*, equity factors or the *HKKW* nine benchmark styles) and highlights the increasing importance of growth (high-tech) firms and international investment to the mutual fund industry.

The rest of this paper is organized as following. We review the related literature and develop the testing hypotheses in Section 2, introduce the methodology and data in Section 3, and report the empirical findings in Section 4. Section 5 concludes the paper.

2. Literature Review and Hypothesis Development

In the mutual fund industry, fund managers are required and have incentive to disclose investment styles in fund prospectus and other public channels (Barberis and Shleifer, 2003), but such self-selected style disclosure is noisy and uninformative as examined by Brown and Goetzmann (1997). Recent style-shifting studies concentrate on whether mutual fund

[7]Recent studies show that machine learning is powerful in selecting the efficient subset of return predictors out of a large set. Karolyi and Nieuwerburgh (2020) provide a survey of studies using machine learning in asset pricing studies. Examples include Rapach, Stauss and Zhou (2013), Rasekhschaffe and Jones (2019), Avramov, Cheng and Metzker (2020), Bianchi, Buchner and Tamoni (2020), Gu, Kelly and Xiu (2020), Freyberger, Neuhierl and Weber (2020), Feng, Giglio and Xiu (2020), and Huang, Zhang, Zhou and Zhu (2021).

styles can be correctly identified and whether mutual funds shift styles. For example, Sharpe (1992), Brown and Goetzmann (1997), and Anaert and Campenhout (2007), among others, propose return-based procedures to identify fund styles while *DGTW,* Kumar (2009), *HKKW,* and Ferson and Mo (2016) propose holding-based style identification procedures. Regardless, existing studies investigate whether mutual funds shift styles and the findings are inconclusive. Chan, Chen and Lakonishok (2002), and Teo and Woo (2004) find that fund styles are persistent. Annert and Campenhout (2007) find that all 62 European mutual funds shift styles at least once over the period between 1991 and 2001 and a significant fraction of funds shift multiple times. Cao, Iliev and Velthuis (2017) find evidence that small-cap funds shift partly to mid- and large-cap stocks.

The literature proposes several explanations on why mutual fund managers shift investment styles. Banerjee (1992), and Bikhchandani, Hirshleifer and Welch (1992) argue that skilled fund managers can infer important information from trading strategies of other funds and herd to those profitable styles. Pastor, Stambaugh and Taylor (2017) argue that active mutual funds generate higher returns than passive funds using fund manager skills. Empirically, Kacperczyk, Sialm and Zheng (2005, 2008), Cremers and Petajisto (2009), Berk and Binsbergen (2015), and Jiang and Zheng (2018) show that active funds with manager skills deliver high returns to investors. Brown and Goetzmann (1997) find that some styles may be superior to others. Teo and Woo (2004) show that style profitability varies over time. Moreover, Daniel, Grinblatt, Titman and Wermers (1997), Becker, Ferson, Myers and Schill (1999), Wermers (2000), Jiang, Yao and Yu (2007), and Ferson and Mo (2016) show that active funds possess significant security selection skills and weak market timing ability. Da, Gao and Jagannathan (2011) find that active mutual funds can trade on informed events. Sun, Wang and Zheng (2012), and Jiang, Liang and Zhang (2021) show that skilled hedge fund managers shift investment strategies and deliver high returns to investors. According to these studies, skilled fund managers may shift to new styles when they expect that these styles will outperform or when they possess expertise in these new styles. In other words, active funds may shift styles because style-shifting is an important part of fund's active strategy to deliver abnormal returns. We categorize this group of shifting motivations as ***style-shifting skill*** and formalize the following hypothesis:

Style-shifting skill hypothesis: skilled mutual fund managers shift to the investment styles in which they possess expertise or when they predict that the new styles will outperform in subsequent periods.

However, the literature suggests that mutual fund managers may shift styles for other reasons. Barberis and Shleifer (2003) argue that fund investors may withdraw capital from funds with ill-performed styles and drive fund managers to shift to popular well-performed styles. Lynch and Musto (2003) predict that ill-performed fund managers have incentives to shift to hot styles to attract fund flows. Empirically, Frijns, Gilbert and Zwinkels (2016) find that most mutual funds chase past winning styles, consistent with Barberis and Shleifer (2003). Chan, Chen and Lakonishok (2002) find that style-shifting may be motivated by window dressing. Cooper, Gulen and Rau (2005) find that mutual fund managers do not have the ability to forecast but chase hot styles to attract fund flows. Cao, Iliev and Velthuis (2017) find that style-shifting funds do not deliver abnormal returns to fund investors. Existing herding studies find that unskilled mutual fund managers may herd and shift to hot styles (see, for example, Lakonishok, Shleifer and Vishny, 1992; Wermers, 1999). Consistently with these arguments, Davis (2001) argues that there is no evidence of persistent superior styles in stock markets. To sum up, these studies suggest that equity funds shift their investment style not because fund managers possess style-shifting skills but because of agency concerns. [8] We categorize these shifting motivations as ***style-chasing*** shifting and formalize the following hypothesis:

[8] In addition, Gallo and Lockwood (1999) find that ill-performed equity funds dismiss their managers and, in turn, shift styles.

***Style-chasing hypothesis*: unskilled mutual fund managers chase the well-performed or popular investment styles when they are ill-performed or when their investors' style preferences shift.

These two competing hypotheses differ from each other in predicting the relationships between style-shifting decision and historical style as well as fund characteristics, even though some of them are not mutually exclusive. First, according to the style-shifting skill hypothesis, style-shifting can be an active trading strategy adopted by skilled fund managers, and they are more likely to shift in future periods to generate profits. As a result, current style-shifting is expected to be positively related to future shifts. The style-chasing hypothesis argues that style-shifting is driven by ill-performance or fund outflow concerns and does not present a positive autocorrelation. Second, the style-chasing hypothesis argues that fund managers are not skilled, suggesting a negative relationship between style-shifting and past fund performance. The style-shifting skill hypothesis suggests that this relation can be either positive or negative because fund managers may shift styles when they have expertise in the new styles or when the current styles are no longer profitable. Third, the style-chasing hypothesis predicts a significant negative relationship between style-shifting and past style returns while the style-shifting skill hypothesis does not imply a relationship. Fourth, the style-chasing hypothesis suggests a significant negative relationship between style-shifting and past fund flows while the shifting skill hypothesis does not suggest that fund flow is an important shifting decision factor.

The two hypotheses contain different implications on style and fund performance before and after style-shifting, and the relation between style-shifting and subsequent fund returns. The corresponding implications can be summarized as follows. Firstly, the style-shifting skill hypothesis implies that shifting funds outperform peer funds in both before and after style-shifting periods, but the style-chasing hypothesis implies that shifting funds underperform in both periods. Secondly, the style-shifting skill hypothesis suggests that shifting funds perform better during post-shifting periods than during pre-shifting periods, but the style-chasing hypothesis does not imply a performance improvement. Thirdly, the style-shifting skill hypothesis implies that style-shifting choice should be positively related to fund performance in subsequent periods, but the style-chasing hypothesis does not have such an implication. Finally, the style-shifting skill hypothesis suggests that shifting funds outperform non-shifting funds because they are skilled while the style-chasing hypothesis suggests the opposite. In this study, we investigate the underlying motivation(s) by examining both the hypothesis predictions and performance implications.

3. Methodology and Data

3.1 Two-Step *LASSO*

Following Cremers, Petajisto and Zitzewitz (2012), Berk and Binsbergen (2015) and *HKKW*, we propose a novel procedure to identify the efficient investable style set in the mutual fund industry rather than taking artificial risk factors for granted. Although active peer benchmarks are widely available, standard statistical methods in estimating and testing style selections result in poor estimates and invalid inference because of the high dimensionality. It is important to identify the efficient low-dimension benchmark set in the mutual fund industry. The literature proposes several dimension-reduction approaches, including principal component analysis (*PCA*), stepwise selection, the *LASSO*, ridge regression, and elastic net. In this study, we use the *LASSO* procedure proposed by Tibshirani (1996, 2011), to reduce style dimensionality and select the efficient and parsimonious set of styles. We use the *LASSO* procedure because it is reliable and effective (see, Raftery, Madigan and Hoeting, 1997, among others). The *LASSO* is recently used in finance area to find the efficient frontier of stock market (*e.g.*, Rasekhschaffe and Jones, 2019; Bianchi, Buchner and Tamoni, 2020; Feng, Giglio and Xiu, 2020; among others). The *LASSO* benchmark selection procedure is a constrained *OLS* regression procedure by imposing a penalty term to select the subset of benchmarks with the highest explanatory power out of a large set of candidate benchmarks and is implemented as the following. Let $R = (R_1, R_2, \dots, R_N)$ denote the left-side matrix of fund excess returns and $X = (X_1, X_2, \dots, X_m)$ denote the right-side return panel of candidate styles, and $\beta = (\beta_1, \beta_2, \dots, \beta_m)$ denote the linear coefficients. The *LASSO* solves β using the following loss function:

$$\mathcal{L}(\beta; \lambda) = (R - X\beta)^2 + \lambda \sum_{j=1}^{m} |\beta_j|, \tag{1}$$

We use all available active style indexes and estimate β by year and partition 20% of the observations as the training sample, 50% as the validating sample and 30% as the testing sample. We use the Corrected Akaike's Information criterion (*AICC*) proposed by Hurvich and Tsai (1989) as the statistical criteria.

Although the *LASSO* procedure can choose a low-dimension style set, Chernozhukov, Hansen and Spindler (2015) show that this procedure may make mistakes in identifying the true low-dimension set because estimations with high dimension style set are locally insensitive to small errors. Consistent with their argument, we find that the number of styles selected varies empirically across partitions and years. To fix this issue, we repeat the *LASSO* estimation 1,000 times and compute the selection frequency for each style in each year as well as over the whole sample period. We choose the most frequently selected styles over the whole period as the style set of the mutual fund industry. This two-step procedure is consistent with but simpler than the double-selection *LASSO* procedure suggested by Feng, Giglio and Xiu (2020).

3.2 Fund Style Identification

There are two style identification procedures employed in existing studies, and both suffer statistical issues. The first procedure identifies fund styles using factor models, that is, investors identify styles by funds' factor loadings. The main shortcoming of this approach is that all identified styles are equally treated and the funds' style weights are unknown to investors (Dor, Budinger, Dynkin and Leech, 2008). Another issue is that the multi-collinearity among factors may drive invalid or imprecise statistical inferences. The second identification procedure follows the *DGTW* matching approach using quarterly stock holdings by mutual funds, which suffers similar issues (Dor, Budinger, Dynkin and Leech, 2008). In this study, we use the quadratic regression proposed by Sharpe (1992) supplemented by our two-step *LASSO* procedure. This approach does not suffer the aforementioned statistical issues and helps precisely examine individual funds' styles and style-weights in a multi-style setting (Brown and Goetzmann, 1997). Specifically, instead of making an assumption on the number of invested styles for each fund, we include all *LASSO*-selected styles in the Sharpe regression to identify funds' styles. To identify the styles selected by a specific fund and to estimate the exact weight on each style, we conduct the following quadratic regression for fund *i* in month *t* over a rolling window of 36 months [*t*-35, *t*]:

$$r_{i,j} = \sum_{s=1}^{S} \beta_s r_j^s + \varepsilon_{i,j}, \tag{2}$$

$$\text{subject to } \sum \beta_s = 1, \text{ and } \beta_s \geq 0,$$

where $r_{i,t}$ and r_t^s are returns of fund *i* and style *s* and *S* is the number of styles. In our main analysis, S equals nine. The inequality constraints require the use of a quadratic programming algorithm. Sharpe (1992) suggests that β_s is the weight of fund *i* in style *s*. Our nine-style set in (2) is determined by a two-step *LASSO* procedure described in the previous section over the whole sample period. Sharpe analysis identifies funds' style weights in each period as the following:

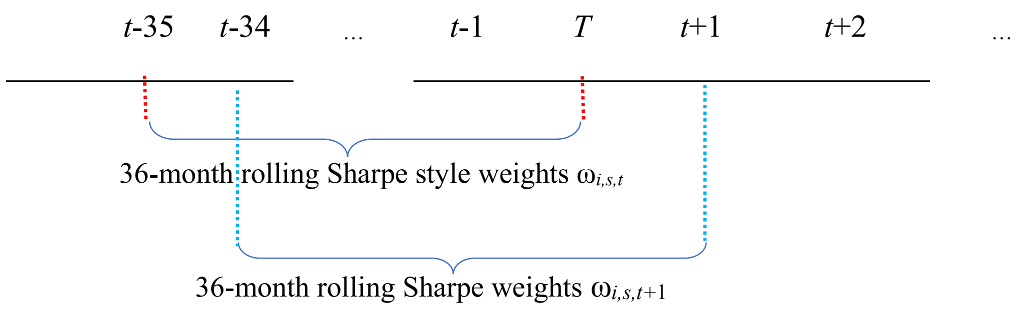

Figure 1: Style weights based on rolling Sharpe regressions

3.3 Style-Shifting Identification

We investigate whether mutual funds dynamically shift investment styles under the context of a multi-style setting. This suggests that it is more appropriate to define style-shifting based on a fraction of fund capital switching from one style to another than based on total fund capital switching, an extreme case. The former is generic and more common in practice while the latter is radical and consistent with the conventional definition. We define style shift using the change of absolute style weight between two consecutive quarters to contain both shift types. Using the difference in style weights between two consecutive quarters from one rolling-window suffers a mechanical issue of overlapped observations. To fix this issue, we identify shifting funds by comparing Sharpe-style weight changes between two rolling-windows, 36-month and 48-month, and examine weight changes with a quarterly frequency.[9] The idea can be illustrated as below:

[9] This procedure does not suffer forward-looking bias as we focus on style-shifting identification rather than style weight forecasts. Moreover, the empirical findings are stronger based on one-rolling window.

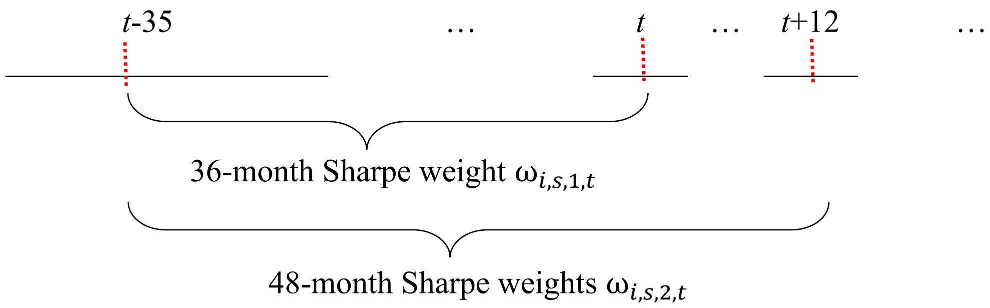

Figure 2: Style-shifting identification

We use two groups of cutoffs to identify style shifts including the largest (absolute) style change cutoffs and the average (absolute) style change cutoffs across all styles over the same period, that is, fund *i* is defined as a shifting fund in quarter *t* if

$$\Delta_{i,s,\omega,t} = |\omega_{i,s,1,t} - \omega_{i,s,2,t}| \geq \text{cutoff, for any } s,$$

or if

$$\Delta_{i,\omega,t} = \frac{1}{N_s}\sum_{s=1}^{N_s} |\omega_{i,s,1,t} - \omega_{i,s,2,t}|) \geq \text{cutoff},$$

and a non-shifting fund otherwise. We consider cutoffs of 30%, 40% and 50% in the former case, and 20%, 25% and 30% in the latter case.[10] The performance of shifting fund is evaluated over the next quarter (*t*+1) (or *t*+2 after shifting one quarter for robustness purpose), and benchmark style return of shifting funds in subsequent quarter is the weighted sum of selected styles as $\sum_{s=1}^{S} \omega_{i,s,2,t} R_{t+1}^{s}$ and fund's abnormal returns in *t*+1 is ($r_{i,t+1} - \sum_{s=1}^{S} \omega_{i,s,2,t} R_{t+1}^{s}$).

3.4 Measuring Style-Shifting Skill

Berk and Binsbergen (2015) argue that mutual fund manager skills can be measured by

[10] Take the 30% cutoff as an example, a fund will be defined as a shifting fund in a quarter if its largest style-weight change in the quarter in the former case or its averaged style-weight change across all investment styles in the latter case is equal to or higher than 30%, and otherwise a non-shifting fund.

style-adjusted fund returns. Brinson, Hood and Beebower (1995), and Jiang, Liang and Zhang (2021) show that active fund returns can be further attributed to selection and timing skills. Following these studies, we decompose fund returns into passive benchmark style returns and active style selection returns, and further link the style-adjusted returns to style expertise and style timing ability.

$$R_{i,t+1} = \underbrace{\sum_{s=1}^{S} \omega_{i,s,1,t} R_{t+1}^{s}}_{\text{Passive style return}} + \underbrace{\underbrace{\sum_{s=1}^{S} (\omega_{i,s,2,t} - \omega_{i,s,1,t})\, R_{t+1}^{s}}_{\text{Gain of style timing}} + \underbrace{\left(R_{i,t+1} - \sum_{s=1}^{S} \omega_{i,s,2,t}\, R_{t+1}^{s}\right)}_{\text{Gain of style expertise}}}_{\text{Active style-selection return}} \tag{3}$$

where $r_{i,t+1}$ and r_{t+1}^{s} denote respectively fund and style returns in period t+1, and $\omega_{i,s,1,t}$ and $\omega_{i,s,2,t}$ denote fund i's portfolio weight on style s based on the 36-month and 48-month rolling Sharpe quadratic regressions.

3.5 Data

This paper utilizes two main databases, including the mutual fund database from the Center for Research on Stock Price (*CRSP*) provided by the University of Chicago and a set of 32 investable investment styles from Bloomberg. The *CRSP* Survivor-Bias-Free *US* Mutual Fund Database contains detailed information on fund characteristics, such as monthly total net assets, net returns, turnover, and expense ratios. We focus on open-end US domestic equity mutual funds and aggregate class-level shares, returns, and other characteristics to the fund level. Following the literature (*e.g.*, Kacperczyk, Sialm, and Zheng, 2008), we exclude funds that hold, on average, less than 80% or greater than 105% of their portfolios in common stocks. To mitigate the potential incubation (or back filling) bias documented in

Elton, Gruber, and Blake (2001) and Evans (2010), we exclude observations prior to the date the fund was first offered and observations where the names of funds are missing from the *CRSP* Survivor-Bias-Free US Mutual Fund Database. As pointed out by Kacperczyk, Sialm, and Zheng (2005), incubated funds tend to be small, thus we further exclude funds with TNA smaller than $5 million at the end of the previous month. Our final sample consists of 5,392 unique funds over the period from January 1996 to December 2020.

Panel A in Table I reports descriptive statistics of the main fund characteristics. We report the time series averages of the cross-sectional mean, standard deviation, 25%tile, 50%tile, and 75%tile of fund return size, turnover ratio, expense ratio, and cash holding. Panel A shows that mutual funds in our sample, on average, deliver a return of 0.74% per month, or about 9% per year. Each fund, on average, has a total net asset of $1.7 billion and holds about 4.6% of its portfolio in cash. The averaged expense ratio is 1.1%. Mutual funds, on average, attract about a fund flow equal to 1.2% of their *TNA*s in each month. The medians of fund *TNA*, age, cash holdings, normalized fund flow, and family *TNA* are smaller than the corresponding means, implying that these characteristics are highly right skewed across all funds.

The investable style data is from Bloomberg terminal, including the main indexes in the mutual fund industry and the stock market. We require that the first available date of each index is January 1996 or earlier and collect 32 active style indexes at a monthly frequency over the period from January 1996 to December 2020. Appendix I lists these styles and their availability periods. Panel A of Table A1 reports the summary statistics of these styles and Panel B reports the pairwise correlations. The average returns of these styles vary from 0.36% per month (the Composite Index of the International Leader Stocks Listed on the NYSE Market, hereafter *NYIID*) to 1.37% per month (the 100 of the largest non-financial stocks listed on the Nasdaq Market, hereafter *NDX*). Out of the 496 (32×31÷2) pairwise correlations among the 32 styles, 351 of them (or 71%) are higher than 0.50, 294 of them (or 59%) of then are high than 0.75, and 80 of them (or 16%) are higher than 0.9.

4. Empirical Findings

4.1 Mutual Fund Industry Style Set

Using the two-step *LASSO* procedure described in Section 3, we find that nine styles, out of the 32 investable market-index based styles available from 1996 or earlier dates, can be used as the proxy of style set in the mutual fund industry, a large dimension reduction. Specifically, the procedure is implemented as the following. In the first step, we use the standard LASSO procedure to identify a parsimonious style set in the mutual fund industry in each year. The empirical results show that the style set varies largely across years. The mean and median number of styles in the selected set are 8.4 and 9 with a minimum of four styles in 2000 and a maximum of 10 styles in 1997, 1999, 2003 and 2013. In the meantime, the mean and median number of years each style selected in the set are 6.5 and 5, with the maximum of 15 (Russell Midcap Growth) and minimum of one (Russell 2000 and Table 1 Russell Large Growth). According to Chernozhukov, Hansen and Spindler (20015), the inconsistency across styles and the number of styles across years can be attributed to selection errors in the standard *LASSO* procedure. To minimize the impact of selection error, we use the second step to remove the inconsistency as much as possible and finalize the style set. We end up with the following the nine styles, the *NASDAQ* composite index (henceforth, *CCMP*), the *NYSE* composite Index (henceforth, *NYA*), Russell Midcap index (henceforth, *RMC*), Russell Midcap Growth Index (henceforth, *RUO*), Russell 2000 Growth Index (henceforth, *RDG*), the S&P400 Midcap Growth Index (henceforth, *MIDG*), S&P 600 Small Cap Growth Index (henceforth, *SMLG*), the *NYSE* Amex Index (henceforth, *XAX*), and the *NYIID*. This active benchmark style set is different from existing studies (*e.g.*, *HKKW*) and none of value styles are selected, implying that value stocks are outweighed in market capitalization-based styles, such as *CCMP* and *NYA*. This is consistent with existing studies that mutual fund managers can exploit positive *NPV* growth opportunities. The selection of *NYIID* is consistent with the fact that more and more investors allocate capital in international markets (Bekaert, Hoyem, Hu, and Ravina, 2017; Bai, Tang, Wan and Yuksel, 2021). It is worth pointing out that comprehensive market portfolios, for example the Russell 3000 Stocks Index (*RAY*) or the S&P 500 Index (*SPX*), are not selected by this two-step procedure. This suggests that most active equity funds do not implement pure passive strategies as they have disclosed in fund prospectus, consistent with the data clean procedure of open-end active equity funds in this study. Overall, this style set suggests that the two-step *LASSO* procedure proposed in this paper is effective in selecting the parsimonious and sufficient style set of the mutual fund industry. Panel B reports summary statistics of the benchmark style set of mutual fund industry. The *NYIID* portfolio delivers the least returns (0.36%/month) and the *MIDG* portfolio is the most profitable (1.13% per month). All style returns are right skewed as their medians are higher than their sample means.

To conclude, the investment style set of the mutual fund industry can be approximated by a parsimonious low dimension set. Our two-step *LASSO* procedure works effectively to identify this subset from a high dimension one. Empirically, nine out of 32 styles can be the sufficient style set in the mutual fund industry over the period from 1996 to 2020.

4.2 Fund Style Selection

After identifying the efficient investable style set in the mutual fund industry, we turn to identify individual funds' investment style(s) using the quadratic Sharpe regression (1992) described in Section 3.2. We require a minimum of 60 observations in each regression for meaningful inferences and end up with 4,412 funds. Table A2 reports the summary statistics of style weights from the Sharpe regressions for each fund over the whole sample period. The first row shows that individual funds, on average, allocate 24% of their capital in one style, suggesting that mutual funds select four styles (1/0.24). The style weight distribution implies that the investment styles of most funds are not single but multiple dimensional. We further examine the popularity of each style, and the results are in rows 2–10. On one side, *NYA* attracts the most capital at 51%, which is much higher than that of *RUO* with the second most allocation of 33%. On the other hand, *RDG* and *XAX* respectively attract around 10% or less mutual fund capital. These numbers suggest that the relative importance of the selected styles in a fund portfolio significantly varies across styles. As a result, it is important to precisely estimate funds' weights on each individual style rather than treat selected styles equally. To achieve this, we take advantage of the Sharpe nonlinear regression.

The first two rows of Table 2 Panel A report the number and fraction of mutual funds selecting single or multiple styles based on the nonlinear Sharpe procedure over the whole sample period. Consistent with the findings that the averaged style weight in Table A2 is small, only 99 funds invest in single styles, which account for about 2.3% of the total number of funds in the whole sample. Most funds select three to five styles. Specifically, the style dimensions of 21.9%, 28.4% and 21.7% mutual funds are respectively three, four and five; 8% funds are two; and 4.5% funds are seven styles. To examine the style selection difference across funds within the same group, we further sort all funds into three groups based on their averaged net asset values (*NAV*) over the sample period using the cutoffs of the top 30%tile, medium 40%tile, and bottom 30%tiles, respectively. The results are reported in the next six rows in Panel A of Table 2, which shows that the fraction of multi-style funds is similar across size groups, consistent with the argument that fund managers select styles with their expertise.

Next, we examine style popularity by examining the number of individual funds attracted by each single style over the sample period. The results are in Panel B of Table 2 and suggest that popularity significantly varies across styles.[11] Specifically, there are two styles, *NYA* and *RDG*, attracting more than 70% funds and there are five styles attracting less than 40% funds. *NYA,* the most popular style, attracts the most funds (76%) while *RUO*, the least popular style, only attracts 29% funds. Taking this table and Table A2 together, we find that *NYA* attracts both the most funds and fund capital (style weight). In contrast, *RDG* attracts 71.5% funds but attracts the least fund capital (style weight of 5.4%). The low correlation of *RDG* with other styles (Panel C of Table 2) suggests that investing in *RDG* may help diversify portfolio risks. The style selection of funds in each size group is reported in the next six rows of Panel B Table 2 and shows that more small funds pick *RUO*, *XAX* and *NYIID* and more large funds select *RMC* and *RDG*.

It is interesting to examine whether fund characteristics vary across style dimensions and the results are reported in Table 3 and suggest that single-style funds, which are quite few, are different from multi-style funds. The first column reports the characteristics of single-style funds and shows that single-style funds deliver the highest returns over the sample while these numbers may suffer small sample bias. This finding is consistent with the finding that highly concentrated funds outperform less concentrated funds (*e.g*., Kacperzyk, Sialm and Zheng, 2005; Bai, Tang, Wan and Yuksel, 2021) although this is not the focus of this paper. This column also shows that return volatility of single-style funds is high, and these funds are relatively small and old. The turnover ratio, expense ratio and cash position of these funds are high. Columns 2–6 report characteristics of multi-style funds and

[11] The sum of percentage of attracted funds across all styles is more than 100% due to that most funds are multi-style funds.

provide several interesting observations. First, these columns show that style and fund returns increase with the number of investment styles and the fund return volatilities are small, suggesting that the returns are stable over time. Second, fund flow increases in the number of styles. Finally, the turnover ratio, expense ratio and cash holding of multi-style funds are similar across style dimensions and lower than those of single-style funds.

It is well-known that fund style(s) may vary over time because mutual fund managers may dynamically shift investment styles (*e.g.*, Huang, Sialm and Zhang, 2011). To capture the nature of dynamic style selection by active funds, we further explore funds' style selections by running the quadratic Sharpe regression for each fund over a 36-month rolling window described in Section 3, and our results quantitatively remain with the 48-month or 60-month windows. This rolling regression allows us to identify each fund's dynamic investment styles and the number of funds in each style in each period. To ensure that the statistical inferences are meaningful, we require a minimum of 30 observations in each rolling-window regression. Table A3 reports the summary statistics of rolling-regression-based style weights. The first row shows that, on average, individual funds allocate 11% of their capital into each single style, significantly less than the static style weight in Table A2 (24%), stronger and consistent evidence that the investment styles of most funds are multi-dimensional. In terms of individual funds' capital allocations into single styles, Table A3 show that style *NYA* attracts the most capital as of 33%, style *RDG* attracts the least of 5%, both are lower than but consistent with that in Table A2.[12]

To summarize, most active equity mutual funds allocate their capitals among three to five styles. In the next subsection, we analyze the performance implications of style

[12] In an untabulated analysis, we find that most funds' style selections using this rolling-window estimating approach are consistently multi-dimensional. Comparing with Panel A of Table 2, there are fewer single-style funds (44 funds) based on rolling-window regressions and there are much more four-style funds (43.8%).

selections with a focus on funds' style-shifting decisions.

4.3 Style-Shifting Analysis

4.3.1 Evidence of Style-Shifting

Following Section 3.3, we define style shift based on absolute style weight changes within one evaluation period using cutoffs of 30%, 40% and 50% of maximum style weight change, and 20%, 25% and 30% of average style weight change. Style weight change is computed as the difference in Sharpe style weight on the same style between a 36-month and a 48-month rolling estimate. Table A4 reports the summary statistics of time series averages of style weight changes of all styles and each single style. The average style weight change is about 0.03% per style in each quarter, and the 75%tile change is 0.07% per style, both are small. The average maximum style weight increase is 84% per style, and the maximum style weight decrease is –80% per style. These numbers suggest that mutual funds do not frequently shift investment styles and that shifting funds only allocate a fraction rather than 100% of their fund capital to new style(s), highlighting the importance of multi-style setting to mutual fund style-shifting analysis.

The number of style-shifting funds identified by various cutoffs is reported in Table 4. The results based on the maximum weight change cutoffs are in Panel A and the results based on the average weight change cutoffs in Panel B. The first row in each panel reports the number of shifts (*i.e.,* shifting funds). Around 150 funds per quarter, or equivalently about 6% (row 2) funds shift their styles based on the lowest cutoff of maximum style weight change of 30% (Panel A) and the shifting funds become 78 based on the average style weight change cutoff of 20% (Panel B).[13] The number of shifts significantly decreases in style-

[13] In an untabulated table, we find that the number of shifting funds (shifting ratio) significantly varies over time with the lowest of 0.1% and the highest of 24%.

shifting cutoffs. For example, the shifting ratio becomes 2.8% based on the 40% cutoff of maximum weight change (Panel A) and 2.7% based on the 25% cutoff of averaged style weight change (Panel B). Regardless, the shifting ratios in both panels are statistically significant at the 1% level. In an untabulated table, we find that the shifting ratio becomes small and close to zero based on the maximum weight change cutoff of 100%, suggesting that radical shifting in existing studies may suffer small sample bias and only accounts for a small fraction of style shifts in the mutual fund industry. Overall, these findings suggest that a small but significant fraction of mutual funds shift their investment styles in each period. The natural question associated with this stylized fact is how frequently shifting funds shift their styles and what factors drive their shifts. We address the first question in this section and the second question in the next section.

The third row in each panel of Table 4 reports the number of shifts per shifting fund over the whole sample period. Take the cutoff of 40% maximum style weight change as an example, the average shifts per shifting funds is about three. The shifts are similar to the 25% cutoff of average weight change. We further explore how long a shifting fund carries its new style(s) by examining the time interval between two shifts. The average time interval between two consecutive shifts is reported in the last row in each panel. On average, shifting funds defined by a maximum cutoff of 40% or an average cutoff of 25% persevere with their new styles about 1.5 years.

4.3.2 Style-Shifting Skill vs Style-Chasing

After documenting evidence that style-shifting is not uncommon in the mutual fund industry. Section 2 summarizes the potential shifting motivations proposed in extant studies, categorizes them into two hypotheses, namely style-shifting skill and style-chasing hypotheses, and suggests empirical analyses to differentiate the two hypotheses. From this section, we turn to investigate the motivation(s) and consequences of style-shifting to differentiate these two hypotheses.

4.3.2.1 Determinants of Style-Shifting

Section 2 proposes two competing style-shifting hypotheses and shows that they imply different relations between style-shifting decision and fund and style characteristics. We conduct *Probit* regressions of style-shifting dummy, which equals one if the fund shifts its style and zero otherwise, on lagged fund characteristics, style and fund returns, and fund flow. Our *Probit* regressions allow us to test with which hypothesis' predictions funds' future style-shifting decisions are relatively consistent. We first consider the important fund characteristics proposed in the literature including fund size, age, expense ratio, turnover ratio, cash holdings and fund family size. To investigate whether shifting funds are more likely to shift, we construct a lagged shifting dummy, which equals one if the fund shifted its style(s) over the past year and zero otherwise. For brevity we only use the representative cutoffs of maximum change of 40% and averaged change of 25% to define style shifts.

The results are reported in Table 5 in which the coefficients are in the first row and the associate *p*-values are in parentheses. The first and fourth columns of Table 5 report the empirical results of the *Probit* regression of what type of funds are more likely to shift styles and whether shifting funds are more likely to shift in future periods. The coefficient of fund size is negative, and the associated *p*-value is zero in both regressions while the coefficients of fund family size, turnover ratio and cash holding are positive and significant. The results suggest that small funds or funds in large families are more likely to shift. High active funds (high turnover ratio) and funds with high cash holdings are more likely to shift. Expense ratio, however, is an important shifting determinant in the regression with the maximum weight change cutoff but insignificant in the regression with the average weight change cutoff. More interestingly, the coefficient of the past shifting dummy is large and the p-value in both cases is zero, significant evidence that current shifting funds are more likely to shift styles in future period and consistent with the style-shifting skill hypothesis that style-shifting may be an active trading strategy adopted by skilled managers.

We further consider whether fund performance and fund flow play an important role in style-shifting. Columns 2 and 5 of Table 5 report the results after including past fund performance and fund flow in the determinant regression. The coefficient of fund return in the past quarter is negative but insignificant. However, this insignificant relation may be partially caused by omitted variables because this coefficient becomes marginally significant in column 3 and significant at 5% in column 6 after style return is controlled in the regression. Over all, these results weakly suggest that ill-performed funds may be more likely to shift styles in future periods. The coefficient of fund return standard deviation is positive and significant, suggesting that funds with highly uncertain returns are more likely to shift styles in future periods. The fund flow coefficient is negative and insignificant in both columns, suggesting that fund flow is not an important factor in fund managers' shifting decisions. This is weakly consistent with the style-shifting skill hypothesis and inconsistent with the style-chasing hypothesis. Consistently, the coefficient of fund flow standard deviation is insignificant.

Finally, we test whether past style performance can predict style-shifting by including past style returns and style standard deviations in the *Probit* regression, and the third and sixth columns of Table 5 report the results. Style return is defined as the weighted average returns of all invested styles in (3). The style return coefficient is negative and significant at 1% in column 3 but insignificant in column 6, weakly suggesting that funds are likely to abandon ill-performed styles. The coefficient of style return standard deviation is negative and significant, suggesting that funds are very likely to abandon styles with highly uncertainty returns. Overall, the empirical results are more consistent with the style-shifting skill hypothesis than with the style-chasing hypothesis while this determinant analysis cannot clearly reject the style-chasing hypothesis. The R-squares in all regressions are small, between 1.6% and 1.8%, suggesting that important factors beyond fund characteristics and past style and fund performance play important roles in funds' style shift decisions.

4.3.2.2 Style-Shifting and Fund Performance

In this section, we further differentiate the style-shifting motivation by investigating the implications of fund performance of the two style-shifting hypotheses summarized in Section 2. We first examine whether shifting funds outperform their peers. We use the averaged return of all funds in the mutual fund industry as the benchmark. The results are reported in Table A5 and suggest that shifting funds outperform the mutual fund industry. Specifically, the average quarterly return delivered by shifting funds is about 5.5% while the industry average is only 1.9%; shifting funds outperform their active benchmarks while the mutual fund industry, on average, does not. These findings are consistent with the style-shifting skill hypothesis but inconsistent with the style-chasing hypothesis, which proposes that shifting funds are underperformed and have to shift to well-performed popular styles.

We further examine the performance of shifting funds before and after style-shifting. Section 2 suggests that the style-shifting skill hypothesis predicts a significant performance improvement after style shifts. More importantly, this hypothesis suggests that shifting funds outperform their peers both before and after style-shifting. In contrast, the style-chasing hypothesis does not imply these two predictions. We evaluate fund performance over the quarters before and after style-shifting (skipping the shifting quarter). To compare with peer funds, we follow Berk and Binsbergen (2015) and further evaluate style-adjusted performance of shifting funds. For completeness, we also evaluate the averaged performance of the mutual fund industry. The results based on the maximum weight change cutoffs are in Panel A of Table 6 and the results based on the averaged weight change cutoffs are in Panel B. Table 6 presents three interesting observations. First, style-shifting funds outperform peers funds within the same style(s) over post-shifting periods while this outperformance is insignificant over pre-shifting periods. Take the 25% cutoff of the averaged style weight change as an example. The shifting funds deliver a return of 3.04% (t-stat=2.53) in the pre-shifting quarter and 9.92% (t-stat=2.62) in the post-shifting quarter, and the corresponding style-adjusted returns are 0.74% (t-stat=1.19) and 8.47% (t-stat=2.28), respectively. The style-adjusted returns of mutual fund industry are –0.02% (t-stat= –0.17) and –0.16% (t-stat= –1.55), respectively. The results are consistent with the style-shifting skill hypothesis but inconsistent with the style-chasing hypothesis that shifting fund managers are not skilled. Second, style-shifting funds perform better over the post-shifting periods, consistent with the style-shifting skill hypothesis that shifting fund managers possess expertise in new styles. Both panels show that shifting funds' returns are improved in the subsequent one quarter. For example, shifting funds defined by the 40% maximum weight change cutoff deliver a return of 9.65%, which is 7.19% (t-stat=1.96) higher than the performance in the pre-shift quarter. After being adjusted by style returns, shifting funds' returns in the subsequent quarter are higher than that in the pre-shifting quarter by 7.74% (t-stat=2.26). Third, the performance improvement over the post-shifting periods cannot be attributed to relative underperformance over the pre-shifting periods, as the average returns delivered by shifting funds in the pre-shifting periods are higher than the average returns of all funds in our sample. Overall, Table 6 shows that style-shifting fund performance is improved after style-shifting and better than that of non-shifting funds, consistent with the style-shifting skill hypothesis.

It is important to investigate whether the post-shifting outperformance of shifting funds in Table 6 is explained by past fund performance and fund characteristics rather than style-shifting. We regress style-adjusted fund returns over the post-shifting quarter on the style-shifting dummy variable, which equals one if a fund shifts its style in the quarter and zero otherwise, and lagged return, flow, and other fund characteristics. For brevity, we only report the results of one representative cutoff for each shifting identification measure, including the 40% maximum weight change cutoff and the 25% averaged weight change cutoff. The results are reported in Table 7, in which the first three columns report the results based on the maximum change cutoff and the other three columns report the results based on the average weight change cutoff. Columns 1 and 4 report the simple regression results and show that the coefficient of the shifting dummy is 0.018 (*t*-stat=3.11) and 0.028 (*t*-stat=2.68), respectively, consistent with Table 6 and suggesting that style shifting can improve fund performance in the subsequent quarter. Columns 2 and 5 report the results after including fund and style returns and fund flow, and the standard deviations of these variables. The results show that the magnitude and significance of the shifting dummy coefficient are unchanged, suggesting that the relationship between styles-shifting and funds' outperformance over post-shifting periods cannot be explained by fund or style returns, or fund flows. Finally, columns 3 and 6 report the empirical results after further including fund characteristics, such as fund and fund family sizes, age, expense ratio, turnover ratio and cash holding positions. The coefficient of the shifting dummy is 0.030 (*t*-stat=4.38) and 0.045 (*t*-stat=3.81), respectively, which suggests that the relationship between styles-shifting and funds' outperformance cannot be explained by fund characteristics either.

Taking the findings of tables A5, 6 and 7 together, this section provides significant evidence that style-shifting is positively related to future fund performance. Shifting funds deliver higher returns to investors after style shifts. Style-shifting is likely an active trading strategy of skilled fund managers and unlikely driven by chasing hot styles. All these findings are consistent with the style-shifting skill hypothesis rather than the style-chasing hypothesis. In the next section, we further explore what skills shifting fund managers possess using the performance decomposition method in Section 3.4.

4.3.3 Style-Expertise vs Style-Timing

We test whether style-shifting is an active strategy adopted by skilled managers to generate high returns to investors by decomposing post-shifting fund returns into one passive and two active components shown in Section 3.4. The style-chasing hypothesis suggests that the active components do not contribute to subsequent fund performance while the style-shifting skill hypothesis suggests that the active components are positive and significantly large because shifting fund managers are skilled. Section 3.4 shows that the active components, if any, can be attributed to two managerial skills, namely style timing and style selection.

The empirical decomposition results are reported in Table 8. The results of maximum style weight change cutoffs are in Panel A and the results of average change cutoffs in Panel B. For completeness, we also report the results of decomposing the returns of all funds in the sample. Table 8 shows that style-shifting funds outperform all funds and the returns on active style trading are large and contribute 50% to 80% to the overall performance of shifting funds. For example, shifting funds identified by the 40% maximum change cutoff deliver an average return of 9.3% (t-stat=3.19) over the subsequent quarter, and out of which 0.5% (t-stat=1.66) can be attributed to style timing ability and 6.5% (t-stat=2.51) to style selection expertise. Similarly, shifting funds identified by the 25% averaged change cutoff deliver a return of 0.7% (*t*-stat=1.64) using their style timing ability and a return of 5.3% (*t*-stat=2.09) using their style selection expertise. To conclude, Table 8 shows that shifting funds exhibit both style timing ability and style selection expertise with the latter being the main contributor. The table shows that the return on passive style investments across all funds is the only source of performance and the return on active style trading is small and negative, suggesting that non-shifting funds do not exhibit either style-timing ability or style-selection expertise, which is consistent with the literature that, on average, mutual fund industry does not beat the market.

The literature suggests that investment opportunity and fund manager skills are time-varying. Kacperczyk, van Nieuwerburgh, and Veldkamp (2014) further argue that fund manager skills condition on the state of macroeconomy and that managers exhibit selection skill during expansion periods and timing ability during recessions. Jiang, Zaynutdinova and Zhang (2021) propose that fund manager skills are time-varying because investment opportunities (mispriced stocks) are related to stock market states. We investigate whether style-shifting managers' style-timing and style-expertise condition on stock market states. We follow Cooper, Gutierrez and Hameed (2004) and define two market states: UP versus DOWN markets. Specifically, a market is in 'UP' state when the three-year cumulative excess return on the S&P 500 index is positive and otherwise in 'DOWN' state.[14] We end up with 24 UP-market quarters and 64 DOWN-market quarters. We evaluate the returns delivered by each skill in the up and down markets, respectively. Table 8 shows that both skills are economically meaningful when the shifting identification cutoffs of the maximum style weight change are 40% and 50% and the cutoffs of the average style weight change

[14] Our findings remain using three-year cumulative excess returns on the Russell 3000 Index or using one-year or two-year cumulative excess returns on either of the two indexes.

are 25% and 30%. We consider all four cutoffs and the results are reported in Table 9, in which the results of managers' style-timing skill are in Panel A and the results of managers' style-expertise are in Panel B.

Table 9 suggests two interesting observations. First, Panel A shows that style-shifting fund managers' style-timing skill is more pronounced following DOWN markets. Take the 40% cutoff of the maximum style change as an example. The average return delivered by the shifting fund managers' style-timing skill is 0.55% following UP markets and 0.84% following DOWN markets while both are insignificant.[15] Second, Panel B shows that style-shifting fund managers' style-expertise is pronounced following UP markets but not following DOWN markets, in contrast to that in Panel A. Take the 40% cutoff of the maximum style change as an example again. The average return delivered by the shifting fund managers' style-expertise is 6.16% and significant at 5% following UP markets and 2.19 % and insignificant following DOWN markets. Overall, the findings in Table 9 are consistent with Kacperczyk et al (2014) and Jiang et al (2021).

After documenting evidence that style-shifting fund managers possess both style timing ability and style expertise, it is important to investigate what are the determinants of shifting funds' outperformance. We conduct a linear regression of shifting fund outperformance, measured as style-adjusted fund returns, on past style trading, and lagged fund performance and characteristics. Table A5 suggests significant differences between shifting funds and non-shifting funds in major fund characteristics, including fund and style returns, fund size, flow, turnover ratio, expense ratio, cash holding and age. Shifting funds attract more flows than the industry average and their fund flows are more stable. They hold more cash and are younger; and their turnover ratio and expense ratio are higher. We consider all these fund

[15] This is not surprising since Table 8 shows that the averaged return of the style-timing is relatively small and marginally significant.

characteristics in the determinant analysis of shifting funds' outperformance. The empirical results are reported in Table 10. The results based on the 40% maximum cutoff are reported in the first three columns and the results based on the 25% average change cutoff in columns 4-6. This table provides several interesting observations. First, the coefficient of style weight change is about 0.1 with a *t*-statistic greater than 2.64, suggesting that style-shifting funds with active style rotations deliver high returns. This is also consistent with the findings in Pastor, Stambaugh and Taylor (2017) that active funds can generate higher returns than other funds to investors. Second, the coefficient of fund returns is about 0.2 and significant at 1% in both panels, suggesting that outperformed shifting funds continuously perform well in future periods. Third, the coefficient of fund flow is positive but insignificant and the coefficients of style returns and style return standard deviation are negative and insignificant. Finally, the coefficient of fund size and fund family size are insignificant, suggesting that these variables are not able to predict future returns of style-shifting funds.

4.4 Robustness Checks

In this section, we perform robustness checks to address potential concerns in our main analyses. First, the new styles that a fund shifts to may be highly correlated with existing styles, which implies that the shifts are spurious. Second, mutual funds may shift investment styles after fund manager turnovers. Third, some styles may not be investable at the style estimation date. We conduct analyses to address each of the above potential concerns.

4.4.1 Spurious Style Shifts

We first address the concern of spurious style-shifts potentially contained in Table 4 because new styles identified by quadratic Sharpe regressions may be highly correlated to and thus very similar to current styles (Buetow, Johnson and Runkle, 2000). We identify these spurious shifts using the variance inflation factor (VIF) approach suggested in Belsley, Kuh and Welsch (1980) and Kutner, Neter and Nachtseim (2004). Specifically, in each quarter we identify the shifting funds and their current style(s) and new style(s) in the next quarter. We run a linear regression of the returns of each new style on current style(s) over a 24-month rolling window as

$$R_{i,t}^{k} = \alpha_k + \sum_{c=1}^{j} \beta_{i,c} R_{i,t}^{c} + \varepsilon_{i,t}^{k}, \tag{4}$$

where $R_{i,t}^{k}$is the return of fund i selected new style k and $R_{i,t}^{c}$ is the return of fund i's old (current) style *c*. All fund *i*'s old styles (1, 2, …, *j*) are included on the left side of regression (4), and the variance inflation factor is defined as $VIF_{i,k} = \frac{1}{1-R_k^2}$, where $R_k^2$is the R-squared of the regression. The conventional cutoff of VIF is 10 in identifying multicollinearity. To be on the conservative side, we set the cutoff of VIF as four to identify spurious new styles. We reidentify style-shifting funds after excluding these spurious new styles. Table A6 reports the summary statistics of style shifts in mutual fund industry after controlling for the impact of spurious new styles and suggests that style shifts are not driven by shifting to these new styles. Take the maximum cutoff of 40% as an example, the style-shifting ratio is 2.5% and statistically significant at 1% level, the numbers of shifting funds per quarter and shifts per funds are respectively 60 and 2.75, and the average duration of staying in new styles is 1.5 years. All figures are slightly smaller than but very close to the ones in Table 4 and these patterns remain across all shift identification cutoffs.

4.4.2 Style-Shift and Fund Manager Turnover

Gallo and Lockwood (1999) show that it is a common practice to pursue a new investment style after the fund manager is replaced. We identify fund manager turnover using the CRSP

Mutual Fund Database that contains the historical portfolio manager information. Specifically, we use the variable of '*Portfolio Manager Name*' and the variable of '*Date Current Portfolio Manager Took Control*' from the database to identify the date of each fund manager turnover. We manually check fund manager names over time to minimize the impact of recording noise in the database. We aggregate manager turnovers at the fund class to the fund level and remove double-counted ones. We reexamine style-shifting in the mutual fund industry after excluding all fund manager turnover events. The results are reported in Table A7 and suggest that the impact of manager turnover on the style-shifting analysis is small and negligible. Take the maximum cutoff of 40% as an example again, the style-shifting ratio is 2.7% and statistically significant at 1%, the numbers of shifting funds per quarter and shifts per funds are 63 and 2.92, respectively, and the average duration of staying in new styles is 1.5 years. The numbers are very close to those in Table 4 and these patterns remain across all shift identification cutoffs.

4.3.3 Time-Varying Style Set

In this subsection, we test whether the above findings are robust when the investable style set in mutual fund industry varies over time. We apply our two-step *LASSO* procedure to select the time-varying style set for the mutual fund industry as described in Appendix AII. Specifically, we split the sample into four subsamples by decade, from 1986 to 2020, apply the two-step *LASSO* procedure to select the style set for each subsample, and use the style set selected in last decade as the proxy of style set in current decade.[16] The main advantage of this time-varying style set is its practical availability for fund managers and investors, that is, the styles of interest are currently investable in stock markets.

[16] Due to the limitation of data availability, the style set for the decade of 1991–2000 is selected by applying the two-step LASSO procedure over the period of 1986-1990.

Specifically, there are 15 investable styles available in 1986–1988, 16 in 1989–1990, 17 in 1991–1992, 18 in 1993, 19 in 1994, 21 in 1995, 32 in 1996–1998 and 33 in 1999 onwards. Regardless, the two-step *LASSO* selection shows that nine styles, including *NYA, OEX, RLV, RUJ, RUO, RDG, RMV, NDX* and *XMI*, selected over period of 1986–1990 can be used as the efficient style set for period 1991–2000, nine styles, including *CCMP*, *RLV, RUO, RDG, RMV, MID, SML, XAX* and *NYIID*, selected over period of 1991–2000 for period 2001–2010, and 10 styles, including *CCMP, NYA, RMC, RUO, RDG, XMI, MIDG*, *SMLG*, *SVX* and *XAX*, for period 2011–2020. Most of the nine styles in Section 3.1 are selected using this time-varying procedure. However, the style set in the mutual fund industry varies across decades. The Nasdaq market index (*CCMP*) was not very influential and excluded in 1980s, and international markets attract much attention from 1990s, and high technology stocks matter after 2000s. Regardless, the results are similar to that in Section 3.1 and suggest that the two-step *LASSO* procedure is effective to reduce style dimension and select the parsimonious set of styles for mutual fund industry.

We turn to explore the style selection of individual funds using the time-varying style sets and applying the quadratic Sharpe regression within each decade. The results over the whole sample period from January 1991 to December 2020 (Panel A) as well as over each decade (Panels B, C and D) are reported in Table A8. The pooled results in Panel A are similar to those in Table 2 and consistently suggest that the majority of active mutual funds invest in multiple styles and only very few funds (2%) are single-style funds. These findings are stronger in the1990s (Panel B). We examine funds' style selection using a 36-month rolling window and the results are consistent with those in Table A4 that less than one percent of mutual funds are single-style funds.[17]

[17] The results are not reported but available upon request.

Next, we explore funds' style-shifting decisions using time-varying style sets. The style-shifting identification procedure is the same as that used in Table 4 except the style set varies over time. The results are reported in Table 11 and the shifting ratios are similar to but slightly lower than those in Table 4. Moreover, mutual funds shift styles more frequently in 1990s and 2010s and less frequently in 2000s, which is an interesting question in our future research. Table 12 reports the empirical results of whether style-shifting is significantly related to funds' future returns, where the style-shifting is identified using the time-varying style sets. The coefficient of the style-shifting dummy variable is positive and statistically significant in all regressions, suggesting that style-shifting helps improve fund performance, consistent with the style-shifting skill hypothesis.

5. Conclusion

Whether mutual fund managers possess asset management skills is essential to mutual fund investors and academic researchers. The literature proposes approaches to examine whether fund managers are able to select securities and whether they are able to time stock market conditions. In this study, we propose a manager skill measure from the prospective of style investments. Mutual funds are recognized and evaluated by investment styles and fund managers have investment mandates within the disclosed styles. We argue that skilled fund managers may dynamically shift investment styles to exploit new investment opportunities and deliver higher returns to investors. Meanwhile existing studies suggest that unskilled fund managers may shift styles because of poor performance and principal-agency concern. We conduct comprehensive analyses to differentiate the two hypotheses and the empirical findings consistently suggest that style-shifting funds, on average, exhibit manager skills. We further show that style-shifting fund managers possess both style expertise and style-timing ability.

Appropriate benchmark set in the mutual fund industry is the first step but one of the most important steps. We propose a new procedure that utilizes machine learning technology to reduce the high dimensional investable styles and effectively select the parsimonious low-dimension style set. We show that this two-step *LASSO* approach is helpful with flexibility to deal with the large number of styles in practice and can overcome style selection errors in the standard *LASSO* procedure. Nine out of 32 indexes are selected as the proxy of style set in the mutual fund industry. We apply the quadratic Sharpe (1992) regression to identify individual funds' style selection and find that most active equity funds are multi-style funds and more than 85% of them allocate capitals among three to six styles. Single-style funds count less than 3% of the total number of funds. We further find that around 3% of funds shift their investment styles in each quarter and each shifting fund switches styles three times over the whole period and the findings are quite robust.

We conduct comprehensive empirical analyses to differentiate the two competing hypotheses on style-shifting. The style-shifting skill hypothesis suggests that style-shifting fund managers are skilled and can generate profits by shifting styles and the style-chasing hypothesis implies that style-shifting fund managers chase hot styles in current market but cannot generate profits from style shifting. We find that shifting funds perform better in the post-shifting quarter than in the pre-shifting quarter in terms of both total returns and style-adjusted returns, but we do not find performance improvement by non-shifting funds. We further find that style-shifting decision is positively related to future fund returns. We decompose shifting funds' abnormal returns into two manager skills, *i.e.*, style timing ability and style expertise. We find that style-shifting in the mutual fund industry is mostly driven by fund managers' expertise in the new style. Our empirical findings are consistent with the style-shifting skill analysis and suggest that mutual fund managers exhibit style-shifting skill.

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Table 1. Summary Statistics of Mutual funds and Investment Style Set

This table reports summary statistics of 5,392 active open-end equity mutual funds (Panel A) and the active peer benchmark styles in mutual fund industry (Panel B). Panel A reports time series average of cross-sectional distribution of major fund characteristics over the sample. Nine active peer benchmark styles are the *NYSE* composite Index (*NYA*), the *NASDAQ* composite index (*CCMP*), Russell Midcap index (*RMC*), Russell Midcap Growth Index (*RDG*), Russell 2000 Growth Index (*RUO*), the S&P400 Midcap Growth Index (*MIDG*), the S&P 600 Small Cap Growth Index (*SMLG*), the *NYSE* Amex Index (*XAX*), and the *NYSE* 100 International Leaders (*NYIID*), which are selected out of 32 candidate styles using a two-step *LASSO* procedure described in Section 1. Panel B reports the distribution of time series of benchmark style returns and Panel C reports the pairwise correlations among the styles. The sample period is from January 1996 to December 2020.

Panel A: Mutual Fund Characteristics					
	Mean	25%tile	Median	75%tile	Stdev
Fund return (%)	0.74	-0.59	0.72	2.04	2.84
Fund size ($M)	1,725	76	282	1,019	7,598
Family size ($M)	76,274	2,522	11,403	42,493	182,123
Fund flow (%)	1.20	-1.36	-0.24	1.24	36.54
Turnover ratio (%)	85.88	27.99	55.95	100.30	193.69
Expense ratio (%)	1.12	0.83	1.11	1.40	0.51
Cash holding (%)	4.57	0.67	2.28	4.91	12.90
Age (years)	12.82	5.56	9.40	15.68	12.13
Panel B: Benchmark Styles					
	Mean	Min	Median	Max	Stdev
NYA	0.74	-19.39	1.08	11.53	4.42
CCMP	1.04	-22.88	1.68	22.00	6.59
RMC	0.98	-22.36	1.47	15.36	4.96
RUO	0.88	-23.09	1.55	23.26	6.66
RDG	1.01	-21.96	1.48	21.02	5.95
MIDG	1.13	-22.17	1.28	19.04	5.56
SMLG	0.97	-21.65	1.49	17.12	5.78
XAX	0.84	-30.19	1.21	26.38	5.19
NYIID	0.36	-22.14	0.76	14.59	5.08

Table 2. Summary Statistics of Style Selection

This table reports summary statistics of Sharpe-regression based style selection among the nine active peer benchmark styles by active open-end equity mutual funds. The non-linear Sharpe regression for fund i is conducted as $r_i = \sum_{s=1}^{9} \beta_s r_s + \varepsilon_i$, *subject to* $\sum \beta_s = 1$ and $\beta_s \geq 0$ over the whole sample period from January 1996 to December 2020. r_s is the return series of style *s*, one of the nine styles listed in Table 1 and identified by a two-step *LASSO* procedure. β_s is defined as the weight of fund i on style s. A selected style is defined as the one with a positive Sharpe weight by the fund of interest. Panel A reports the number of styles selected by individual funds and Panel B reports the number of funds in each index. In each panel, mutual funds are further sorted into three groups based on fund size: the largest 30% funds, the medium 40% funds and the smallest 30% funds.

	Number of styles								
	1	2	3	4	5	6	7	8	9
Panel A: Number of funds across style dimension									
No of funds	99	339	932	1,208	922	511	190	40	6
% of total funds	2.33	7.98	21.94	28.44	21.71	12.03	4.47	0.94	0.14
Small funds	40	105	263	355	285	164	57	4	1
Fraction (%)	0.94	2.47	6.19	8.36	6.71	3.86	1.34	0.09	0.02
Medium funds	39	147	383	480	370	175	82	22	1
Fraction (%)	0.92	3.46	9.02	11.30	8.71	4.12	1.93	0.52	0.02
Large funds	20	87	286	373	267	172	51	14	4
Fraction (%)	0.47	2.05	6.73	8.78	6.29	4.05	1.20	0.33	0.09
Panel B: Number of funds with exposure to each style									
	NYA	CCMP	RMC	RUO	RDG	MIDG	SMLG	XAX	NYIID
No of funds	3,233	2,393	1,619	1,248	3,037	1,478	1,457	2,028	1,292
% of total funds	76.12	56.35	38.12	29.39	71.51	34.80	34.31	47.75	30.42
Small funds	955	698	430	415	873	454	427	645	437
Fraction (%)	22.49	16.44	10.12	9.77	20.56	10.69	10.05	15.19	10.29
Medium funds	1,246	970	639	552	1,182	592	626	800	507
Fraction (%)	29.34	22.84	15.05	13.00	27.83	13.94	14.74	18.84	11.94
Large funds	1,032	725	550	281	982	432	404	583	348
Fraction (%)	24.30	17.07	12.95	6.62	23.12	10.17	9.51	13.73	8.19

Table 3. Style Selection and Fund Characteristics

Funds are sorted into subsamples based on number of investment styles. This table reports the summary statistics of funds in each subsample. Fund's investment styles are estimated using the quadratic Sharpe regression over the sample period from January 1996 to December 2020. Investment styles are identified by positive Sharpe weights. *t*-statistics based on Newey-West standard errors with four lags are in parentheses.

Characteristics	Fund style group (by number of styles)					
	1	2	3	4	4	≥6
Fund return (%)	0.84	0.71	0.71	0.73	0.77	0.76
Fund return vol. (%)	1.15	0.47	0.24	0.26	0.25	0.25
Fund size ($M)	1,052	2,030	1,943	1,360	1,866	1,792
Family size ($M)	83,374	86,070	75,074	85,238	68,729	70,398
Fund flow (%)	2.47	1.39	1.05	1.45	1.27	0.63
Turnover ratio (%)	141.67	111.63	81.61	86.50	79.91	81.51
Expense ratio (%)	1.40	1.20	1.10	1.10	1.10	1.10
Cash holding	14.12	5.03	4.87	4.28	3.98	3.95
Age (years)	15.69	13.38	13.61	12.15	13.00	12.13

Table 4: Summary Statistics of Style-Shifting

This table reports summary statistics of the style shifts of equity mutual funds, including the number of shifting funds, shifting ratio over the sample period and the duration of each shift. Panel A reports the summary of style shifting defined by the maximum style weight change and Panel B reports the results of style shifting based on the averaged style weight changes. Fund's portfolio weight on each style is estimated using the Sharpe quadratic regression over a 36-month rolling window. Shifting funds and their shifting dates are determined by the change of funds' style weights estimated from a 36-month and a 48-month rolling windows. *** and ** denote statistical significance at the 1% and 5% levels, respectively. The sample period is from January 1996 to December 2020.

Panel A: Style shifting identified by the maximum weight change cutoffs

	Maximum style weight change cutoffs		
	≥30%	≥40%	≥50%
Shifting funds/quarter	147.85	67.00	35.59
Shifting ratio (%)	5.99***	2.83***	1.56**
Shifts/shifting fund	4.29	2.99	2.39
Duration/Shift (years)	1.41	1.45	1.27

Panel B: Style shifting identified by the average weight change cutoffs

	Average style weight change cutoffs		
	≥20%	≥25%	≥30%
Shifting funds/quarter	77.84	66.67	41.74
Shifting ratio (%)	3.14***	2.70***	1.71 ***
Shifts/shifting fund	3.57	3.38	3.64
Duration/Shift (years)	1.48	1.50	1.07

Panel A: Style shifting identified by the maximum weight change cutoffs

	Maximum style weight change cutoffs		
	≥30%	≥40%	≥50%
Shifts/shifting fund	4.29	2.99	2.39
Duration/Shift (years)	1.41	1.45	1.27

Panel B: Style shifting identified by the average weight change cutoffs

	Average style weight change cutoffs		
	≥20%	≥25%	≥30%
Shifts/shifting fund	3.57	3.38	3.64
Duration/Shift (years)	1.48	1.50	1.07

Table 5. Determinants of Style-Shifting

This table reports the *Probit* regression results of the style-shifting dummy on lagged fund characteristics. The style-shifting dummy equals one if a fund shifts its style, *i.e.*, its maximum style weight change equal or higher than 40% (Panel A) or its averaged style weight change equal or higher than 25% (Panel B), during a given quarter and zero otherwise. All time-varying independent variables are lagged by at least one quarter. In each model, we report the multivariate *Probit* regression coefficients and the associated *p*-value (in parentheses). ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Dependent: Shifting dummy in next quarter					
Lagged variables	Max weight change (≥40%)			Averaged weight change (≥25%)		
Fund size	-0.065***	-0.067***	-0.065***	-0.091***	-0.091***	-0.090***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Family size	0.023***	0.024***	0.021***	0.033***	0.033***	0.032***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(age)	0.004	0.002	-0.001	-0.007	-0.003	-0.008
	(0.52)	(0.73)	(0.36)	(0.33)	(0.66)	(0.29)
Expense ratio	0.053***	0.059***	0.006**	0.072	0.023	0.004
	(0.00)	(0.00)	(0.00)	(0.54)	(0.85)	(0.77)
Turnover ratio	0.013***	0.013***	0.013***	0.011***	0.011***	0.011***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Cash	0.004***	0.004***	0.003***	0.005***	0.005***	0.005***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Past shifting	0.970***	0.990***	0.981***	1.327***	1.269***	1.267***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fund return		-0.054	-0.083*		-0.056	-0.120**
		(0.22)	(0.06)		(0.21)	(0.01)
Return stdev.		0.010***	0.145***		0.174***	0.251***
		(0.00)	(0.00)		(0.00)	(0.00)
Fund flow		-0.003	-0.003		-0.001	-0.001
		(0.66)	(0.67)		(0.77)	(0.78)
Flow stdev.		0.001	0.010		0.002	0.002
		(0.47)	(0.63)		(0.31)	(0.38)
Style return			-0.002***			-0.010
			(0.00)			(0.12)
Style return stdev.			-0.076***			-0.036***
			(0.00)			(0.00)
Intercept	-2.172***	-2.123***	-1.894***	-2.298***	-2.600***	-2.247***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Joint test (Wald)	9,023	9,088	9,503	10,248	10,411	10,489
Adj-R^2 (%)	1.59	1.60	1.72	1.77	1.81	1.83

Table 6. Fund Performance Before and After Style-Shifting

This table reports the cumulative total and style-adjusted returns (in %) delivered by shifting funds before and after style shift skipping one quarter. Shifting funds and their style-shifting dates are determined by the difference in funds' style weights estimated from a 36-month rolling window and a 48-month rolling window. Style shifting is defined based on the largest style weight change cutoffs in Panel A and averaged style change cutoffs in Panel B. The *t*-statistics based on the Newey-West standard errors with four lags are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1996 to December 2020.

Panel A: Style-shifting using cutoffs of maximum style weight change

	All funds	Maximum style weight change cutoffs		
		≥30%	≥40%	≥50%
		Before shifting		
Raw return	2.15 **	2.82**	2.45 **	2.66 * *
	(2.40)	(2.55)	(2.19)	(2.03)
Style-adjusted	-0.02	0.59	0.10	0.15
	(-0.17)	(1.04)	(0.24)	(0.26)
		After shifting		
Raw return	1.64 *	5.34 ***	9.65 ***	12.25 * *
	(1.76)	(2.90)	(2.76)	(2.33)
Style-adjusted	-0.16	3.27**	7.84**	10.27**
	(-1.55)	(1.97)	(2.29)	(1.98)
		After-before		
Raw return	-0.51	2.52*	7.19**	9.59*
	(-0.38)	(1.65)	(1.96)	(1.77)
Style-adjusted	-0.14	2.68*	7.74**	10.12*
	(-1.02)	(1.71)	(2.26)	(1.91)

Panel B: Style-shifting using cutoffs of averaged style changes

	All funds	Averaged style weight change cutoffs		
		≥20%	≥25%	≥30%
		Before shifting		
Raw return	2.15 **	2.12*	3.04 **	3.72 ***
	(2.40)	(1.79)	(2.53)	(2.87)
Style-adjusted	-0.02	0.18	0.74	1.15
	(-0.17)	(0.36)	(1.19)	(1.46)
		After shifting		
Raw return	1.64 *	7.26**	9.92 **	12.97 **
	(1.76)	(2.67)	(2.62)	(2.44)
Style-adjusted	-0.16	5.67**	8.47 **	11.67**
	(-1.55)	(2.18)	(2.28)	(2.22)
		After-before		
Raw return	-0.51	5.14*	6.88*	9.24*
	(-0.38)	(1.74)	(1.76)	(1.68)
Style-adjusted	-0.14	5.49**	7.73**	10.52**
	(-1.02)	(2.09)	(2.08)	(1.97)

Table 7. Style-Shifting and Fund Performance

This table reports the regression results of style-adjusted fund returns in next quarter (skipping one quarter) on a shifting dummy variable, which equals one if a fund experienced one maximum style weight change over current quarter no less than 40% (or averaged style weight change no less than 25%) and zero otherwise. Style weight is estimated from the Sharpe nonlinear regression using a 36-month rolling window and style return is the weighted sum of all invested styles as $\sum_{s=1}^{S} \omega_{i,s,1,t} R_{t+1}^{s}$. Style weight change is the difference in funds' style weights estimated from a 36-month rolling window and a 48-month rolling window. The sample period is from January 1996 to December 2020. t-statistics are based on Newey-West standard errors with 4 lags. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Dependent: style-adjusted fund returns over next quarter					
Lagged variable	Shifting based on max weight change			Shifting based on average weight change		
Shifting dummy	0.018***	0.019***	0.030***	0.028***	0.028***	0.045***
	(3.11)	(3.56)	(4.38)	(2.68)	(3.08)	(3.81)
Fund return		0.048***	0.030***		0.048***	0.030***
		(4.63)	(2.81)		(4.66)	(2.88)
Return stdev.		-0.032	-0.009		-0.041*	-0.025
		(-1.31)	(-0.34)		(-1.65)	(-0.94)
Style returns		-0.046***	-0.027**		-0.047***	-0.028**
		(-4.32)	(-2.50)		(-4.37)	(-2.63)
Style return stdev.		0.033	-0.012		0.040	-0.175
		(1.25)	(-0.45)		(1.54)	(-0.06)
Fund flow		0.004**	0.004***		0.004**	0.004***
		(2.28)	(2.79)		(2.33)	(2.82)
Flow stdev.		-0.006**	-0.006***		-0.006***	-0.006***
		(-2.53)	(-2.66)		(-2.66)	(-2.74)
Fund size			-0.061***			-0.058***
			(-6.13)			(-5.80)
Family size			0.041***			0.039***
			(3.40)			(3.21)
Log (age)			0.067***			0.068***
			(3.32)			(3.34)
Expense ratio			-0.114**			-0.097**
			(-2.43)			(-2.03)
Turnover ratio			-0.074***			-0.075***
			(-4.28)			(-4.35)
Cash holding			-0.006***			-0.007***
			(-2.98)			(-3.23)
Intercept (%)	-0.272***	-0.258***	-0.164	-0.265***	-0.243***	-0.143
	(-27.80)	(-6.33)	(1.37)	(-24.48)	(-5.69)	(-1.20)
Adj-R^2 (%)	0.15	0.24	0.50	0.20	0.31	0.62

Table 8. Style-Shifting and Manager Skills

This table reports the decomposition of multi-style shifting fund i's return in subsequent quarter (skipping one quarter) $R_{i,,t+1}$, into passive gain $\sum_{s=1}^{S} \omega_{i,s,1,t} R_{t+1}^{s}$ the style-timing gain, $\sum_{s=1}^{S} (\omega_{i,s,2,t} - \omega_{i,s,1,t})\, R_{t+1}^{s}$, and the style expertise, $(R_{i,,t+1} - \sum_{s=1}^{S} \omega_{i,s,2,t}\, R_{t+1}^{S})$, where S is nine and the corresponding styles are selected by a two-step *LASSO* procedure. Fund's style weights are estimated by a rolling-window based on the quadratic Sharpe regression and style change is defined by style weight change in terms of maximum or averaged style weight changes. In each panel, the first column reports the time series average of cross-sectional means of fund returns, the gain of style-timing, and the gain of expertise in new styles over the whole sample period. The other columns report the results of multi-style shifting funds defined using various cutoffs. Newey-West t-statistics with four lags are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Shifting defined by cutoffs of the maximum style weight change

	TNA-weighted fund performance in subsequent quarter			
		Maximum style weight change cutoffs		
	All funds	≥30%	≥40%	≥50%
Fund return	1.85**	5.03***	7.67***	8.95***
	(2.15)	(2.69)	(3.24)	(2.94)
Passive	2.04 **	2.45***	1.97**	2.05**
	(2.31)	(2.76)	(2.27)	(2.44)
Style-Timing	-0.004	0.11	0.63*	0.94*
	(-0.14)	(0.49)	(1.78)	(1.87)
Style-Expertise	-0.19*	2.47	5.07**	6.00**
	(-1.81)	(1.50)	(2.35)	(2.17)

Panel B: Shifting defined by cutoffs of the averaged style weight change

	TNA-weighted fund performance in subsequent quarter			
		Averaged style weight change cutoffs		
	All funds	≥20%	≥25%	≥30%
Fund return	1.85**	6.33***	8.54***	7.28**
	(2.15)	(3.03)	(2.91)	(2.17)
Passive	2.04**	2.12**	2.13**	1.38
	(2.31)	(2.33)	(2.55)	(1.20)
Style-Timing	-0.004	0.30	0.86*	1.05*
	(-0.14)	(1.35)	(1.83)	(1.71)
Style-Expertise	-0.19*	3.90**	5.55**	4.85
	(-1.81)	(2.13)	(2.07)	(1.57)

Table 9. Market States and Style-shifting Skills

We split the sample period into *UP* and *DOWN* periods based on whether the 3-year cumulative excess returns on the S&P 500 Index is positive. This table reports the quarterly returns delivered by style-timing (Panel A) and style-expertise (Panel B) of style-shifting funds following the up and down-market periods, respectively. Newey-West *t*-statistics with four lags are in parentheses. ** and * denote statistical significance at the 5% and 10% levels, respectively.

Market state	TNA-weighted fund performance in subsequent quarter			
	Maximum style weight change		Average style weight change	
	40%	≥50%	≥25%	≥30%
	Panel A: Style-timing			
UP	0.55	0.76	0.71	0.93
	(1.44)	(1.42)	(1.44)	(0.36)
DOWN	0.84	1.49	1.28	1.49
	(1.03)	(1.33)	(1.20)	(1.50)
	Panel B: style-expertise			
UP	6.16 **	6.78 *	7.02*	6.00
	(2.03)	(1.67)	(1.77)	(1.36)
DOWN	2.19	3.70	1.37	0.73
	(1.46)	(1.10)	(0.77)	(0.25)

Table 10. Determinants of Style-Shifting Fund Performance

This table reports the results of determinants of shifting fund performance from a pooled OLS regression of abnormal shifting fund returns in subsequent quarter (skipping one quarter) on various fund characteristics. Shifting funds are defined using a cutoff of 40% style max weight change or 25% of average weight change over current quarter. The sample period is from January 1996 to December 2020. *t*-statistics are in parentheses and based on Newey-West standard errors with 4 lags. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Dependent: next-quarter abnormal fund returns					
Lagged variable	Shifting based on 40% of the max weight change			Shifting based on 25% of the average weight change		
Style weight change	0.090***	0.090***	0.106***	0.107***	0.108***	0.134**
	(3.14)	(3.06)	(2.87)	(2.84)	(2.87)	(2.62)
Fund returns	0.178***	0.190**	0.149*	0.235***	0.254***	0.154**
	(4.30)	(2.48)	(1.92)	(4.40)	(2.91)	(2.05)
Return stdev.	-0.407**	-0.356**	-0.523***	-0.307*	-0.172	-0.414**
	(-2.50)	(-2.48)	(-3.09)	(-1.82)	(-1.21)	(-2.63)
Fund flow	0.378*	0.369*	0.425	0.006*	0.005**	-0.023
	(1.86)	(1.78)	(0.50)	(-1.82)	(2.10)	(0.03)
Flow stdev.	0.105	0.096	-0.958	0.055	0.019	0.041
	(0.67)	(0.60)	(-0.43)	(0.31)	(0.10)	(0.02)
Style returns		-0.018	0.046		-0.015	0.001
		(-0.15)	(0.34)		(-0.09)	(0.73)
Style return stdev.		-0.184	0.601		-0.781	0.036
		(-0.59)	(1.26)		(-1.33)	(0.05)
Fund size			0.020			0.512
			(0.05)			(0.94)
Family size			-0.180			-0.748
			(-0.36)			(-0.69)
Log (age)			0.010			0.025
			(0.99)			(1.06)
Expense ratio			0.011			0.026
			(0.62)			(0.96)
Turnover ratio			-0.113			-0.164
			(-1.00)			(-1.08)
Cash			-0.014			-0.041*
			(-0.86)			(-1.76)
Intercept (%)	-5.085***	-4.495***	-8.906**	-6.349***	-3.412	-9.752
	(-2.76)	(-2.65)	(-1.68)	(-2.65)	(-1.33)	(-1.06)
Adj-R^2 (%)	1.27	1.26	1.85	1.40	1.45	2.43

Table 11. Summary of Style-Shifting: Time-Varying Style Set

This table reports summary statistics of style shifts of equity mutual funds, including the number of shifting funds, shifting ratio over the sample period and the duration of each shift over the whole sample as well as over each decade. The time-varying benchmark style set in mutual fund industry in each decade is determined from last decade by a two-step *LASSO* procedure, i.e., benchmark styles in current decade are selected among available styles in last decade. Fund's portfolio weight on each style is estimated using the Sharpe quadratic regression over a 36-month rolling window and shifting funds and their shifting dates are determined by the difference in funds' style weights on one style estimated from a 36-month rolling window and a 48-month rolling window. The sample period is from January 1991 to December 2020.

	Style-shifting cutoffs			
	Maximum style weight change		Average style weight change	
	≥40%	≥50%	≥25%	≥30%
	Whole period			
Shifting funds/quarter	61.01	26.31	25.49	12.95
Shifting ratio (%)	3.10***	1.33***	1.15***	0.55 ***
Shifts/shifting fund	2.89	2.27	2.61	2.35
Duration/Shift (years)	1.60	1.48	1.54	1.25
	1991–2000			
Shifting funds/quarter	70.92	31.76	17.80	7.70
Shifting ratio (%)	5.15***	2.24**	1.30 ***	0.54**
Shifts/shifting fund	2.58	2.05	2.01	1.74
	2001–2010			
Shifting funds/quarter	39.20	16.72	16.84	8.52
Shifting ratio (%)	1.61***	0.69**	0.69 ***	0.35**
Shifts/shifting fund	2.22	2.02	2.09	2.13
	2011–2020			
Shifting funds/quarter	72.92	30.44	41.84	22.20
Shifting ratio (%)	2.55***	1.06***	1.45***	0.77**
Shifts/shifting fund	2.43	2.04	2.47	2.37

Table 12. Style-Shifting and Fund Performance: Time-Varying Style Set

This table reports the regression results of style-adjusted fund return in the subsequent quarter (skipping one quarter) on a shifting dummy variable, which equals one if a fund experienced one style-change over current quarter equal or higher than 40% (or averaged style weight change equal or higher than 25%) and zero otherwise. Fund style and style-shift are estimated by rolling Sharpe nonlinear regressions of excessive fund returns on time-varying style set in mutual fund industry. The sample period is from January 1991 to December 2020. *t*-statistics are in parentheses and based on Newey-West standard errors with 4 lags. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Dependent: style-adjusted fund returns over next quarter					
Lagged variable	Shifting based on 40% of the max weight change			Shifting based on 25% of the average weight change		
Shifting dummy	0.034***	0.034***	0.041***	0.053***	0.052***	0.052***
	(10.26)	(9.91)	(9.78)	(7.23)	(6.95)	(6.26)
Fund return		0.087***	0.107***		0.086***	0.106***
		(16.07)	(14.78)		(15.94)	(14.68)
Return stdev.		-0.122***	-0.138***		-0.126***	-0.143***
		(-10.38)	(-9.56)		(-10.43)	(-9.63)
Style return		-0.288***	-0.337***		-0.287***	-0.336***
		(-19.69)	(-15.37)		(-9.43)	(-15.12)
Style return stdev.		0.184***	0.161***		0.187***	0.162***
		(11.72)	(8.97)		(11.84)	(8.95)
Fund flow		0.018	0.031		0.017	0.029
		(1.02)	(1.48)		(0.93)	(1.40)
Flow stdev.		-0.013***	-0.014***		-0.013***	-0.014***
		(-3.41)	(-3.55)		(-3.38)	(-3.59)
Fund size			0.002			0.004
			(0.16)			(0.33)
Family size			0.044***			0.041***
			(3.60)			(3.33)
Log (age)			0.370***			0.372***
			(5.67)			(5.83)
Expense ratio			-0.209***			-0.171***
			(-4.17)			(-3.37)
Turnover ratio			-0.006			-0.004
			(-0.34)			(-0.21)
Cash holding			-0.003			-0.003*
			(-1.58)			(-1.88)
Intercept	-0.756***	-0.699***	-1.567***	-0.728***	-0.666***	-1.552***
	(-8.84)	(-16.14)	(-11.62)	(-7.62)	(-15.18)	(-11.50)
Adj-R^2 (%)	0.16	2.07	2.88	0.17	2.08	2.85

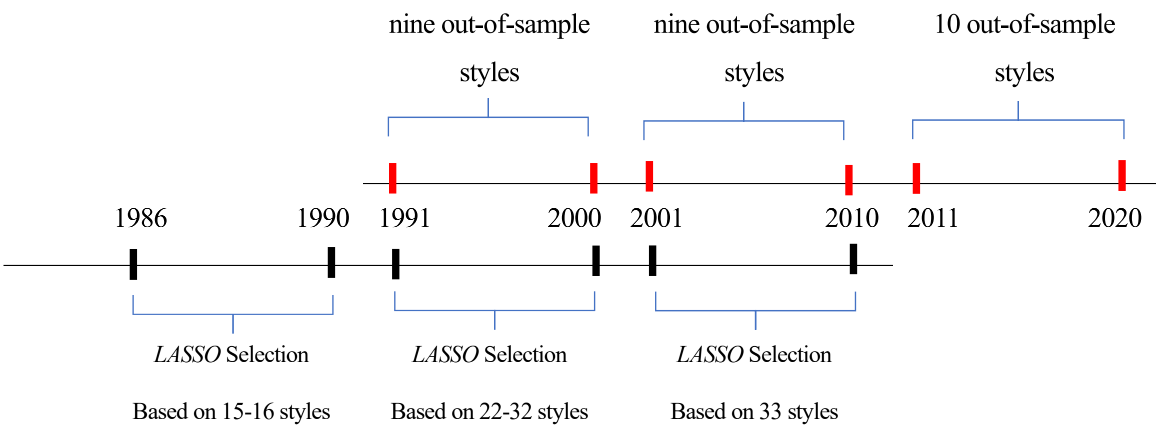
Appendix I. High-Dimension Style List

This appendix reports the full name, abbreviation and sample period of the candidate styles used by the two-step LASSO procedure. The data is collected from Bloomberg.

1. CCMP: the *Nasdaq* Stock Market Composite Index,1986–2020
2. NYA: the *NYSE* Stock Market Composite Index,1986–2020
3. OEX: the S&P 100 Leading Stocks Composite Index,1986–2020
4. RAY: Russell 3000 Stocks Composite Index,1986–2020
5. RIY: Russell 1000 Composite Index,1986–2020
6. RLG: Russell 1000 Growth Index,1986–2020
7. RLV: Russell 1000 Value Index,1986–2020
8. RMC: Russell Midcap Composite Index,1986–2020
9. RTY: Russell 2000 Index,1986–2020
10. RUJ: Russell 2000 Value Index,1986–2020
11. RUO: Russell 2000 Growth Index,1986–2020
12. SPX: the S&P 500 Stocks Composite Index,1986–2020
13. RDG: Russell Midcap Growth Index,1986–2020
14. RMV: Russell Midcap Value Index,1986–2020
15. NDX: the *Nasdaq* 100 Index,1986–2020
16. XMI: the *ARCA* Major Index of NYSE Stock Market,1989–2020
17. MID: the S&P 400 Midcap Index,1991–2020
18. SGX: the S&P 500 Growth Index,1993–2020
19. SML: the S&P 600 Small Stocks Composite Index, 1994–2020
20. SPR: the S&P 1500 Stocks Composite Index,1995–2020
21. SPK: the S&P 1000 Stocks Composite Index,1995–2020
22. RAG: Russell 3000 Growth Stocks Composite Index,1996–2020
23. RAV: Russell 3000 Value Stocks Composite Index,1996–2020
24. MIDG: the S&P 400 Growth Stocks Composite Index,1996–2020
25. MIDV: the S&P 400 Value Stocks Composite Index,1996–2020
26. SMLG: the S&P 600 Growth Stocks Composite Index,1996–2020
27. SMLV: the S&P 600 Value Stocks Composite Index,1996–2020
28. SVX: the S&P 500 Value Stocks Composite Index,1996–2020
29. XAX: the *AMEX* Composite Index of NYSE Stock Market,1996–2020
30. NYID: the *NYSE* US 100 Stocks Composite Index, 1996–2020
31. NYIID: the *NYSE* International 100 Stocks Composite Index,1996–2020
32. NYLID: the *NYSE* World Leading Stocks Composite Index,1996–2020

Appendix II. Time-Varying Style Set Selection

Time-varying style set refers to the style set in current decade are selected by applying the two-step *LASSO* procedure to styles in last decade. The timeline is illustrated as the follows:



Specifically, there are 15 styles available in 1986-1988, 16 styles in 1989-1990, 17 styles in 1991-1992, 18 styles in 1993, 19 styles in 1994, 21 styles in 1995, 32 styles in 1996-1998 and 33 styles in 1999 and afterwards. The nine out-of-sample styles for period 1991-2000 include *NYA, OEX, RLV, RUJ, RUO, RDG, RMV, NDX* and *XMI*; the nine styles for period 2001-2010 include *CCMP, RLV, RUO, RDG, RMV, MID, SML XAX* and *NYIID*; the 10 styles for period 2011-2020 include *CCMP, NYA, RMC, RUO, RDG, XMI, MIDG, SMLG*, *SVX* and *XAX*.

Appendix III: Tables

Table A1: Summary of Style Indexes

This table reports the summary statistics of all 32 styles used by the *LASSO* procedure, including mean, median, standard deviation, min and max returns of each style and pairwise correlations. The sample period is from January 1996 to December 2020.

Panel A: Index summary

	Mean (%)	Min (%)	Median (%)	Max (%)	Stdev (%)
NYA	0.81	-21.88	1.15	12.91	4.32
CCMP	1.11	-27.23	1.74	22.00	6.16
OEX	0.91	-21.32	1.35	13.79	4.40
RAY	0.91	-22.60	1.36	13.24	4.44
RIY	0.92	-21.88	1.31	13.21	4.40
RLG	0.98	-23.30	1.30	14.80	4.90
RLV	0.84	-20.48	1.27	13.45	4.29
RMC	1.08	-60.53	1.42	163.16	9.99
RTY	0.89	-30.69	1.68	18.42	5.64
RUJ	0.90	-28.37	1.50	19.29	5.18
RUO	0.87	-32.98	1.54	23.26	6.40
SPX	1.00	-21.54	1.35	13.47	4.36
RDG	1.11	-27.47	1.45	21.02	5.72
RMV	1.02	-22.76	1.35	16.69	4.65
NDX	1.37	-26.97	1.99	24.99	6.88
XMI	0.88	-16.16	1.11	14.21	3.99
MID	1.11	-21.74	1.41	14.86	4.94
SGX	0.95	-16.51	1.26	14.45	4.40
SML	0.99	-22.40	1.55	18.16	5.49
SPR	0.94	-17.32	1.43	12.89	4.38
SPK	1.01	-21.32	1.52	15.53	5.18
RAG	0.96	-17.93	1.41	14.80	5.02
RAV	0.83	-17.58	1.30	13.79	4.42
MIDG	1.14	-22.17	1.30	19.04	5.55
MIDV	0.81	-24.48	1.38	16.36	5.27
SMLG	1.00	-21.65	1.50	17.12	5.76
SMLV	0.91	-25.69	1.42	18.98	5.64
SVX	0.79	-17.10	1.32	12.88	4.57
XAX	0.84	-30.19	1.21	26.38	5.19
NYID	0.54	-15.22	0.87	11.54	4.18
NYIID	0.36	-22.14	0.76	14.59	5.08
NYLD	0.47	-18.22	0.94	11.49	4.40

Panel B: Pairwise correlations

	N	Mean	25%tile	Median	75%tile
All pairs	496	0.779	0.755	0.847	0.922
CORR<0.1	91	0.081	0.074	0.080	0.080
[0.1,0.25]	36	0.185	0.159	0.188	0.213
(0.25, 0.5]	19	0.281	0.261	0.277	0.298
(0.5,0.75]	56	0.700	0.679	0.715	0.736
(0.75,0.9]	214	0.829	0.795	0.835	0.859
(0.9,1.0]	80	0.946	0.922	0.948	0.967

Table A2. Summary Statistics of Style Weights

This table reports the distribution of style weights across all mutual funds from the quadratic Sharpe regression over the whole sample period from January 1996 to December 2020. The Sharpe regression for fund i is conducted as $r_i = \sum_{s=1}^{10} \beta_s r_s + \varepsilon_i$, *subject to* $\sum \beta_s = 1$ and $\beta_s \geq 0$. r_s is the return series of style *s,* one of the nine styles listed in Table 1, which are identified by a two-step *LASSO* procedure. β_s is defined as the weight of fund i on style *s*.

	Cross-sectional distribution of style weights by funds (%)						
Style	Mean	Stdev.	Min	25%tile	50%tile	75%tile	Max
All styles	24.36	25.13	0.10	4.91	14.44	36.68	100.00
NYA	50.70	27.25	0.12	28.35	51.92	73.47	100.00
CCMP	23.82	20.27	0.13	9.42	18.78	31.92	100.00
RMC	24.35	20.65	0.10	7.29	18.14	36.82	100.00
RUO	32.88	27.89	0.11	8.95	25.46	50.82	100.00
RDG	7.72	10.05	0.10	2.41	4.50	8.55	100.00
MIDG	15.92	14.74	0.12	4.91	11.53	23.20	100.00
SMLG	25.20	24.38	0.14	5.51	15.80	40.71	100.00
XAX	10.17	13.98	0.11	2.41	6.03	12.50	100.00
NYIID	19.65	20.79	0.11	4.64	11.59	27.33	100.00

Table A3. Summary Statistics of Time Series Style Weights

This table reports time series average of the distribution of style weights by individual mutual funds using the Sharpe regression over a rolling window of 36 months. Nine styles, identified by the two-step LASSO procedure, are used as the proxy of style set in mutual fund industry. The sample period is from January 1996 to December 2020.

	Time series average of cross-sectional distribution of style weights (%)						
Style	Mean	Stdev.	Min	25%tile	50%tile	75%tile	Max
All styles	11.11	20.41	0.00	0.00	0.04	12.71	100.00
NYA	33.30	30.85	0.00	0.17	29.11	61.12	99.39
CCMP	14.47	19.89	0.00	0.00	5.42	22.45	99.96
RMC	8.87	16.69	0.00	0.00	0.17	10.21	96.70
RUO	10.08	20.99	0.00	0.00	0.00	7.83	99.97
RDG	5.44	8.70	0.00	0.18	2.67	6.81	93.41
MIDG	7.10	13.04	0.00	0.00	0.53	8.21	95.04
SMLG	9.00	18.20	0.00	0.00	0.03	8.16	96.03
XAX	5.94	12.07	0.00	0.00	0.63	7.32	97.69
NYIID	5.83	12.59	0.00	0.00	0.16	6.15	99.93

Table A4. Summary Statistics of Style Weight Change

This table reports the summary statistics of style weight changes by mutual funds examined as the difference in the same-style weights between the one from the quadratic Sharpe regression over a 36-month rolling window and the one over a 48-month rolling window. The sample period is from January 1996 to December 2020.

	Time series average of cross-sectional distribution of style weight change (%)						
Style	Mean	Stdev.	Min	25%tile	50%tile	75%tile	Max
All styles	0.03	6.33	-79.60	-0.17	0.00	0.07	84.08
NYA	0.77	8.64	-62.39	-2.04	0.22	3.97	52.62
CCMP	0.30	5.28	-45.56	-0.77	0.01	1.72	42.16
RMC	-0.49	7.92	-58.77	-1.41	0.00	0.37	56.53
RUO	0.02	6.16	-50.14	-0.18	0.00	0.03	55.92
RDG	-0.17	2.57	-23.25	-0.83	-0.06	0.45	30.33
MIDG	-0.19	5.24	-42.02	-0.74	0.00	0.35	46.16
SMLG	-0.21	6.11	-57.18	-0.67	0.00	0.38	47.05
XAX	-0.06	4.50	-38.57	-0.81	0.00	0.59	45.08
NYIID	0.02	5.06	-46.42	-0.30	0.00	0.54	51.45

Table A5. Characteristics of Style-shifting Funds

This table reports the summary statistics of style-shifting funds defined by the cutoffs of maximum style weight change of 40% and the averaged style weight change of 25%. Fund's quarterly style weight change between two consecutive quarters is estimated using the quadratic Sharpe regression over a 36-month rolling window and a 48-month rolling window. The characteristics of all funds over the same shifting periods defined by maximum style weight change are also reported. The sample period is from January 1996 to December 2020. *t*-statistics based on Newey-West standard errors with four lags are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	All funds	Shifting funds			
		Max style weight change ≥40%		Average style weight change ≥25%	
		Shifting	Shift- all funds	Shifting	Shift-all funds
Style weight change	0.269***	1.162***	0.893***	1.135***	0.862***
	(12.71)	(66.62)	(32.92)	(37.7)	(27.66)
Quarterly style returns (%)	1.913**	2.066**	0.153	1.457	-0.195
	(2.04)	(2.21)	(0.90)	(1.41)	(-0.53)
Quarterly fund returns (%)	1.864**	5.474**	3.610**	5.383**	3.651***
	(2.25)	(3.26)	(2.61)	(3.35)	(2.79)
Style-adjusted returns (%)	-0.050	3.408**	3.458**	3.926***	3.846***
	(-0.14)	(2.34)	(2.56)	(2.92)	(3.05)
Annual fund returns (%)	8.360***	10.71***	2.346	13.482***	4.452*
	(3.09)	(2.83)	(1.29)	(2.97)	(1.69)
Fund return volatility	0.286***	0.539***	0.253***	0.981***	0.697***
	(8.25)	(6.13)	(3.82)	(5.23)	(4.21)
Fund size ($M)	1,806***	747***	-1,059***	633***	-1,195***
	(17.42)	(6.31)	(-7.15)	(7.04)	(-8.45)
Family size ($M)	81,270***	71,975***	-9,295	60,013***	-22,491**
	(9.51)	(7.36)	(-0.98)	(5.87)	(-1.97)
Quarterly fund flow (%)	1.032***	1.275	0.243	3.189	2.168
	(3.71)	(0.67)	(0.13)	(1.56)	(1.05)
Annual fund flow (%)	12.035***	22.732***	10.697***	28.980***	16.808**
	(6.27)	(5.30)	(2.69)	(4.57)	(2.63)
Flow volatility	4.392**	0.229*	-4.163**	0.423	-4.074*
	(2.11)	(1.72)	(-2.00)	(1.52)	(-1.89)
Turnover ratio (%)	83.580***	138.969***	55.389***	143.782***	60.202**
	(48.57)	(11.76)	(4.71)	(10.89)	(4.66)
Expense ratio (%)	1.110***	1.351***	0.241***	1.331***	0.226***
	(44.46)	(29.88)	(7.27)	(38.55)	(8.01)
Cash holding (%)	4.342***	7.328***	2.986***	8.046***	3.736***
	(26.33)	(9.22)	(3.69)	(7.80)	(3.49)
Age (year)	13.363***	11.787***	-1.576***	11.216***	-2.206***
	(33.42)	(18.70)	(-2.69)	(16.34)	(-2.92)

Table A6: Impact of Spurious New Styles

This table reports summary statistics of the style shifts of equity mutual funds, including number of shifting funds, shifting ratio over the sample period and duration of each shift, after spurious shifts are excluded. Spurious shifts are defined as the ones if the corresponding new styles are highly correlated with current styles identified using a variance-information-ratio procedure. Panel A reports the summary of style shifting defined by the maximum style weight change and Panel B reports the results of style shifting based on the average weight changes. *** and ** denote statistical significance at the 1% and 5% levels, respectively. The sample period is from January 1996 to December 2020.

Panel A: Style shifting identified by the maximum weight change cutoffs

	Maximum style weight change cutoffs		
	≥30%	≥40%	≥50%
Shifting funds/quarter	135.42	59.80	30.39
Shifting ratio (%)	5.48***	2.51***	1.32**
Shifts/shifting fund	4.01	2.75	2.21
Duration/Shift (years)	1.49	1.47	1.34

Panel B: Style shifting identified by the average weight change cutoffs

	Average style weight change cutoffs		
	≥20%	≥25%	≥30%
Shifting funds/quarter	59.12	63.41	38.04
Shifting ratio (%)	2.42***	2.58***	1.57***
Shifts/shifting fund	3.33	3.31	3.51
Duration/Shift (years)	1.39	1.43	1.09

Table A7: Impact of Fund Manager Turnover

This table reports summary statistics of style shifts of equity mutual funds, including number of shifting funds, shifting ratio over the sample period and duration of each shift, after excluding style shifts around fund manager turnovers. Panel A reports the summary of style shifting defined by the maximum style weight change and Panel B reports the results of style shifting based on the average weight changes. *** and ** denote statistical significance at the 1% and 5% levels, respectively. The sample period is from January 1996 to December 2020.

Panel A: Style shifting identified by the maximum weight change cutoffs

	Maximum style weight change cutoffs		
	≥30%	≥40%	≥50%
Shifting funds/quarter	144.11	63.35	35.00
Shifting ratio (%)	5.81***	2.74***	1.53**
Shifts/shifting fund	4.20	2.92	2.34
Duration/Shift (years)	1.44	1.47	1.30

Panel B: Style shifting identified by the average weight change cutoffs

	Average style weight change cutoffs		
	≥20%	≥25%	≥30%
Shifting funds/quarter	75.60	64.80	40.46
Shifting ratio (%)	3.04***	2.62***	1.65***
Shifts/shifting fund	3.50	3.31	3.54
Duration/Shift (years)	1.51	1.54	1.10

Table A8. Summary Statistics of Style Selection: Time-Varying Style Set

The table reports summary statistics of the Sharpe regression-based styles selection among the time-varying active peer benchmark styles by equity mutual funds. The Sharpe quadratic regression for fund i is conducted as $r_i = \sum_{s=1}^{S} \beta_s r_s + \varepsilon_i$, *subject to* $\sum \beta_s = 1$ and $\beta_s \geq 0$ over each of the three decades from January 1991 to December 2020. r_s is the return series of style *s,* the time-varying style set S is selected by a two-step LASSO procedure among last-decade investable styles. β_s is defined as the weight of fund i on style s. Mutual funds are sorted into three groups based on fund size: the largest 30% funds, the medium 40% funds and the smallest 30% funds. This table reports the number of indexes selected by individual funds.

	Number of styles invested by mutual funds									
	1	2	3	4	5	6	7	8	9	10
Panel A: whole period (1991–2020)										
Number of funds	107	378	995	1,391	1,393	734	265	65	19	2
% of total funds	2.00	7.07	18.60	26.00	26.04	13.72	4.95	1.22	0.36	0.04
Small funds (%)	0.65	3.01	6.09	7.87	6.66	3.87	1.40	0.34	0.07	0.02
Medium (%)	0.86	2.86	7.14	10.23	11.10	5.55	1.85	0.34	0.06	0.02
Large funds (%)	0.49	1.20	5.37	7.91	8.28	4.30	1.70	0.54	0.22	0.00
Panel B: 1991–2000										
Number of funds	15	208	348	562	562	295	89	13	0	NA
% of total funds	0.72	9.94	16.63	26.86	26.86	14.10	4.25	0.62	0.00	NA
Small funds (%)	0.19	3.11	5.50	7.98	8.22	3.78	1.10	0.10	0.19	NA
Medium (%)	0.48	4.73	6.69	10.42	10.42	5.40	1.67	0.24	0.48	NA
Large funds (%)	0.05	2.10	4.45	8.46	8.22	4.92	1.00	0.29	0.05	NA
Panel C: 2001–2010										
Number of funds	63	138	446	892	1,067	686	181	23	1	NA
% of total funds	1.80	3.95	12.75	25.51	30.51	19.62	5.18	0.66	0.03	NA
Small funds (%)	0.71	1.74	5.00	7.89	7.86	5.26	1.37	0.14	0.00	NA
Medium (%)	0.26	0.89	2.86	6.69	10.27	7.06	1.72	0.26	0.00	NA
Large funds (%)	0.26	0.89	2.86	6.69	10.27	7.06	1.72	0.26	0.00	NA
Panel D: 2011–2020										
Number of funds	79	275	731	917	911	482	195	58	18	2
% of total funds	2.15	7.50	19.93	25.00	24.84	13.14	5.32	1.58	0.49	0.05
Small funds (%)	0.87	3.76	6.19	7.01	6.60	41.60	1.58	0.41	0.11	0.03
Medium (%)	0.85	2.62	8.04	10.17	10.11	5.48	2.10	0.52	0.11	0.03
Large funds (%)	0.44	1.12	5.70	7.82	8.12	4.23	1.64	0.65	0.27	0.00