Hedge Fund Manager Skill and Style-Shifting

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Hedge Fund Manager Skill and Style-Shifting

Abstract

Utilizing a novel style identification procedure, we show that style-shifting is a dynamic strategy commonly employed by hedge fund managers. Three quarters of hedge funds shifted their investment styles at least once over the period from January 1994 to December 2013. We perform empirical tests of two hypotheses for the motivations of hedge fund style-shifting, namely backward-looking and forward-looking hypotheses. We find no evidence that style-shifting funds are backward-looking. Instead, we show evidence that managers of style-shifting funds exhibit both style-timing ability and the skill of generating abnormal returns in new styles. The new styles that hedge funds shift to on average outperform their old styles by 0.76% and style-shifting funds on average outperform their new style benchmark by 1.10% over the subsequent 12-month horizon. Finally, we show that small funds, winner funds, and funds with net inflows are more likely to shift styles.

Keywords: Hedge funds; Style-shifting; Fund manager skill; Fund performance; Fund flow

JEL Classification: G11, G23

1. Introduction

The hedge fund industry is known for innovation, speculation, high leverage, derivative usage, and dynamic trading (e.g. Cao, Liang, Lo, and Petrasek, 2017; Cao, Chen, Goetzmann, and Liang, 2018; among others). Nevertheless, it is important to examine whether hedge fund managers possess skills and, if any, what exactly these skills are. The literature has proposed approaches for the attribution of active portfolio performance. Based on portfolio holdings, Brinson, Hood and Beebower (1995) argue that fund performance can be attributed to passive strategy investment, market timing and security selection. Daniel, Grinblatt, Titman, and Wermers (1997) further propose the characteristic-based DGTW skill measures, namely, "characteristic timing" "characteristic selectivity" and "average style", by matching stocks held in the portfolios against the size, book-to-market, and momentum benchmarks. Lo (2008) proposes a new measure for active portfolio management that captures both the static and dynamic contributions of a portfolio manager's decisions. This measure decomposes a portfolio's expected return into two distinct components: a static weighted-average of the individual securities' expected returns, and the sum of covariance between the returns and portfolio weights to reflect the manager's dynamic choices. Extending the performance attribution literature, in this paper we evaluate hedge fund managers' skill by decomposing the performance of style-shifting funds into two components, namely the gain from fund managers' style-timing ability or their ability to ride on style momentum, and the gain from fund managers' expertise in the new styles.

Hedge fund investment styles differ dramatically from traditional buy-and-hold strategies. Each style represents unique investment opportunities and risk profile for investors (Brown, Goetzmann and Ibbotson, 1999; Fung and Hsieh, 1997, 2004; Bollen and Whaley, 2009). Fund managers choose an investment style that most appropriately matches their expertise and investment philosophy. Accordingly, their performance is evaluated relative to their peers in the same style. However, hedge funds may choose to shift investment styles when the investment environment changes. Fung and Hsieh (1997, 1999, 2004), Bollen and Whaley (2009), and Cai and Liang (2012) document evidence that hedge funds' investment styles are dynamic. For example, Passport Capital, founded by

John Burbank in 2000, shifted its style almost every year (14 times) over the period from 2000 to 2018.[1] Although the literature provides evidence that hedge fund managers shift their investment styles, it is not clear what drives them to make these shifts and, more importantly, what are the consequences of style-shifting on fund performance.

Identifying a hedge fund's true investment style is an essential prerequisite for the analysis of hedge funds' style-shifting decisions. The literature documents that a hedge fund' self-reported investment style, which is a snapshot of the fund's style during the most recent reporting period, may not be very informative. Using the Lipper Hedge Fund Database (TASS), a comprehensive hedge fund database, over the period from January 1994 to December 2013, we implement a novel approach to identify hedge fund style shifting. Specifically, we employ the principal component analysis (PCA) approach proposed by Pukthuanthong and Roll (2009) to construct 20 out-of-sample PCs as proxies of hedge fund styles. The corresponding 20 eigenvalues cumulatively explain more than 95% of the cross-sectional variation of hedge fund returns. We show that the out-of-sample style proxies are stable over time and across subsamples with very low correlations with each other. We identify hedge fund styles based on the highest correlation among those between fund returns and out-of-sample PCs and identify style-shifting funds if a style change occurs between quarter t and quarter t-2. The results show that style-shifting is a common strategy among hedge funds. Out of the 2,875 self-reported single-strategy funds, on average 7.7% of funds shift their styles per quarter and funds are more likely to shift styles during a down market and during periods of high aggregated flows to the hedge fund industry.

The key research questions of our study are: why do hedge fund managers shift investment styles and, more importantly, do style-shifting funds deliver superior performance? The literature suggests that hedge fund managers may shift investment styles due to different reasons. For example, unskilled fund managers may be backward-looking as they chase styles with high past performance and popularity. On the other hand, skilled managers may be forward-looking as they shift to styles with better future performance and better investment opportunities. These

[1] Details on Passport Capital's style-shifting can be found at https://www.passportcapital.com/what-we-do. Its performance summary is available at https://www.bloomberg.com /news/articles/2017-12-12/passport-to-shut-global-hedge-fund-after-unacceptable-returns and https://www.zerohedge. com/news/2017-08-13/passport-global-slammed-over-60-redemptions-q2.

reasons are not necessarily mutually exclusive. For a more complete literature review, please refer to Section 2. We categorize hedge fund style-shifting motivations into the following two hypotheses:

Backward-looking: Fund managers shift to new styles solely based on the past popularity and performance of these styles.

Forward-looking: Fund managers shift to new styles because they predict that the new style will outperform the current style and/or they have better abilities to invest in new styles.

These two hypotheses have distinct implications on style popularity, style performance, and fund performance during the pre- and post-shifting periods. The backward-looking hypothesis implies that new styles are more popular and deliver higher returns than old styles before, but not necessarily after, style shifts. The forward-looking hypothesis implies that new styles deliver higher returns than old styles after, but not necessarily before, style shifts and/or fund managers are able to generate positive abnormal returns against new style benchmarks. In other words, managers of style-shifting funds have the ability to time the outperformance of new styles in the future and/or outperform their peers in the new style. At the minimum, i.e., in the absence of managerial skills, the forward-looking hypothesis implies that style-shifting funds will do better in the new styles than they would have in the old styles had they not shifted styles. We propose a performance decomposition following Brinson, Hood and Beebower (1995) to explore whether style-shifting funds improve their performance and whether the outperformance is attributed to fund managers' style timing skill or their expertise in new styles, or both.

We first test the backward-looking versus the forward-looking hypotheses by comparing new styles' popularity and performance with those of old styles over the pre- and post-shifting periods. Our results show that based on net shift-in ratio, the new styles that funds shift to are on average more popular than old styles over the three months preceding and following style shifts. However, we find no evidence that style-shifting funds chase past style performance. The average cumulative return of old styles over the 12 months prior to style shifts is 6.95%, while that of new styles during the same period is 6.30%. The difference is statistically insignificant (t=-1.40). Instead, we find that, consistent with the forward-looking hypothesis, style-shifting funds exhibit the ability to time the outperformance of new styles. The average cumulative return of new styles over the 12 months following the shifts is about 6.52%, which is 0.76% higher than that of old styles. The difference is statistically significant (t=2.04). In a multivariate analysis, we regress future return spreads between new and old styles on a style-shifting dummy by controlling for past style return spreads and past returns of style-shifting funds. The results show that style-shifting dummy has a significantly positive relation with style return spreads over the six to 12 months following the shifts, evidence that style-shifting fund managers have the ability of shifting to outperforming styles.

We then test whether style-shifting fund managers have the skill of generating positive abnormal returns in new styles. First, we examine the returns of style-shifting funds and compare their performance with their peers in the same style and also with non-shifting funds. The results suggest that, consistent with the forward-looking hypothesis, style-shifting funds outperform their peer funds in both new and old styles. Specifically, over the 12 months preceding style shifts, style-shifting funds deliver an average return of 9.85% and outperform their peer funds by 2.49% (t=3.56). More importantly, over the 12 months following style shifts, style-shifting funds outperform their peers by 1.10% (t=2.18). In addition, style-shifting funds also outperform non-shifting funds over both pre- and post-shifting periods. The difference in abnormal returns between style-shifting funds and non-shifting funds over the 12 months following style shifts is 1.79% and statistically significant (t=2.06). Over the same period, the Sharpe ratio for shifting funds (0.51) is also significantly higher than that of non-shifting funds (0.41). Second, we perform regressions of hedge funds' future abnormal returns on a style-shifting dummy by controlling for fund characteristics. The results show that the style-shifting dummy is positively related to fund abnormal returns over three- to 12-month horizons following style shifts.

Taken together, both the style-level and fund-level analyses support the forward-looking hypothesis. That is, style-shifting funds exhibit both the ability to time the outperformance of new styles and the skill of generating positive abnormal returns in new styles. We further investigate the relative contributions of these two skills to the total gain of style-shifting. Using the performance attribution approach mentioned above, we show that style-shifting funds on average outperform their peers in old styles by 0.54%, 1.12% and 1.86% over the subsequent three, six and 12 months, respectively, out of which 0.46%, 0.69% and 1.10% are attributed to fund managers' expertise in new styles, respectively. The results suggest that fund managers' expertise in new styles is likely the primary motivation of style-shifting.

We perform a number of robustness checks and confirm our main findings. We make our best efforts to minimize the impact of potential sample biases on our style-shifting analyses, including selection bias, survivorship bias, and backfilling bias (Fung and Hsieh, 2000; Agarwal, Fos, and Jiang, 2013; Cao, Chen, Liang, and Lo, 2013). We follow the convention in the hedge fund literature to include both live and defunct funds to mitigate the impact of survivorship bias. The attrition rate of our fund sample is similar to that in existing studies (e.g. Liang, 2000). To examine the extent to which potential survivorship bias may affect our empirical findings, we randomly draw a number of hedge funds, equal to the attrition rate multiplied by the total number of funds in our sample, and then either remove them from or add them to the original sample. The shifting ratios based on the new samples are close to those based on the original sample, implying that the impact of survivorship bias is small. To evaluate the impact of potential backfilling bias, we delete observations before the date a fund is added to the TASS database and replicate our analyses. We also rule out the possibility that our findings are attributed to fund manager turnover.[2] Moreover, as a robustness check we replicate our main analysis based on the top eight out-of-sample PCs as proxies of investment styles, which cumulatively explain about 74% of the return variation across all hedge funds. The results are consistent with those based on the top 20 out-of-sample PCs. We further perform our main analysis using an alternative style identification procedure, similar to that in Brown and Goetzmann (1997, 2003) and Sun, Wang, and Zheng (2012), to identify fund styles based on the highest correlation among all correlations between fund returns and style returns. The results based on this style identification procedure are similar to our main findings.

In addition, we extend our single-style shifting analysis to multi-style shifting analysis under a more general setting. We employ the quadratic regression proposed by Sharpe (1992) to conduct a style-shifting analysis where funds may invest in multiple styles. Specifically, we consider all 5,375 qualified funds in the TASS database, including self-reported individual funds and funds of funds, and allow funds to allocate capital among their top five styles. For each fund, we regress fund excess returns on style returns over the most recent 24 months, where we impose the same constraints as in Sharpe (1992), i.e., the weight of each fund on each style is between 0 and 100% and the sum of all style weights is equal to 100%. We define multi-style-shifting funds as those with large shifts of

[2] Over a 10-year span (half of the sample period), there is a small difference in fund manager turnover ratio between style-shifting funds (0.68% per quarter) and non-shifting funds (0.59% per quarter).

style weights over two consecutive quarters. Our results show that multi-style-shifting hedge funds deliver higher returns in subsequent periods and also exhibit both style-timing ability and style expertise. The evidence again is consistent with the forward-looking hypothesis.

Finally, we investigate the determinants of fund managers' style-shifting decisions. We consider fund characteristics related to operational constraint, incentive, past performance and fund flow as well as fund size and age. We find that the lockup and redemption notice periods are longer for style-shifting funds than for non-shifting funds. Style-shifting funds require higher minimum investments than non-shifting funds, have higher incentive fees, are less levered and are more likely to have high-water-market covenants than non-shifting funds. Moreover, style-shifting funds are relatively smaller, older, and have better past performance as well as higher inflows than non-shifting funds. We then perform a Probit regression of style-shifting dummy on lagged fund characteristics in a multivariate setting. The results confirm that small funds, winner funds, and funds with net inflows are more likely to shift styles.

Our study contributes to the literature in several dimensions. First, we introduce a novel identification procedure of hedge fund styles using the out-of-sample PCs proposed in Pukthuanthong and Roll (2009) as proxies of styles. Compared with the existing procedures proposed in the hedge fund literature, e.g., the factor-exposure based approach by Brown and Goetzmann (2003), and Bollen and Whaley (2009), and the return-correlation based approach by Sun, Wang and Zheng (2012), the styles identified from out-of-sample PCs have low correlations with each other and explain a large fraction of cross-sectional variation of hedge fund returns. We also show that these styles are stable over time and across subsamples. Second, we extend the literature and perform a comprehensive analysis on hedge fund managers' style-shifting decisions. Our paper is closely related to Bollen and Whaley (2009) who find evidence that the factor loadings of hedge fund returns are time-varying. The style-shifting identification procedure implemented in our study requires no assumption of an ex ante number of shifts or structural changes and allows us to investigate how hedge funds shift in or out of specific investment styles. This is useful because it allows us to decompose fund performance into style-timing ability and style expertise. Our analysis is also related to studies on hedge fund manager skill, such as Brunnermeier and Nagel (2004), Griffin and Xu (2009), Titman and Tiu (2011), and Sun, Wang, and Zheng (2012). We extend these studies by documenting evidence that hedge fund managers shift investment strategies and style-shifting managers are skilled. Third, our study extends the literature on performance attribution (Brinson, Hood and Beebower, 1995; Daniel, Grinblatt, Titman, and Wermers, 1997; Lo, 2008). We propose fund performance decomposition to measure hedge fund managers' style-timing ability and style expertise. As such, we are able to examine the extent to which the superior performance of style-shifting funds is attributed to fund managers' style-timing ability or fund managers' style expertise. Finally, our study highlights the differences between hedge fund managers and mutual fund managers. Several studies examine the risk-shifting behavior of mutual fund managers and document evidence that risk-shifting is mostly driven by poor past performance and agency concerns (Brown, Harlow, and Starks, 1996; Chavalier and Ellison, 1997; Chan, Chen and Lakonishok, 2002; Elton, Gruber and Blake, 2003; Kempfl, Ruenzi and Thiele, 2009; and Huang, Sialm and Zhang, 2011). Moreover, Huang, Sialm and Zhang (2011) find that risk-shifting mutual funds underperform other funds in subsequent periods. Our study suggests that style-shifting by hedge funds is forward-looking and motivated by fund managers' skill to time the outperformance of new styles and to exert expertise in new styles.

The remainder of this paper is organized as follows. Section 2 briefly reviews the literature and develops hypotheses for style-shifting motivations. Section 3 describes the data as well as methodology for fund style identification and fund performance decomposition. Section 4 reports the main empirical findings and Section 5 performs robustness checks and additional analyses. Section 6 concludes.

2. Literature Review and Hypothesis Development

It is well-known that hedge funds' trading strategies are dynamic and that hedge fund managers may take advantage of their managerial discretion to shift investment styles (e.g., Fung and Hsieh, 1997, 2001, 2004; Brown and Goetzmann, 2003; Agarwal, Daniel, and Naik, 2009; Bollen and Whaley, 2009; Cai and Liang, 2012). The literature presents alternative hypotheses to explain why hedge fund managers shift their investment styles. On the one hand, as reported in 2017 by Katherine Burton of Bloomberg News, some funds may be forced to shift styles for survival if current styles are not profitable.[3] Consistent with this observation, Chan, Chen and Lakonishok (2002),

[3] https://www.bloomberg.com/news/articles/2017-12-12/what-hedge-funds-will-do-after-the-hedge-fund-model-dies.

O'Connell and Teo (2009), Huang, Sialm and Zhang (2011), and Aragon and Nanda (2012), among others, show that institutional investors may change their risk profiles after experiencing bad performance. Moreover, Brown, Goetzmann, and Park (2001) find that hedge fund managers facing financial trouble may gamble on investments and take different strategies. Getmansky (2012) shows that hedge funds within a capacity-constrained style are more likely to shift style. Getmansky (2012) and ter Horst and Salganik (2014) find that fund flows are impacted by style preference trends. Theoretically, Glode and Green (2011) argue that unskilled hedge fund managers have incentives to shift investment styles to exploit the information spillover among hedge funds. Huang, Sialm and Zhang (2011) argue that unskilled mutual funds may shift styles due to agency concerns and underperformance relative to other funds. These studies suggest that fund managers lacking skills may be backward-looking and shift to hot styles.

On the other hand, skilled fund managers may shift styles when they predict that new styles will outperform current styles and/or their expertise ensures that they can generate better returns in the new styles. Generally, hedge fund managers have higher managerial discretion relative to mutual fund or pension fund managers, with fewer constraints for skilled managers to switch investment strategies. For example, Brunnermeier and Nagel (2004) document that hedge fund managers shifted their investments in technology stocks to time dot com bubble in 2000 and that these stock-holding shifts lead to outperformance. Agarwal, Daniel, and Naik (2009) find that fund's managerial discretion, proxied by longer lockup and redemption periods, is positively related to fund returns or alphas. Bollen and Whaley (2009) apply a structural change regression methodology to hedge fund return factor models and find evidence of both style shifts and superior performance delivered by style-shifting funds. Jagannathan, Malakhov, and Novikov (2010) show evidence that superior hedge funds have "hot hands". Griffin and Xu (2009) find that hedge funds exhibit stock-picking ability by switching their stock holdings. Titman and Tiu (2011) document evidence that hedge funds with lower R-squares with respect to systematic risk factors deliver higher Sharpe ratios and alphas. Sun, Wang, and Zheng (2012) suggest that the correlations of skilled managers' fund returns with style index returns are lower than those of other funds' returns. They explain these low correlations as a reflection of some funds' strategic deviation from peer funds within the same style and find that the deviating funds outperform their peers. These studies suggest that hedge fund managers shift their investment styles because they are forward-looking and have the expertise to generate higher returns in the new styles.

We categorize the motivations of style-shifting into *backward-looking* and *forward-looking* hypotheses. The two hypotheses have different implications regarding style popularity as well as expected style and fund performance. According to the backward-looking hypothesis, new styles are popular during pre-shifting periods but not necessarily during post-shifting periods. Hedge funds' shifting decisions are positively related to the outperformance of new styles in recent periods but not necessarily in future periods. In contrast, the forward-looking hypothesis implies that new styles become popular during post-shifting periods but not necessarily during pre-shifting periods. More importantly, fund managers have the ability to predict that new styles will deliver better performance than old styles and/or they have the skill to generate positive abnormal returns relative to new style benchmarks. We do not rule out the possibility that the timing ability on future style performance may be related to factor momentum (Barberis and Shleifer, 2003). At the minimum and in the absence of managerial skills, the forward-looking hypothesis implies that style-shifting funds will do better in the new styles than they would have in the old styles had they not shifted styles. In our subsequent analysis, we refer to the skill of successfully timing the outperformance of new styles as *style timing ability* and the skill of generating positive abnormal returns in the new style as *style expertise*.

Lastly, fund flows may play an important role in funds' style-shifting decisions. Berk and Green (2004), Lan, Wang, and Yang (2013) propose theoretical models to show that fund flows significantly influence a fund's trading strategy. The literature provides evidence that fund investors have a significant impact on the manager's asset allocation. Sun, Wang, and Zheng (2012) find that historical flows are positively related to the fund's strategy choice. Getmansky (2012) and ter Horst and Salganik (2014) document that fund investors chase hot styles and that skilled managers attract more fund flows. Fung, Hsieh, Naik, and Ramadorai (2008), Li, Zhang, and Zhao (2011) find that winner funds attract more fund flows than other funds. Similarly, the backward-looking and forward-looking hypotheses have different implications for fund flows. The backward-looking hypothesis implies that style-shifting funds may be motivated by low fund flows relative to their peers in old styles. The forward-looking hypothesis, in contrast, suggests that shifting funds may actively seek additional investment opportunities given net fund inflows. Finally, both hypotheses suggest that funds are more likely shift styles during periods of high aggregate fund flows to the hedge fund industry.

3. Data and Methodology

3.1 Data

The hedge fund data is collected from TASS, a comprehensive and widely used database in the hedge fund literature. We follow the main steps described in Cao, Chen, Liang, and Lo (2013) to minimize the impact of sample biases documented in Ackermann, McEnally, and Ravenscraft (1999) and Fung and Hsieh (2000) on our analysis, including selection bias, backfilling bias, and survivorship bias. We remove the first 12 observations, and include both live and defunct funds and focus on the period from January 1994 onward. We restrict our sample to funds that have an asset under management (AUM) greater than $10 million, report net returns on a monthly basis, and have 36 or more return records in the database.[4] We use all qualified funds in our sample to construct out-of-sample PCs. We include only self-reported single-strategy funds in the single-style shifting analysis in Section 4 and all qualified TASS funds in the multi-style-shifting analysis in Section 5.2. The self-reported single styles in TASS include convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event-driven, fixed income arbitrage, global macro, long-short equity, and managed futures. We end up with 5,375 funds over the sample period from January 1994 to December 2013 for the estimation of out-of-sample PCs and 2,875 single-strategy funds for single-style-shifting analysis.

Table 1 reports summary statistics of the characteristics of self-reported single-strategy funds, including fund return, return volatility, Sharpe ratio, fund flows, and AUM. Return volatility is the standard deviation of fund returns over the most recent 12 months up to the current month. Following the hedge fund literature (e.g. Sun, Wang and Zheng, 2012), fund flow is defined as the AUM at the end of the current month minus AUM at the end of the prior month multiplied by the fund return over the month, scaled by AUM in the prior month: $(AUM_{i,t} - AUM_{i,t-1} * (1 + R_{i,t}))/AUM_{i,t-1}$. Sharpe ratio is the average of fund returns in excess of the one-month T-bill rates over the past 12 months divided by the standard deviation of the excess returns over the same period. Fund age is defined as the number of years between the inception date and the last month in the sample. The ages of funds with missing inception dates are defined based on the number of observations of fund returns in the TASS database. Table 1

[4] Our findings hold when the threshold is $5 million.

shows that, on average, hedge funds generate a net-of-fee return of 0.87% per month, with a volatility of 4.71%. The average fund flow to all hedge funds each month is 1.06%. The average age of all funds is about 12 years. Managers charge investors an average (median) management fee of 1.47% (1.30%), and an average (median) incentive fee of 17.95% (20%). About 61% of hedge funds have high-water-mark provisions and two-thirds of funds are levered. The average lockup period is about three months and the average length of the redemption notice is about 30 days. The average minimum investment requirement is $0.92 million.

3.2. Methodology

In this section, we briefly describe the methodology used to identify hedge funds' investment styles and the return decomposition procedure used to investigate the skills of style-shifting funds.

3.2.1 Fund Style Identification

In the context of our analysis, correctly identifying each fund's style dynamics is critical. We implement two procedures to identify hedge funds' styles rather than using funds' self-reported styles for two reasons. First, although the TASS database provides comprehensive fund information, it only provides a snapshot of funds' most recent investment styles at the time of download (e.g. Bollen and Whaley, 2009; Sun, Wang, and Zheng, 2012). Second, previous studies (e.g. Brown and Goetzmann, 2003; Bollen and Whaley, 2009; Sun, Wang, and Zheng, 2012; among others) suggest that self-reporting hedge fund style is voluntary and may be subject to errors.

Two common methods are used in existing studies to identify fund investment styles and both are based on the idea that fund returns are more likely to co-move with the returns of funds within the same style (Barberis and Shleifer, 2003). Neither is ideal because both approaches require simultaneous estimation of investment styles and funds' styles. In this study, we propose a new style identification procedure based on the work by Pukthuanthong and Roll (2009). In this approach, we employ a PCA analysis of hedge fund returns to generate time series of out-of-sample PCs as proxies of investment styles. This approach allows us to construct style proxies using all funds in the TASS database, including individual funds, funds of funds and style-undefined funds. According to Connor and Korajczyk (1986, 1988), PCs of hedge fund returns are comparable to risk factor realizations. The main advantages of the PCA approach are that it is computationally efficient, and the out-of-sample PCs have low correlations with each other and are time-varying (Pukthuanthong and Roll, 2009). These features allow us to effectively capture the dynamic exposure to risk factors and the risk profile of hedge fund returns. As shown in later sections, style proxies based on the PCA approach are stable over time and across subsamples of hedge funds.

Specifically, the identification of a hedge fund's style involves two steps. In the first step, we estimate the eigenvalues of the balanced monthly returns of all qualified TASS funds over the most recent eight quarters. We sort the eigenvectors from the largest to the smallest and pick the first 20 eigenvalues to generate the out-of-sample PCs from returns of all funds in the subsequent quarter. On average, the first 20 eigenvalues cumulatively explain more than 95% of the cross-sectional variation of hedge fund returns. In the second step, we identify styles for self-reported single-strategy funds based on the pairwise Pearson correlations between fund returns and the 20 out-of-sample PCs over a rolling window of eight quarters. That is, for each quarter, we calculate and rank the Pearson pairwise correlations of a fund's returns with the 20 PCs, respectively, over the most recent 24 months, and define the PC with the highest Pearson correlation as the style of the fund. A fund is assumed to shift styles when its style in quarter t is different from its style in quarter t-2. For more details, please refer to Appendix A.

We use the procedure by Sun, Wang, and Zheng (2012) as an alternative identification procedure. This correlation-based approach identifies a fund's style as the style whose index return has the highest correlation with fund return. For each quarter, we calculate and rank the correlations of a fund's returns with the returns of each of the eight unique style indexes (defined as the average return across all funds within a style) over the most recent 24 months, and define the style with the highest correlation as the style of the fund. For more details, please refer to Online Appendix Section A1.

3.2.2 Style-Shifting Motivation: Style-Timing and Style-Expertise

The literature has proposed several approaches for performance attribution. For example, Brinson, Hood and Beebower (1995) show that fund performance can be attributed to passive strategy return, gain from market timing, and gain from security selection. Daniel, Grinblatt, Titman, and Wermers (1997) propose the characteristic-based DGTW skill measures. Lo (2008) proposes a measure to capture both the static and dynamic contributions of a portfolio manager's decisions. In this section, we extend the approach by Brinson, Hood and Beebower (1995) and attribute the gain of style-shifting to fund managers' style-timing ability and expertise in new styles.

Specifically, let $R_{i,[t+1,t+k]}^{New}$ denote style-shifting fund *i*'s cumulative return over the period [*t*+1, *t*+*k*] after the fund shifts to a new style in period *t* and $R_{[t+1,t+k]}^{Old}$ be the cumulative benchmark return of the "Old" style over the period [*t*+1, *t*+*k*]. Fund return over the period [*t*+1, *t*+*k*] can be decomposed as $R_{i,[t+1,t+k]}^{New} = R_{[t+1,t+k]}^{Old}$ + $(R_{i,[t+1,t+k]}^{New} - R_{[t+1,t+k]}^{Old})$, where the first term measures the return of passively investing in the "Old" style, and the second term measures the total gain from actively investing in the "New" style. For a non-shifting fund that invests passively in the "Old style", fund return would be $R_{[t+1,t+k]}^{Old}$. The total gain from actively investing in the "New" style, i.e., $R_{i,[t+1,t+k]}^{New} - R_{[t+1,t+k]}^{Old}$ can be further decomposed into the gain from fund managers' style-timing ability and the gain from fund managers' expertise in the new style:

$$\underbrace{R_{i,[t+1,t+k]}^{New} - R_{[t+1,t+k]}^{Old}}_{\text{Total style-shifting gain}} = \underbrace{\left(R_{[t+1,t+k]}^{New} - R_{[t+1,t+k]}^{Old}\right)}_{\text{Gain of style-timing}} + \underbrace{\left(R_{i,[t+1,t+k]}^{New} - R_{[t+1,t+k]}^{New}\right)}_{\text{Gain of style expertise}}, \tag{1}$$

where $R_{[t+1,t+k]}^{New}$ is the cumulative benchmark return of the "New" style over the period [*t*+1, *t*+*k*]. The first term in Eq. (1) measures the out- or under-performance of "New" style relative to "Old" style, and the second term measures the abnormal return of fund *i* relative to its "New" style benchmark.

4. Main Empirical Analyses

Our main analysis focuses on single-style shifting, assuming that funds only invest in a single style in each period. The sample only contains self-reported single-strategy funds in the TASS database. In Section 5.2, we conduct multi-style shifting analyses by relaxing this assumption and using all qualified TASS funds, including singe- and multiple-strategy funds, funds of funds and strategy-undefined funds.

4.1 Style Analysis

In this section, we summarize the empirical results of the style proxies and corresponding index returns. The out-of-sample PCs are based on all qualified hedge funds in the TASS database, which helps recover the risk factors common to hedge fund returns. We conduct several analyses to test whether the out-of-sample PCs are robust proxies of investment styles. We first examine whether a reasonable number of in-sample eigenvalues are able to explain a large portion of return variation of all hedge funds. Figure 1 plots the average cumulative power of the top 20 eigenvalues over the whole sample period and Figure 2 plots the time series of the cumulative power of these eigenvalues. The eigenvalues are sorted from the largest to the smallest. The figures show that the first eigenvalue can explain, on average, about 34% of the variation of hedge fund returns with a range between 20% and 40% and the top 20 eigenvalues cumulatively explain more than 95% of the variation. Table 2 reports the summary statistics of the top 20 out-of-sample PCs. The results show large variations across the PCs; the 1st PC has the largest mean and standard deviation while the 19th PC has a negative mean.

We further examine whether the 20 out-of-sample PCs are orthogonal to each other as the in-sample PCs. We compute the pairwise correlations among all out-of-sample PCs and the results are reported in Table A1 in the Online Appendix. The pairwise correlations are mostly small and insignificant, suggesting that the out-of-sample PCs capture distinct risk factors of hedge fund returns. We also test whether the principal components are stable over time and across fund subsamples. We test the time-serial stability by examining whether the PCs based on 2-year and 3-year rolling windows are highly correlated. The pairwise correlations between the two sets of PCs are reported in the 3rd column of Table A2 in the Online Appendix, which shows that the correlation between the first pair of PCs is close to 100%, and the top eight pairs of PCs are also highly correlated with each other. This is evidence that the out-of-sample PCs are robust to using 2-year or 3-year rolling window in our estimation. In the cross-sectional stability test, we split the whole hedge fund sample into two equal subsamples and conduct the principal component analysis for each subsample. The pairwise correlations between the two sets of PCs are reported in the 8th column of Table A2 and suggest that the PCs are robust across subsamples. The means and standard deviations of the first six pairs of PCs are similar and highly positively correlated with each other. This is evidence that the out-of-sample PCs are robust in capturing risk factors common to hedge fund returns.

Next, we conduct style identification analysis using the out-of-sample PCs for self-reported single-strategy funds. We identify hedge funds' styles in each quarter using the style identification procedure in Section 3.2.1 and identify whether a fund shifts its style in a given quarter. Based on the identified style for each fund in each quarter, we define style return as the AUM-weighted return of all funds within the same style. Columns 6-8 of Table 2 report the mean, median and standard deviation of style returns over the whole sample period. They are comparable to the conventional Fung-Hsieh factors and Fama-French risk factors in terms of magnitude and standard deviation.

Before summarizing the results on hedge fund style-shifting, we test the effectiveness of the style identification procedure from three perspectives. First, we examine the correlations of style-shifting funds' returns with their old and new styles, respectively, during style-shifting periods. The time series averages of the cross-sectional mean and median of these correlations are reported in the first three columns of Table A3 in the Online Appendix. The returns of style-shifting funds have an average correlation of 0.29 with old styles and 0.52 with new styles, a difference of 0.23. For each unique investment style, the differences between correlations with new styles and those with old styles are all positive and range from 0.15 (for the 1st style) to 0.31 (for the 8th style). Second, we examine the correlations of shifting funds' returns with their own styles and with other styles during periods when they do not shift styles. The results are reported in columns 4-6 of Table A3 and show that the correlations of shifting fund returns with their own styles are large (between 0.45 and 0.66), while the average correlations with other styles are close to zero. Moreover, compared to the correlation of shifting funds' returns with their new styles during periods when they shift styles (column 1), the average correlation of shifting funds' returns with their own styles during periods when they do not shift styles is higher at 0.60 (column 4). Lastly, we examine the correlations of non-shifting funds' returns with their own and other styles over the whole sample period and report the results in the last three columns in Table A3. Across all non-shifting funds, the average correlation with their own styles is 0.71, which is higher than that of shifting funds (columns 1 and 4), and the average correlation with other styles is 0.03.

4.2 Evidence of Style-Shifting

In this section, we first count the number of style-shifting funds and compute the fraction of style-shifting funds in each period. Table 3 reports summary statistics of style shifts for all qualified funds with self-reported single-strategy as well as style shifts for each investment style. Panel A reports the number of hedge funds per quarter for the whole sample as well as for each investment style and the corresponding style-shifting ratio. The first and second columns report the time series averages of the number of hedge funds and the number of style-shifting funds (including both funds shifting into and out of a style) in each quarter. The style-shifting ratio in a quarter is defined as the number of style-shifting funds divided by the total number of funds in that quarter, and the time series average of this ratio is reported in the last column. On average, there are 1,169 individual hedge funds in each quarter, and 7.68% of them, or equivalently 90 funds, shift styles. Style-shifting is present across all styles but with a large variation: funds of the 9th style have the highest shifting ratio (16.11%) while funds of the 1st style have the lowest (3.52%). Given the fact that the first PC represents a predominant style, it is not surprising that it has the lowest shifting ratio. Table A4 in the Online Appendix reports the transition matrix of style-shifting and suggests that funds in the 1st style do not frequently shift styles, while funds in other styles are more likely to shift to the 1st style (based on the 1st PC). Specifically, the average ratios for funds in the 1st style shifting to other styles are equal to or lower than 0.5% while the ratios for funds in other styles shifting to the 1st style vary between 1.65% (the 8th style) and 4.77% (the 3rd style). Panel B in Table 3 summarizes hedge funds' style shifting frequency. On average, a fund shifts its style 2.32 times throughout the sample period. Shifting funds stay in the new styles for an average of 1.76 years. Overall, Table 3 suggests that style-shifting is common in the hedge fund industry, consistent with the findings in previous studies (e.g., Bollen and Whaley, 2009; Cai and Liang, 2012; among others) and underscoring the importance of a further analysis of this dynamic strategy.

Hedge fund regulations became stricter in the second half of our sample period, particularly following the passage of Dodd-Frank Wall Street Reform and Consumer Protection Act in 2010 and the Securities and Exchange Commission requiring registered investment advisors to deliver the Part 2 of Form ADV to their customers with more information since 2011. Figure 3 plots the time series of the style-shifting ratio and suggests that style-shifting is not clustered in the first half of the sample period, evidence that regulation does not seem to deter hedge funds' style-shifting decisions.

Previous studies show that hedge fund trading strategies may be related to market conditions. Bollen and Whaley (2009) document evidence that macroeconomic conditions significantly affect style-shifting decisions. Liang (2001), Boyson, Stahel, and Stulz (2010), and Sadka (2010) document evidence that hedge fund performance is highly impacted by market liquidity conditions. Teo (2011), and Ben-David, Franzoni, and Moussawi (2012) find that hedge fund managers change their equity portfolio allocations when market conditions change. To examine the extent to which hedge fund managers' style-shifting decisions are impacted by market conditions, we split the sample period into two sub-periods: up-market and down-market. A quarter is defined as an up-market period if the average excess return on the market portfolio in the quarter is positive and a down-market period otherwise. We then test whether the average style-shifting ratio during the down-market periods differs from that during the up-market periods. The results are reported in the first three columns in Table A5 in the Online Appendix, which suggests that the style-shifting ratio is higher during the down-market periods than during the up-market periods. The average shifting ratio across all funds is 7.27% over the up-market periods and 8.38% over the down-market periods, and the difference in shifting ratio between the two market condition periods is statistically significant.

Existing studies show that investors' money flows may impact hedge funds' style-shifting decisions. Lan, Wang, and Yang (2013) argue that fund flows significantly impact a fund's investment strategy. Fung, Hsieh, Naik, and Ramadorai (2008), and Li, Zhang, and Zhao (2011) find that winner funds attract more fund flows. Sun, Wang and Zheng (2012) find that historical flows are positively related to a fund's strategic deviation from the peers in its style. We examine the extent to which fund flows may influence a fund's style-shifting decision by splitting the whole sample period into high- and low-flow subperiods using the median level of the aggregated fund flows to hedge funds. The results are reported in columns 4-6 of Table A5 in the Online Appendix and suggest that, on average, hedge funds are more likely to shift styles during high-flow periods than during low-flow periods. Nevertheless, the impact of fund flows on hedge funds' shifting decisions is small. The shifting ratio over all hedge funds in the sample is 7.87% during high-flow periods and 7.50% during low-flow periods.

4.3 Style-Chasing versus Style-Timing

Section 2 proposes two competing hypotheses to explain hedge funds' style-shifting decisions: backward-looking or forward-looking, and further proposes empirical analyses to differentiate the hypotheses from two perspectives. In this section, we conduct the first part of the analysis to differentiate the two hypotheses, that is, to investigate whether shifting funds chase past popular styles or time future outperforming styles. The backward-looking hypothesis implies that new styles are more popular and deliver higher returns than old styles during pre-shifting periods but not necessarily during post-shifting periods, i.e., shifting funds chase past popular styles. The forward-looking hypothesis predicts that new styles deliver higher returns than old styles during post-shifting periods but not necessarily during pre-shifting periods, i.e., shifting funds are able to time new styles.

We first examine the popularity of new styles relative to old styles by comparing the net shifting-in ratio of the two styles over pre- and post-shifting periods. At the end of each quarter, we compute the net shift-in ratio as the average shift-in ratio minus the average shift-out ratio across all new and old styles over the past and future three to 12 months, and compute the differences in net shift-in ratio between the new and old styles. The time series averages of these ratios are reported in Panel A of Table 4 and suggest that new styles are indeed more popular than old styles during periods both prior to and following style-shifting. The net shift-in ratio for new styles is 3.00% in the quarter just prior to the shifting quarter, compared to -2.48% for old styles. The difference between the new and old styles is statistically significant (t=5.18). The net shift-in ratio for new styles is 2.29% in the quarter following the shifting quarter, compared to -2.88% for old styles. The difference between the ratios for the new and old styles is statistically significant (t=11.00).

We further differentiate the two hypotheses by directly examining the difference in performance between new and old styles over both pre- and post-shifting periods. As discussed in Sections 2, the backward-looking hypothesis implies that new styles outperform old styles during pre-shifting periods but not necessarily during post-shifting periods. In contrast, the forward-looking hypothesis implies that the new styles outperform old styles during post-shifting periods but not necessarily during pre-shifting periods. In each month and for each style, we define style return as the average of the AUM-weighted returns of all funds in the same style. We then compute the cumulative style returns over the past three to 12 months and over the subsequent three to 12 months. The average returns for all new and old styles are reported in Panel B of Table 4, which shows that the average returns of new styles over the three to 12 months prior to style shifts are similar to those of old styles. In contrast, the average returns of new styles in the subsequent 12 months are significantly higher than those of old styles. Specifically, the cumulative return of new styles over the 12 months prior to style shifts is about 6.30%, compared to 6.95% for old styles. New styles generate an average cumulative return of 3.17% over the six-month horizon after style shifts, outperforming old styles by 43 bps (t=1.87), and 6.52% over the 12-month horizon after style shifts, outperforming old styles by 76 bps (t=2.04). These findings are consistent with the forward-looking hypothesis.

The results in Panel B of Table 4 imply that style-shifting funds have the ability to time the relative outperformance of new styles particularly over longer horizons. In the following, we perform further tests by regressing future return spreads between the new and old styles on a style-shifting dummy, controlling for the lagged spreads in style returns and the lagged shifting fund returns:

$$\Delta R_{[t+1,t+k]}^{New-Old} = c + \beta * SF_{i,t}^{Old\rightarrow New} + \delta^T X_t + \varepsilon_{i,t}, \tag{2}$$

where $\Delta R_{[t+1,t+k]}^{New-Old}$ denotes return spread between the new and old styles over the months [t+1, t+k], $SF_{i,t}^{Old\rightarrow New}$ is a shifting dummy variable that equals one if a fund shifts its style in a given quarter and zero otherwise, and X are control variables, including the return spread between new and old styles and the returns of style-shifting funds over the past three to 12 months. The forward-looking hypothesis suggests a positive β in Eq. (2). We perform analyses with k equal to three, six and 12, respectively, and report the results in Table 5. The first column for each time period reports the regression results after controlling for the return spread between the new and old styles and the second column reports the regression results after further controlling for the past returns of the shifting funds. The results show that the coefficients of lagged style return spread and shifting funds' past returns are significant. More importantly, the coefficient of the style-shifting dummy variable is positive in all regressions and significant for regressions based on six- and 12-month horizons. The results suggest that style-shifting funds have the ability to time the outperformance of new styles.

4.4 Style-Shifting and Style-Expertise

In this section, we further differentiate the backward-looking and forward-looking hypotheses by examining the performance of style-shifting funds relative to their peers in the new styles and relative to non-shifting funds. Following the discussions in Section 2, we first conduct univariate analysis to compare the performance of style-shifting funds with that of their peer funds in the same style and with that of non-shifting funds over both pre- and post-shifting periods. Then we perform multivariate regressions to test whether the style-shifting decision is associated with the fund's abnormal returns in subsequent periods by controlling for fund characteristics.

We divide hedge funds into style-shifting and non-shifting groups and compute the average fund returns and style-adjusted returns for both subsamples as well as their differences over the past and future three, six and 12 months. We also compute the cross-sectional means of fund return volatility, Sharpe ratio, information ratio, and Sortino ratio, and Fung-Hsieh 7-factor alpha over the past or future periods for style-shifting and non-shifting funds. Sharpe ratio is the average of fund returns in excess of the one-month T-bill rates over the past or future 12 months divided by the standard deviation of the excess returns over the same period, information ratio is the average of fund returns in excess of the corresponding style returns over the past or future 12 months divided by the standard deviation of the style-adjusted returns over the same period, and Sortino ratio is the average of fund returns in excess of the one-month T-bill rates divided by the downside standard deviation of the excess return from its mean over past or future 12 months. Fund alpha is computed as the intercept from the Fung and Hsieh 7-factor model over the most recent or subsequent 24 months. The time series average of each cross-sectional statistic is reported in Table 6 and suggests that style-shifting funds outperform both their peer funds and non-shifting funds during both the pre- and post-shifting periods. Specifically, over the 12 months prior to shift, style-shifting funds significantly outperform their peer funds by 2.49% and outperform non-shifting funds by 0.14% in fund return and 1.28% in style-adjusted fund return. Over the 12 months following the shift, they outperform their peers by 1.10% and outperform non-shifting funds by 0.91% in fund return and 1.79% in style-adjusted return. The average Sharpe ratio, information ratio, Sortino ratio, and Fung-Hsieh alpha delivered by style-shifting funds are significantly higher than those of non-shifting funds both before and after shifts. The results in Table 6 suggest that style-shifting funds have relatively better expertise than their peer funds and non-shifting funds.

Next, we investigate whether style-shifting funds attract more fund flows by examining the time series average of the cross-sectional mean of fund flows to style-shifting and non-shifting funds over the three to 12 months preceding and following style shift. In an untabulated table, we find that style-shifting funds attract more flows than their peers, while non-shifting funds attract less flows than their peers. For example, net fund flow to style-shifting funds over the three months prior to the shift is 2.37% (*t*=7.48), and 0.12% (*t*=2.54) higher than that of peer funds in the same style. The differences in fund flow between style-shifting and non-shifting funds, measured by both net fund flow and style-adjusted fund flow, are statistically significant.

Lastly, we perform a multivariate test of whether style-shifting decisions are associated with style-shifting funds' outperformance. We measure a fund's outperformance (i.e., abnormal return) as the cumulative fund returns minus the cumulative style returns over the same period. We regress fund abnormal returns on a style-shifting dummy, controlling for fund characteristics:

$$AR_{i,[t+1,t+k]} = c + \beta * SF_{i,t}^{Old \to New} + \delta^T X_t + \varepsilon_{i,t}, \tag{3}$$

where $AR_{i,[t+1,t+k]}$ denotes fund i's abnormal return over the months [t+1, t+k], $SF_{i,t}^{Old \to New}$ is the shifting dummy variable and X are fund characteristics included as control variables. We take k to be three, six and 12, respectively. The empirical results are reported in Table 7. The positive coefficients of funds' past return and return volatility suggest that these two fund characteristics predict funds' future performance. Fund flows can also predict future abnormal returns. The level of the management fee, the length of the redemption notice, and the minimum investment requirement also have power to predict funds' future abnormal returns, consistent with previous studies (e.g. Sun, Wang, and Zheng, 2012; Bali, Brown, and Caglayan, 2014). Fund size and age are also significant indicators of future abnormal returns while their predictive directions are opposite. More importantly, consistent with the findings in Table 6, Table 7 shows that the style-shifting dummy variable is significantly related to abnormal fund returns over future periods. In the regressions of three-month abnormal fund returns (the first two columns), the coefficient of the shifting dummy is 0.14 (t=1.87) in the first regression and 0.160 (t=1.53) in the second regression. This coefficient becomes 0.57 (t=4.12) and 0.36 (t=2.54), respectively, in the regressions of 12-month abnormal fund returns. To conclude, the results in Table 7 suggest that style-shifting improves funds' future performance.

4.5 Fund Return Decomposition: Style-Timing versus Style-Expertise

Our empirical results in previous sections are consistent with the forward-looking hypothesis; style-shifting funds exhibit both style-timing ability and expertise in new styles. In this section, we follow Eq. (1) and further determine the relative importance of these two skills by decomposing the total gain from style-shifting. Specifically, we compute the total style-shifting gain as well as the components of style-timing and style-expertise for all shifting funds over the subsequent three, six and 12 months. The time series averages of the cross-sectional mean of these gains are reported in Table 8. Panel A reports the results based on equal-weighted fund returns and Panel B reports the results based on AUM-weighted fund returns. For completeness, we also report the cumulative returns of the new and old styles over the same horizons. Panel A shows that, on average, style-shifting funds deliver 2.04% (t=6.67) over the three months following style shifts and 7.62% (t=5.49) over the 12 months following style shifts. The average cumulative returns of the new styles over the three, six and 12 months following style shifts are 1.58% (t=4.44), 3.17% (t=4.65) and 6.52% (t=5.14), respectively, while the average cumulative returns of the old styles are 1.50% (t=3.85), 2.74% (t=3.55) and 5.76% (t=4.40), respectively. The total gains from actively investing in new styles over the three, six and 12 months following style shifts are 0.54% (t=1.99), 1.12% (t=2.20) and 1.86% (t=2.05), respectively. The magnitudes suggest that style-shifting gains are also economically significant. Out of the total style-shifting gain over subsequent three, six and 12 months, the gain from style-timing are 0.08% (t=0.53), 0.43% (t=1.87) and 0.76% (t=2.04), respectively, and the gain from expertise in new styles are 0.46% (t=2.61), 0.69% (t=2.37) and 1.10% (t=2.18), respectively. The evidence suggests that fund managers' expertise in new styles is likely the primary motivation of style-shifting. The results based on AUM-weighted fund returns in Panel B show that the total gain from style-shifting and the gain from style-expertise over the same evaluation horizon are smaller and less significant than the equal-weighted counterparts in Panel A. These findings suggest that the style-shifting gains are more significant among small funds.

5. Robustness Checks and Further Analyses

In this section, we first perform robustness checks of our main findings. We then replicate our main analyses using an alternative style identification procedure. Moreover, we extend our analysis on single-style shifting to multi-style shifting under a more general setting. Finally, we explore the determinants of style-shifting decisions.

5.1 Robustness Checks

In this section, we conduct several robustness checks for our main findings. In our base analysis, we follow the hedge fund literature and focus on the period from January 1994 through December 2013 to include both live and defunct funds to minimize the impact of survivorship bias.[5] In this section, we further examine whether the impact of possible survivorship bias in our sample on our analysis is significant. The average fund attrition rate in our sample is about 7.25%, similar to Brown, Goetzmann, and Ibbotson (1999) and Liang (2000), suggesting that survivorship bias in our sample is mild. To examine the impact of survivorship bias on our style-shifting analysis, we conduct two types of analysis based on the sample attrition rate. In the first analysis, we randomly withdraw a number of funds equal to the total number of funds multiplied by the attrition rate from our actual sample and then compute the style-shifting ratio over the sample period. In the second analysis, we add the randomly drawn funds to our actual sample and then compute the style-shifting ratio. Moreover, we replicate the above analyses using the worst-performing funds rather than randomly drawn funds. The style-shifting ratios of the whole sample and each investment style for these alternatives are reported in columns 2 to 5 of Table A6 in the Online Appendix. The style-shifting ratio is about 7.66% after deleting the randomly drawn funds and is 7.63% after adding the drawn funds to the actual sample. Compared with Table 2, the shifting ratio drops by 0.02% to 0.05%, suggesting that the impact of survivorship bias in our analysis is trivial. To examine the impact of backfilling bias in our sample on our analysis, we follow the convention in the hedge fund literature by further deleting the observations during the backfilling period for each fund. The average backfilling period in our sample is 25.8 months, comparable to Cao, Chen, Liang, and Lo (2013). We end up with 2,816 funds and conduct the style-shifting test on these funds. The results are in the last column of Table A6. The style-shifting ratio over the whole sample is 6.90%, slightly lower than but comparable to that of 7.68% in the base case (Table 3).

In untabulated analyses, we conduct robustness checks without skipping one quarter to define style-shifting. That is, we define style-shifting between quarters t and t-1 and evaluate post-shifting performance from quarter t+1. The results are consistent. Another important robustness check is whether the style-shifting decisions are driven

[5] The information of defunct funds in the TASS database is only available since 1994 (see, Cao, Chen, Liang, and Lo, 2013).

by the turnover of fund managers. Our results show that this is unlikely the case. Since we do not have monthly or quarterly fund manager information throughout the sample period, we examine fund managers' turnover ratio between two snapshots of July 2004 and November 2013. We find that 26.82% of style-shifting funds and 23.75% of non-shifting funds replaced their fund managers over this 10-year window. This means that the fund manager turnover ratio is 0.67% per quarter for style-shifting funds and 0.59% for non-shifting funds;[6] both are much smaller than the average style-shifting ratio over the same period and the difference in this turnover ratio between the style-shifting and non-shifting funds is too trivial to account for the frequency in style-shifting.

We further examine the persistence of the style-timing ability and style-expertise among shifting funds. Specifically, we explore whether style-shifting funds still exhibit skills over subsequent one, two and three years. The results are reported in Table A7 in the Online Appendix and suggest that funds' style-expertise persists but their style-timing ability diminishes in three years. The averaged cumulative gain of style-timing becomes 1.46% (t=1.87) over subsequent two years and 1.18% (t=0.97) over subsequent three years. The averaged cumulative gains of style-expertise over the same periods are 4.67% (t=3.50) and 9.86% (t=4.95).

So far, our analyses are based on the top 20 out-of-sample PCs as proxies of investment styles which cumulatively account for about 97% of the return variation across all hedge funds. We acknowledge that, similar to Pukthuanthong and Roll (2009), the choice is somewhat arbitrary. Given that there are eight distinct strategies employed by funds in our sample, as a robustness check we also replicate our main analysis based on the top eight out-of-sample PCs, which cumulatively explain about 74% of the return variation across all hedge funds. The results are reported in Table A8 in the Online Appendix. Panel A shows that, similar to findings in Table 3, on average 6.82% of funds shift styles and funds in the 1st style shift least frequently (3.44%). Panel B of Table A8 reports the return decomposition of shifting funds following Eq. (1) and suggests that, consistent with the base case in Table 8, shifting funds gain from both style-timing and style-expertise. Over subsequent 12 months, the average AUM-weighted gain of style timing is about 0.22% and the gain of expertise is 1.5%.

Lastly, we conduct another important robustness check using the alternative procedure of fund style identification

[6] However, the ratios may be slightly underestimated if some funds replaced fund managers multiple times during the 10 years.

in Section 3.2.1, that is, funds' styles are identified using fund return correlations. We apply this procedure for funds with self-reported single-strategy and the main results are reported in Tables A9 through A11 in the Online Appendix. The results show that style-shifting is not uncommon in the hedge fund industry, and that style-shifting funds are forward-looking and exhibit both style timing skill and expertise in new styles. Please refer to Section I in the Online Appendix for detailed analyses.

5.2 Multi-Style Shifting Analysis: Sharpe Regressions

Our main analyses so far are restricted to single-style shifting, that is, in a given period a hedge fund only allocates its assets within one style category. Given the complicate asset allocation of hedge fund portfolios, it is useful to relax this assumption to examine hedge funds' managerial skills in a general setting with investments in multiple style categories. That is, hedge funds may invest in multiple styles in each period and style-shifting can be defined as large shifts in style weights. In this section, we utilize the quadratic regression approach by Sharpe (1992) to examine funds' asset allocations among multiple styles, and to explore hedge funds' multi-style shifting across styles. We use all qualified TASS funds, including self-reported single- and multi-strategy funds, funds of hedge funds, and strategy-undefined funds, in this alternative style-shifting analysis. Similar to our base case, we use out-of-sample principal components as the proxies of hedge fund styles and use the procedure in Section 3.2.1 to estimate style returns. To estimate style weights for each fund, we conduct the following quadratic regression for fund *i* in quarter *t* over a rolling window of eight quarters [*t*-7, *t*]:

$$r_{i,j} = \sum_{s=1}^{S} \beta_s r_j^s + \varepsilon_{i,j}, \tag{4}$$

Subject to

$$\sum \beta_s = 1, \ \beta_s \geq 0$$

where $r_{i,t}$ and r_t^s are fund and style returns in month *j* and *S* is the number of styles. Sharpe (1992) suggests that β_s is the weight of fund *i* in style *s*.

To obtain a reasonable degree of freedom over the 24-month rolling window and without loss of generosity, we consider the case *S*=5. That is, we assume that hedge fund managers can allocate their capital among as many as five styles. In the regression, the first of the five styles is the one identified in Section 3.2.1 which has the highest correlations with the fund returns, and the other four are the additional styles that have the 2nd to 5th highest correlations with the fund returns over the same rolling window. The summary statistics of each style weight and the corresponding weight shift are reported in Table A12 in the Online Appendix, respectively. The first panel reports the time series average of cross-sectional mean of fund weights on all five styles as well as on each style. Overall, the average weight on each style over the whole sample is about 20% and the first style attracts about 40% of hedge fund capital and the fifth attracts 8%. The second panel reports the time series average of change of fund weights between two consequent quarter for all five styles and for each individual style. The average change of fund weights for all five styles between two consecutive quarters over the whole sample is close to zero (-0.10%) while the weight change varies within a large range (between -97% and 96%) with a standard deviation of 13.67%. These patterns remain across investment styles. Moreover, the average of the 75th percentile style weight changes of hedge funds is about 2%, consistent with the findings in Table 3 that only a small fraction (7.68%) of hedge funds in each quarter shift styles.

Next, we define multi-style shifts based on the change of style weights and test whether multi-style-shifting hedge fund managers still exhibit skills. To illustrate this point, we decompose fund returns as follows:

$$R_{i,[t,t+q]} = \underbrace{\sum_{s=1}^{S} \omega_{i,s,t-1} R^{s}_{[t,t+q]}}_{\text{Passive strategy return}} + \underbrace{\sum_{s=1}^{S} (\omega_{i,s,t} - \omega_{i,s,t-1})\, R^{s}_{[t,t+q]}}_{\text{Gain of style timing}} + \underbrace{\left(R_{i,[t,t+q]} - \sum_{s=1}^{S} \omega_{i,s,t}\, R^{s}_{[t,t+q]}\right)}_{\text{Gain of style expertise}} \tag{5}$$

where $r_{i,[t,t+q]}$ and $r^{s}_{[t,t+q]}$ are fund and style returns over period $[t, t+q]$ and $\omega_{i,s,t}$ denotes fund *i*'s portfolio weight on style *s* based on the Sharpe quadratic regression. Following the spirit of Brinson, Hood and Beebower (1995), Eq.(5) suggests that the return of fund *i* in time *t* can be attributed to a passive strategy (the first term on the right side), style timing ability (the second term) and expertise in picking styles (the third term). To investigate whether multi-style shifting fund managers have skills, we focus on a subset of funds with relatively large shifts in style weights. Specifically, in each quarter we define multi-style shifting funds as the funds having at least one style weight change equal to or higher than 25%. We then apply Eq.(5) and examine fund manager skills over subsequent one, two and four quarters, and the empirical results are reported in Table 9. For completeness, we also report the results based on the whole sample, that is, all shifting and non-shifting funds.

Panel A of Table 9 reports the results based on the whole sample and suggests that, on average, fund return is mainly driven by the returns of passive style investments. The gains from both timing styles and style expertise are small and insignificant, which is not surprising since most hedge funds in the sample do not shift styles. The results for multi-style shifting funds based on the 25% cutoff are reported in Panel B of Table 9. The average returns of these funds in subsequent three, six or 12 months are close to but slightly higher than that of all funds in Panel A. More interestingly, this subset of multi-style shifting funds exhibit both style-timing ability and expertise in new styles, while the gains from expertise in new styles are relatively larger. For example, the style-timing gain of these funds is about 7 basis points (bps) (t=2.39) over subsequent one quarter and 12 bps (t=1.71) over subsequent one year; the gain of expertise in styles is 0.71% (t=2.00) and 3.11% (t=2.32) over these periods, respectively. In Panel C of Table 9, we define multi-style shifting funds as the funds having at least one style weight change equal to or higher than 50% and test whether this subset of shifting funds are able to perform better and yield higher gains of style-timing and style-expertise than other funds. The results are stronger than those with the cutoff of 25% (in Panel B) from the perspective of fund manager skill examination. All of the average fund returns, the gains of style-timing and the gains of expertise in new styles in Panel C are higher than the counterparts in Panels A and B. To conclude, the multi-style shifting analysis shows consistent findings as the single-style shifting analysis and confirm that style-shifting decisions by hedge funds are likely motivated by skills. Style-shifting hedge fund managers possess both style-timing ability and expertise in new styles.

Similar to the single-style shifting analysis in Section 5.1, as a robustness check we also replicate the multi-style shifting analysis based on the top eight out-of-sample PCs as proxies of investment styles. The results are reported in Table A12 in the Online Appendix and are consistent with the findings based on the top 20 out-of-sample PCs. For example, for funds with at least one style weight change equal to or higher than 50%, the average gain from style-timing is 0.15% (t=2.06) over subsequent one quarter, and the average gain from style-expertise over the same period is about 1.89% (t=2.82).

5.3 Determinants of Style-Shifting

In this section, we investigate whether certain types of funds are more likely to shift their investment styles than other funds. We first conduct a univariate analysis to examine whether there are significant differences in fund characteristics between single-style-shifting funds and non-shifting funds. We consider both static and time-varying fund characteristics, including the lengths of the lockup period and redemption notice, the minimum investment requirement, leverage, incentive and management fees, high-water mark covenant, fund size defined as log (AUM), the logarithm of fund age, fund return, Fung-Hsieh 7-factor alpha, Sharpe ratio, information ratio, Sortino ratio, return volatility, fund flows and flow volatility. The definitions of the variables are provided in Section 3 and Section 4.4. We divide these variables into various categories, including operational constraint variables (lockup period, redemption notice, minimum investment requirement, and leverage), incentive-related variables (incentive and management fees and high-water-mark covenant), performance variables (fund return, alpha, and the Sharpe ratio), fund flows, and other variables (size and age). The summary statistics of static variables are reported in Panel A of Table A14 in the Online Appendix, in which shifting funds are defined as the ones shifted styles during the whole sample period. At the end of each quarter, we divide all funds into style-shifting funds and non-shifting funds based on whether they shift styles in that quarter. The time series average of the cross-sectional mean for each time-varying fund characteristic is reported in Panel B of Table A14.

Panel A shows that style-shifting funds are less operationally constrained than non-shifting funds, that is, style-shifting funds require longer lockup and redemption notice periods. The average lockup period required by style-shifting funds is 2.95 months, compared to 2.61 months for non-shifting funds. The redemption notice period is 35 days among style-shifting funds and 33 days among non-shifting funds. There are 56% style-shifting funds are levered, compared to 66% non-shifting funds. Taken together, the results suggest that shifting funds face fewer operational constraints than non-shifting funds. The average incentive fee for style-shifting funds is about 19.05%, higher than the corresponding fee for non-shifting funds (17.69%). The average management fee for style-shifting funds is about 1.45%, slightly higher than that for non-shifting funds (1.40%). However, style-shifting funds are more likely to be subject to high-water-mark covenants. 63% style-shifting funds face a high-water-mark requirement; this fraction is 47% among non-shifting funds.

Panel B in Table A14 shows that style-shifting funds are smaller and younger than non-shifting funds. The averaged log (AUM) of style-shifting funds is 17.20, compared to 20.06 among non-shifting funds. The log (age) of style-shifting funds is 2.40, compared to 2.59 among non-shifting funds. Style-shifting funds outperform non-shifting funds and attract more fund flows than non-shifting funds. Style-shifting funds' 12-month average return is 0.87% per month versus 0.78% for non-shifting funds, a statistically significant difference. The Fung-Hsieh alpha, Sharpe ratio, information ratio and Sortino ratio of style-shifting funds are 0.74%, 0.56, 0.05 and 0.60, significantly higher than those for non-shifting funds by 0.19%, 0.16, 0.03 and 0.21, respectively. The average 12-month flow to style-shifting funds is 10.46%, 1.63% higher than that to non-shifting funds; this difference is statistically significant. Panel B also shows that returns and fund flows among style-shifting funds are slightly less volatile than those of non-shifting funds.

We further perform the multivariate Probit regressions to explore the determinants of style-shifting decisions:

$$SF_{i,t}^{Old \to New} = \alpha + \beta^T X_{i,t-1} + \varepsilon_{i,t}, \tag{6}$$

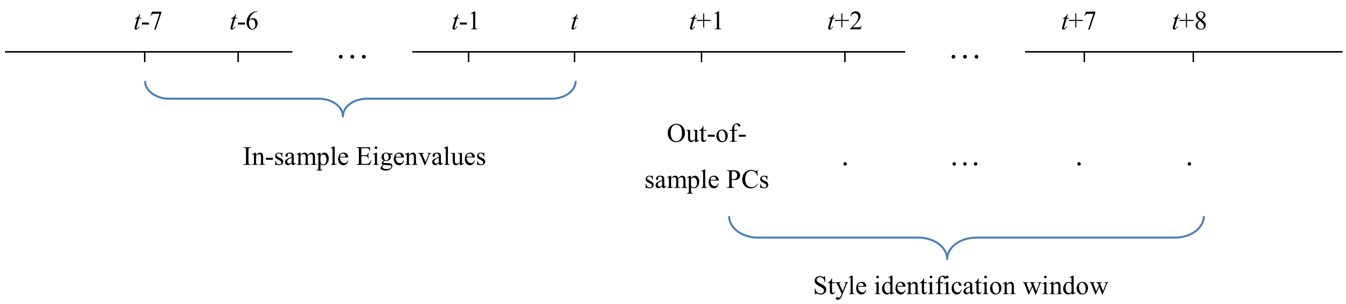
where $SF_{i,t}^{Old \to New}$ is a style-shifting dummy that equals one if fund i shifts its style at the end of period t and zero otherwise and X is a vector of the main fund characteristics defined in Table A14. The coefficients and their associated p-values are reported in Table 10. The first column explores whether operational constraint variables are important in determining a fund's style-shifting decision. The coefficients of lockup period and redemption notice are positive and significant, indicating that these two characteristics can predict style-shifting decisions. The coefficient of log of required minimum investment is positive but marginally significant. The coefficient of leverage is negative and significant, suggesting that high leverage discourages style-shifting. The second column reports the results of regressing the style-shifting dummy variable on funds' incentive variables, including both management and incentive fees and the high-water mark covenant. All three coefficients are positive and the first two are significant. The 3rd column reports the results of a regression testing whether fund size (log of AUM) and log of fund age are able to predict style shifts. Both coefficients are negative, indicating that small funds and young funds are more likely to shift their investment styles. Columns 4 and 5 report whether historical performance and fund flows are important in driving funds to shift their styles, respectively. The coefficients of fund alpha and fund flows are positive and the coefficients of returns and flow volatilities are negative, implying that winner funds and funds with high fund flows are more likely to shift their styles. These findings are consistent with Bollen and Whaley (2009) and Aragon and Nanda (2012) that winner funds are more likely to shift investment styles. In the last column, we include all variables; their predictability is qualitatively unchanged. Overall, our determinant analysis of style-shifting suggests that less constrained funds, small funds, young funds, winner funds and funds with higher flows are more likely to shift their investment styles.

6. Conclusions

In this paper, we conduct a comprehensive analysis of hedge fund managers' decisions to shift investment styles. First, we find that about three quarters of single-strategy hedge funds have shifted their investment styles at least once over the 20-year sample period from 1994 to 2013, and that, on average, 7.68% of funds, or equivalently 90 out of 1,169 funds, shift their investment styles each quarter. We categorize motivations for hedge funds' style-shifting decisions into two competing hypotheses: backward-looking or forward-looking. Each hypothesis has different implications for style and fund performance as well as fund flows. Consistent with the forward-looking hypothesis, the empirical results show that new styles of style-shifting funds on average outperform old styles. Style-shifting funds outperform their peers in the new styles. We further decompose gains from style-shifting into style-timing ability and style expertise. The results suggest that style-shifting decision is primarily driven by fund managers' expertise in the new styles. Finally, we show that small funds, young funds, winner funds, and funds with higher inflows are more likely to shift their styles.

Appendix: PCA-Based Style Identification

The PCA based style-identification procedure involves two steps: out-of-sample principal components (PCs) estimation as proxies of hedge fund style and fund style identification. The timeline of the procedure is illustrated as follows:



In the first step, starting from December 1995, in each quarter *t* we compute the covariance matrix of a balanced panel of hedge fund returns using all available observations over a rolling eight-quarter window [*t*-7, *t*], and obtain the eigenvalues. We include all qualified funds in the TASS database including individual funds and funds of funds. We sort the eigenvectors from the largest to the smallest and pick the first 20 eigenvalues, which on average cumulatively explain more than 95% of the cross-sectional variation of hedge fund returns. We then compute the 20 out-of-sample PCs using the returns of all funds in the subsequent quarter *t*+1 and the in-sample eigenvectors estimated over the most recent eight quarters [*t*-7, *t*]. We repeat this process over the whole sample period from January 1996 to December 2013 and generate a time series for each of the 20 out-of-sample PCs.

In the second step, based on the estimated out-of-sample PCs and fund returns over a rolling window of eight quarters [*t*+1, *t*+8], we calculate the Pearson pairwise correlations of a fund's returns with each of the top 20 PCs, and define the PC that has the highest correlation as the style of the fund in quarter *t*+8. We repeat this procedure for the whole sample period, and obtain the style for each fund in each quarter. To avoid spurious style identification and over-identification of style-shifting, an identified style for a fund based on the above procedure is considered as valid only if the fund maintains the same style for at least two consecutive quarters; otherwise, the style from the prior quarter is retained as the fund style.

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Table 1. Summary Statistics of Fund Characteristics

This table reports summary statistics of the characteristics of self-reported single-strategy hedge funds in the sample, including fund return, return volatility, the Sharpe ratio, AUM, fund flow, fund age, incentive fee, management fee, dummy variables for funds with high-water mark covenants or leverage, the length of the lockup periods, the days required for the redemption notice, and the minimum investment requirement. The Sharpe ratio is defined as the average cumulative return in excess of the one-month Treasury bill rate over month t to month t-11 divided by the standard deviation of the excess return over the same period. Return volatility is calculated based on monthly returns over the past 12 months. Fund flow in period t is defined as the fund's AUM in period t minus AUM in period t-1 multiplied by the total fund return over the period, and scaled by the AUM at the end of period t-1. Each month, we compute the cross-sectional statistics of all variables. The table reports the time series averages of these statistics. The sample period is from January 1994 to December 2013.

Variable	Mean	Median	Std. Dev.	Skewness	Kurtosis	Minimum	Maximum
Fund return (%)	0.87	0.74	4.71	0.56	16.96	-26.86	34.14
Return vol. (%)	4.02	3.33	3.06	2.18	11.31	0.06	26.93
Sharpe ratio	0.52	0.30	3.82	13.21	319.91	-0.99	121.62
AUM ($Mil)	189.77	71.43	444.80	10.78	216.08	10.16	8,956.21
Fund flow (%)	1.06	0.14	18.46	0.66	7.74	-6.48	10.40
Age (year)	12.23	10.25	6.54	0.46	-1.22	1.13	30.25
Incentive fee (%)	17.95	20.00	5.42	-1.70	8.25	0	50
Management fee (%)	1.47	1.30	0.60	1.37	8.81	0	7
High-water mark (dummy)	0.61	1.00	0.46	-0.91	-1.17	0	1
Leverage (dummy)	0.69	1.00	0.47	-0.59	-1.66	0	1
Lockup (months)	2.98	0.00	6.88	3.10	19.99	0	90
Redemption (days)	30.01	35.00	29.90	2.44	17.22	0	365
Min investment ($Mil)	0.92	0.50	1.92	10.09	184.61	0	50

Table 2. Summary Statistics of PCs and PC-based Style Returns

This table reports summary statistics of out-of-sample monthly PCs and PC-based style returns using the style identification procedure described in Section 3.2.1. Out-of-sample PCs are derived from monthly hedge fund returns in the current quarter based on Eigenvalues estimated over the most recent 24 months. Style returns are defined as the AUM-weighted returns of all funds within the same style, and fund style is identified as the PC to which the fund has the highest exposure. PCs are estimated based on the whole sample funds, including self-reported single- and multiple-strategy funds, and funds of funds, and style returns are computed with self-reported single-strategy funds. The sample period is from January 1994 to December 2013.

	Statistics of PCs				Statistics of PC-based styles returns		
PC	Mean (%)	Median (%)	Stdev. (%)	Style	Mean (%)	Median (%)	Stdev.(%)
1st	14.98	23.92	69.47	1st	0.65	1.00	2.72
2nd	3.51	3.97	41.98	2nd	0.18	0.47	2.41
3rd	0.93	-1.33	26.77	3rd	0.56	0.60	2.49
4th	1.74	1.23	23.19	4th	0.46	0.41	2.77
5th	0.26	0.62	17.60	5th	0.78	0.94	1.49
6th	1.86	-0.69	15.03	6th	0.54	0.71	2.24
7th	0.58	0.25	12.82	7th	0.43	0.51	2.03
8th	2.16	1.61	12.06	8th	0.61	0.60	2.56
9th	1.40	1.37	9.94	9th	0.76	0.71	2.03
10th	1.52	0.86	9.15	10th	0.66	0.61	2.43
11th	0.17	0.03	9.74	11th	0.53	0.55	1.62
12th	0.49	0.73	8.91	12th	0.42	0.57	2.43
13th	0.02	0.02	8.06	13th	0.59	0.37	2.77
14th	0.78	-0.10	7.68	14th	0.49	0.54	2.35
15th	0.61	-0.31	8.85	15th	0.50	0.49	1.69
16th	0.03	-0.11	7.21	16th	0.39	0.44	1.88
17th	0.16	0.21	7.72	17th	0.52	0.66	1.68
18th	0.85	0.50	7.01	18th	0.45	0.46	2.44
19th	-0.62	-0.61	7.65	19th	0.05	0.52	5.03
20th	0.51	0.50	7.08	20th	0.57	0.60	1.92

Table 3. Summary Statistics of Hedge Fund Style-Shifting

Panel A reports summary statistics of style-shifting for the whole sample and for each style, including the average number of self-reported single-strategy funds per quarter, the average number of style-shifting funds per quarter based on the style identification procedure as described in Section 3.2.1, and the average percentage of funds shifting styles each quarter. Panel B reports summary statistics of the number of style shifts per fund during the sample period and the duration in new styles for style-shifting funds. *** denotes statistical significance at the 1% levels. The sample period is from January 1994 to December 2013.

Panel A: Number of Funds in Each Style and Percentage of Style-Shifting Funds

Style	Avg. no. of funds/quarter	Avg. no. of style-shifting funds/quarter	Avg. style-shifting ratio
All styles	1,169.05	90.17	7.68***
1^{st}	612.55	21.28	3.52***
2^{nd}	82.43	7.55	11.52***
3^{rd}	54.93	7.00	13.26***
4^{th}	42.97	5.15	12.18***
5^{th}	27.73	3.75	13.51***
6^{th}	28.55	3.65	13.24***
7^{th}	24.58	3.15	12.45***
8^{th}	18.08	2.63	14.52***
9^{th}	18.92	2.72	16.11***
10^{th}	21.40	2.80	14.00***
11^{th}	23.55	3.05	13.26***
12^{th}	35.88	4.33	12.33***
13^{th}	20.38	2.38	12.23***
14^{th}	30.78	4.42	14.02***
15^{th}	17.18	2.12	12.64***
16^{th}	22.55	2.80	12.16***
17^{th}	19.38	2.47	12.87***
18^{th}	25.43	3.55	14.51***
19^{th}	20.93	2.70	13.09***
20^{th}	20.82	2.67	12.58***

Panel B: Frequency and Duration of Shifting for Style-Shifting Funds

	Mean	Median	Std. dev.	Min	Max
Number of style shifts/fund	2.32	2.00	1.56	1.00	9.00
Time in new style (year)	1.76	1.25	1.32	0.50	12.25

Table 4. Popularity and Performance of New and Old Styles

This table reports the popularity and performance of the new and old styles of style-shifting funds before and after shift. Panel A reports the popularity, measured by the difference in shifting-in and shifting-out ratios (percent), for the new and old styles of shifting fund's over the 3-, 6-, and 12-month horizons before and after style shift. Panel B reports the cumulative returns (percent) for the old and new styles of shifting funds over the 3-, 6-, and 12-month horizons before and after style shift. The differences in performance and popularity between the new and old styles are also reported. The Newey-West *t*-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1994 to December 2013.

Panel A: Style Popularity

Horizon	New style	Old style	New-old
	Historical in-out shifting ratio (%)		
Past 3-month in-out ratio	3.00	-2.48	5.48***
			(5.16)
Past 6-month in-out ratio	2.33	-1.94	4.27***
			(10.59)
Past 12-month in-out-ratio	1.40	-0.39	1.79***
			(6.66)
	Future in-out shifting ratio (%)		
Subsequent 3-month in-out ratio	2.29	-2.88	5.18***
			(11.00)
Subsequent 6-month in-out ratio	1.58	-2.66	4.23***
			(10.66)
Subsequent 12-month in-out ratio	0.05	-2.01	2.06***
			(7.03)

Panel B: Style Performance

	Historical performance (%)		
Past 3-month return	1.33	1.53	-0.20
			(-0.89)
Past 6-month return	2.93	3.08	-0.15
			(-0.41)
Past 12-month return	6.30	6.95	-0.65
			(-1.40)
	Future performance (%)		
Subsequent 3-month return	1.58	1.50	0.08
			(0.53)
Subsequent 6-month return	3.17	2.74	0.43*
			(1.87)
Subsequent 12-month return	6.52	5.75	0.76**
			(2.04)

Table 5. Style-Shifting and Future Style Performance

This table reports the results of regressing future return spreads between the new and old styles, which equals zero if the fund does not shift style, on a style-shifting dummy variable $SF_{i,t}^{Old\rightarrow New}$ which equals one if fund *i* shifts its style in quarter *t* and zero otherwise. Control variables include the cumulative return spread between the new and old styles and the cumulative returns of style-shifting funds over the past three to 12 months. The Newey-West *t*-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1994 to December 2013.

Dependent	$\Delta R_{[t+1,t+3]}^{New-Old}$		$\Delta R_{[t+1,t+6]}^{New-Old}$		$\Delta R_{[t+1,t+12]}^{New-Old}$	
Intercept (%)	0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.01)	(-0.11)	(-0.72)	(-0.78)	(-0.56)	(-0.66)
$SF_{i,t}^{old\rightarrow new}$	0.00	0.00	0.26**	0.26**	0.44***	0.50***
	(0.54)	(0.19)	(2.43)	(2.20)	(2.98)	(2.97)
$\Delta R_{[t-1,t-3]}^{New-Old}$	-0.05***	-0.05***	0.03	0.04	-0.01	0.00
	(-3.19)	(-2.90)	(1.24)	(1.55)	(-0.41)	(0.06)
$\Delta R_{[t-1,t-6]}^{New-Old}$	0.04***	0.04***	-0.02	-0.02	-0.01	-0.00
	(3.36)	(3.59)	(-1.23)	(-1.11)	(-0.21)	(-0.02)
$\Delta R_{[t-1,t-12]}^{New-Old}$	-0.01**	-0.02***	-0.03***	-0.03***	-0.05***	-0.06***
	(-2.44)	(-2.88)	(-3.33)	(-3.63)	(-4.57)	(-4.96)
$Ret_{i,[t-1,t-3]}^{Shiftingfund}$		-0.06***		-0.09***		-0.14***
		(-4.38)		(-4.28)		(-4.49)
$Ret_{i,[t-1,t-6]}^{Shiftingfund}$		0.05***		0.07***		0.07***
		(4.09)		(3.63)		(2.72)
$Ret_{i,[t-1,t-12]}^{Shiftingfund}$		-0.01**		-0.01		-0.01
		(-2.17)		(-0.97)		(-0.52)
R^2 (%)	0.44	1.11	0.48	1.13	0.85	1.60

Table 6. Performance of Shifting and Non-Shifting Funds

This table reports the average performance of style-shifting and non-shifting funds over various rolling windows. We report both gross and style-adjusted performances (in percent). Sharpe ratio, information ratio, Sortino ratio, and volatilities of fund returns are based on a 12-month rolling window, and Fung-Hsieh alphas are based on a 24-month rolling window. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1994 to December 2013.

Variable	Shifting funds		Non-Shifting funds		Shifting – Non-Shifting	
	Fund return	Style-adj.	Fund return	Style-adj.	Fund return	Style-adj.
			Past performance			
3-month before shift	2.11***	0.48***	1.88***	0.11	0.22	0.38*
	(3.89)	(3.60)	(2.99)	(0.50)	(0.55)	(1.85)
6-month before shift	4.55***	1.10**	4.46***	0.43	0.09	0.67*
	(4.94)	(2.48)	(3.41)	(1.33)	(0.13)	(1.90)
12-month before shift	9.85***	2.49***	9.71***	1.21***	0.14	1.28**
	(5.55)	(3.56)	(6.42)	(2.65)	(0.13)	(2.42)
Return VOL before shift	3.71***	3.54***	4.48***	3.48***	-0.07	0.42***
	(11.03)	(12.36)	(6.02)	(5.85)	(-0.52)	(2.94)
Sharpe/information ratio	0.57***	0.09***	0.46***	0.07***	0.13**	0.02**
	(5.61)	(2.84)	(4.09)	(2.73)	(2.30)	(2.07)
Sortino ratio	0.66***	0.05**	0.56***	0.04**	0.10*	0.01*
	(4.41)	(2.13)	(5.08)	(2.35)	(1.68)	(1.66)
F-H alpha	0.71***	-0.02	0.65***	0.002*	0.06***	-0.02
	(7.60)	(-1.23)	(5.99)	(1.79)	(3.34)	(-1.03)
			Future performance			
3-month after shift	2.04***	0.46**	1.44***	-0.21	0.60**	0.67**
	(6.67)	(2.61)	(4.34)	(-1.49)	(2.51)	(2.03)
6-month after shift	3.86***	0.69**	3.12***	-0.33	0.75**	1.02*
	(6.25)	(2.37)	(5.49)	(-1.60)	(2.34)	(1.86)
12-month after shift	7.62***	1.10**	6.71***	-0.69*	0.91**	1.79**
	(5.14)	(2.18)	(7.42)	(-1.77)	(2.24)	(2.06)
Return VOL after shift	3.57***	3.27***	3.65***	2.87***	-0.08	0.40***
	(12.75)	(12.77)	(6.19)	(5.84)	(-0.65)	(3.68)
Sharpe/information ratio	0.51***	0.02**	0.41***	0.01	0.10**	0.01**
	(4.61)	(2.11)	(4.97)	(1.38)	(1.96)	(2.13)
Sortino ratio	0.57***	0.03***	0.48***	0.01***	0.09**	0.02***
	(5.31)	(4.09)	(4.19)	(2.26)	(2.59)	(3.34)
F-H alpha	0.71***	0.02*	0.48***	-0.00**	0.08***	0.02**
	(7.82)	(1.89)	(7.97)	(-2.41)	(5.05)	(2.11)

Table 7. Style-Shifting and Future Fund Performance

This table reports the results of regressing a fund's future style-adjusted (abnormal) returns ($AR_{i,[t+1,t+k]}$) on the style-shifting dummy ($SF_{i,t}^{Old\rightarrow New}$) which equals one if fund i shifts its style in quarter t and zero otherwise. Control variables include the fund return, return volatility over the past 12 months, fund size (AUM), fund flow over the past 12 months, fund age, incentive fee, management fees, a high-water mark dummy, the lengths of the lockup period and redemption notice, an indicator of leverage, and the minimum investment requirement. The associated Newey-West *t*-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1994 to December 2013.

Dependent variable	$AR_{i,[t+1,t+3]}$		$AR_{i,[t+1,t+6]}$		$AR_{i,[t+1,t+12]}$	
Intercept	1.35***	0.81***	2.56***	1.46***	4.55***	2.63***
	(6.78)	(3.87)	(8.54)	(4.62)	(10.18)	(5.64)
$SF_{i,t}^{Old\rightarrow New}$	0.14*	0.10	0.22**	0.12*	0.57***	0.36**
	(1.87)	(1.53)	(2.42)	(1.70)	(4.12)	(2.54)
Return	0.09***	0.09***	0.11***	0.10***	0.14***	0.13***
	(11.24)	(11.10)	(10.14)	(9.59)	(8.90)	(8.02)
Return volatility	0.22***	0.23***	0.43***	0.45***	0.80***	0.85***
	(16.93)	(16.50)	(24.77)	(24.27)	(31.54)	(31.32)
Log (AUM)	-0.11***	-0.17***	-0.21***	-0.34***	-0.37***	-0.66***
	(-10.30)	(-15.38)	(-12.94)	(-19.97)	(-15.65)	(-26.21)
Fund flow	0.15***	0.21***	0.30***	0.42***	0.45***	0.73***
	(5.63)	(6.55)	(7.73)	(9.15)	(7.10)	(11.01)
Flow volatility	-0.46***	-0.63***	-0.96***	-1.27***	-0.02***	-0.02***
	(-4.53)	(-5.50)	(-6.44)	(-7.55)	(-6.61)	(-9.77)
Log (age)		0.31***		0.65***		1.44***
		(11.89)		(16.51)		(24.33)
Incentive fee		0.02***		0.04***		0.06***
		(9.33)		(12.23)		(13.10)
Management fee		0.12***		0.26***		0.54***
		(4.14)		(6.29)		(8.81)
High water mark		0.02***		0.05***		0.01***
		(6.62)		(9.64)		(13.52)
Lockup		0.01**		0.01***		0.03***
		(2.48)		(3.51)		(5.74)
Redemption		0.01***		0.01***		0.03***
		(12.41)		(17.33)		(22.20)
Leverage		0.07**		0.13***		0.15**
		(2.19)		(2.84)		(2.14)
Min investment		0.05***		0.10***		0.21***
		(10.14)		(12.98)		(16.75)
R^2 (%)	1.29	1.69	1.87	2.55	2.31	3.29

Table 8. Return Decomposition: Style-Timing vs. Style-Expertise

We decompose the cumulative returns of style-shifting funds over subsequent k–quarter $R_{i,[t,t+k]}$ into passive investment returns $R^{old}_{[t,t+k]}$, the gain $(R^{New}_{[t,t+k]} - R^{Old}_{[t,t+k]})$ of timing new styles, and the gain of expertise in new styles $(R_{i,[t,t+k]} - R^{New}_{[t,t+k]})$. This table reports the time series average of cross-sectional means of returns of style-shifting funds and the gains of style-timing and style expertise, respectively. Style returns are AUM-weighted and Panel A reports the results based on equal-weighted fund returns and Panel B reports the results based on AUM-weighted fund returns. Newey-West *t*-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1994 to December 2013.

	1-quarter	2-quarter	1-year
Panel A: Equal-weighted shifting fund returns			
$R_{i,t+k}$	2.04***	3.86***	7.62 ***
	(6.67)	(6.25)	(5.49)
R^{New}_{t+k}	1.58***	3.17***	6.52 ***
	(4.44)	(4.65)	(5.14)
R^{old}_{t+k}	1.50***	2.74***	5.76 ***
	(3.85)	(3.55)	(4.40)
$(R_{i,t+k} - R^{Old}_{t+k})$	0.54**	1.12**	1.86 **
	(1.99)	(2.20)	(2.05)
$\left(R^{New}_{t+k} - R^{Old}_{t+k}\right)$	0.08	0.43*	0.76**
	(0.53)	(1.87)	(2.04)
$(R_{i,t+k} - R^{New}_{t+k})$	0.46**	0.69**	1.10 **
	(2.61)	(2.37)	(2.18)
Panel B: AUM-weighted shifting fund returns			
$R_{i,t+k}$	2.01***	3.72***	6.87 ***
	(6.86)	(6.44)	(5.65)
R^{New}_{t+k}	1.58***	3.17***	6.52 ***
	(4.44)	(4.65)	(5.14)
R^{old}_{t+k}	1.50***	2.74***	5.76 ***
	(3.85)	(3.55)	(4.40)
$(R_{i,t+k} - R^{Old}_{t+k})$	0.51	0.98*	1.11
	(1.60)	(1.68)	(1.25)
$\left(R^{New}_{t+k} - R^{Old}_{t+k}\right)$	0.08	0.43*	0.76 **
	(0.53)	(1.87)	(2.04)
$(R_{i,t+k} - R^{New}_{t+k})$	0.43**	0.55*	0.35
	(1.96)	(1.68)	(0.66)

Table 9: Multi-style Shifting Analysis – Future Fund Performance

This table reports the decomposition of multi-style shifting fund i's cumulative return over future k-quarter $R_{i,[t,t+k]}$, into passive gain $\sum_{s=1}^{S} \omega_{i,s,t-1} R_{[t,t+k]}^{s}$ the style-timing gain, $\sum_{s=1}^{S} (\omega_{i,s,t} - \omega_{i,s,t-1}) R_{[t,t+K]}^{s}$, and the style expertise, $(R_{i,[t,t+k]} - \sum_{s=1}^{S} \omega_{i,s,t} R_{[t,t+k]}^{S})$, where S is set to be five and the corresponding styles are selected as those closely correlated with fund returns. Fund's style weights are estimated using the quadratic Sharpe regression of Equation (4). Panels A 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 based on whole sample of funds. Panels B and C report the results of multi-style shifting funds defined as those funds with shifts in style weights between two consecutive quarters equal to or higher than 25% and 50%, respectively. Newey-West t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1994 to December 2013.

	Cumulative fund performance in subsequent periods		
	1-quarter	2-quarter	1-year
Panel A: All funds			
Fund return	1.51***	3.01***	6.08***
	(2.86)	(3.00)	(3.32)
Passive	1.62***	3.13***	6.32***
	(4.96)	(4.94)	(5.36)
Style-Timing	0.01	0.05	0.002
	(0.61)	(1.30)	(0.03)
Style-Expertise	-0.11	-0.17	-0.24
	(-0.45)	(-0.36)	(-0.29)
Panel B: Funds with at least one style weight shift ≥25%			
Fund return	1.57***	3.15***	6.13***
	(3.06)	(3.28)	(3.35)
Passive	0.79***	1.46***	2.91***
	(6.03)	(5.37)	(5.13)
Style-Timing	0.07**	0.15**	0.12*
	(2.39)	(2.47)	(1.71)
Style-Expertise	0.71**	1.53***	3.11**
	(2.00)	(2.08)	(2.32)
Panel C: Funds with at least one style weight shift ≥50%			
Fund return	2.08***	4.05***	7.03***
	(3.68)	(3.88)	(3.44)
Passive	0.89***	1.51***	2.96***
	(5.56)	(6.01)	(5.23)
Style-Timing	0.13**	0.35***	0.20*
	(2.27)	(3.07)	(1.72)
Style-Expertise	1.06**	2.19**	3.86**
	(2.05)	(2.49)	(2.37)

Table 10. Determinants of Style-Shifting – Multivariate Analysis

This table reports the results of the Probit regression of the style-shifting dummy on lagged fund characteristics. The style-shifting dummy equals one if a fund shifts its style during a given quarter and zero otherwise. Fund characteristics include: the lengths of the lockup period and redemption notice, the minimum investment requirement, a leverage dummy, incentive and management fees, a high-water mark dummy, log (AUM), log (age), fund alpha over past 24 months, fund flow, and volatilities of fund returns and flow over past 12 months. All time-varying independent variables are lagged by at least one quarter. In each model, we report the multivariate Probit regression coefficients in the first column and the associated *p*-value in the second column. The Wald test results of whether all independent variables are jointly significant are reported in the last row. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Model	1	2	3	4	5	6
Intercept	-1.74***	-1.82 ***	-1.83***	-1.47***	-1.50***	-1.49***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lockup period	0.14***					0.31***
	(0.01)					(0.00)
Redemption notice	0.11***					0.16***
	(0.00)					(0.00)
Log min investment	0.43*					0.07
	(0.07)					(0.81)
Leverage	-0.11***					-0.06***
	(0.00)					(0.00)
Incentive fee		0.59 ***				1.28***
		(0.00)				(0.00)
Management fee		1.28 ***				3.58***
		(0.00)				(0.00)
High-water mark		0.59				2.31
		(0.46)				(0.11)
Log (AUM)			-0.80***			-0.93***
			(0.00)			(0.95)
Log (age)			-0.05***			-0.04***
			(0.00)			(0.00)
Fund alpha				3.23***		1.47***
				(0.00)		(0.013)
Return Volatility				-2.32***		-4.37***
				(0.00)		(0.00)
Fund flow					0.39***	0.32***
					(0.01)	(0.03)
Flow volatility					-1.17***	-1.72***
					(0.00)	(0.01)
Joint (Wald) test	356.84	797.77	73.37	113.88	32.37	494.12
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pseudo *R*-squared	0.31	0.71	0.06	0.33	0.09	1.41

Figure 1. Average Cumulative Percentage of Variance Explained by Sorted Eigenvalues.

This figure plots the average cumulative explanatory power of the top 20 eigenvalues (sorted from the largest to the smallest) for the cross-sectional variation across hedge fund returns over the whole sample period. Eigenvalues in each period are estimated based on a rolling window over the most recent 24 months. The sample period is from January 1994 to December 2013.

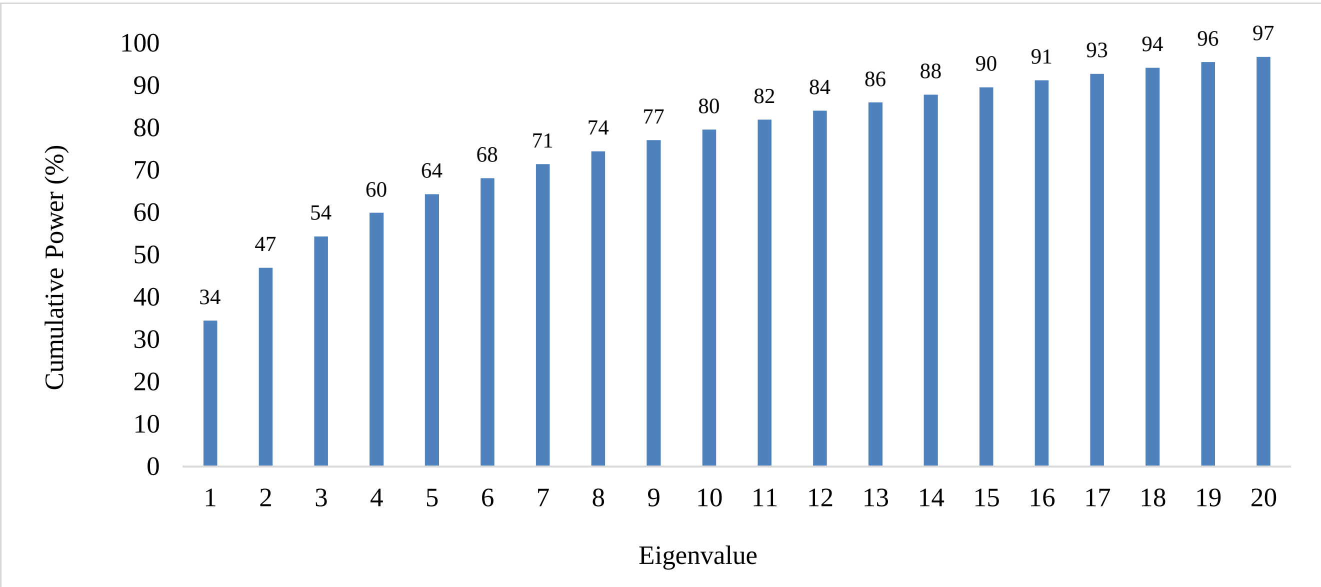


Figure 2: Time Series of Cumulative Percentage of Variance Explained by Sorted Eigenvalues.

This figure plots the explanatory power of the top 20 eigenvalues (sorted from the largest to the smallest) for the cross-sectional variation of hedge fund returns in each period. Eigenvalues in each period are estimated based on a rolling window over the most recent 24 months. The sample period is from January 1994 to December 2013.

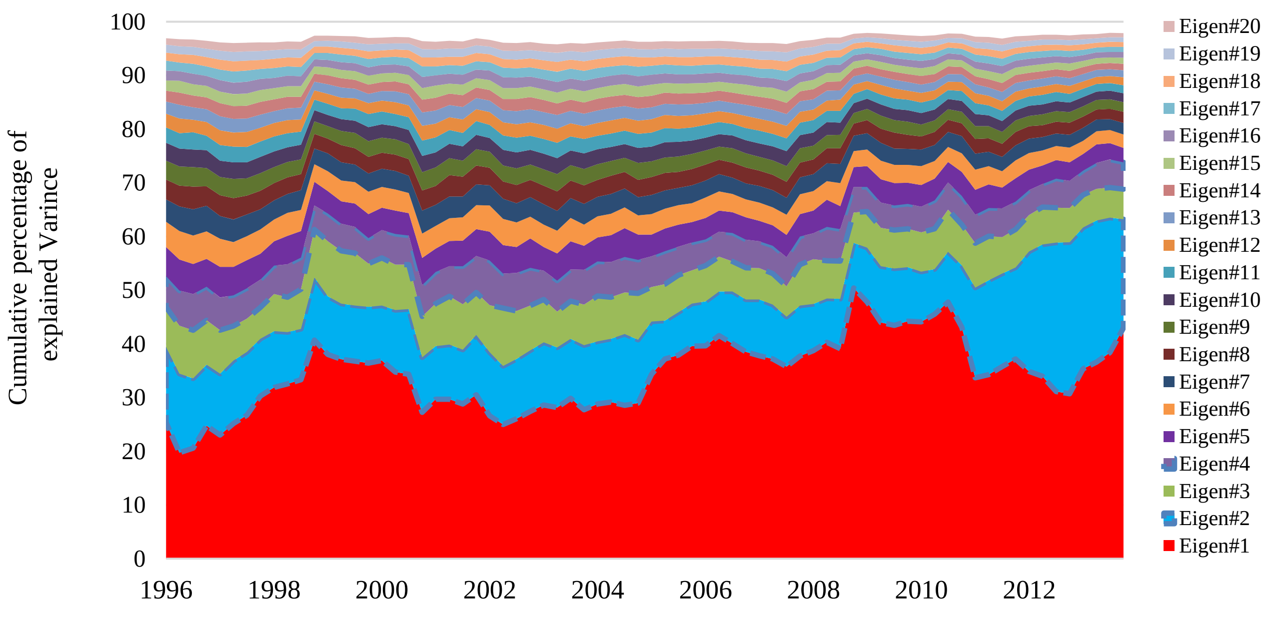
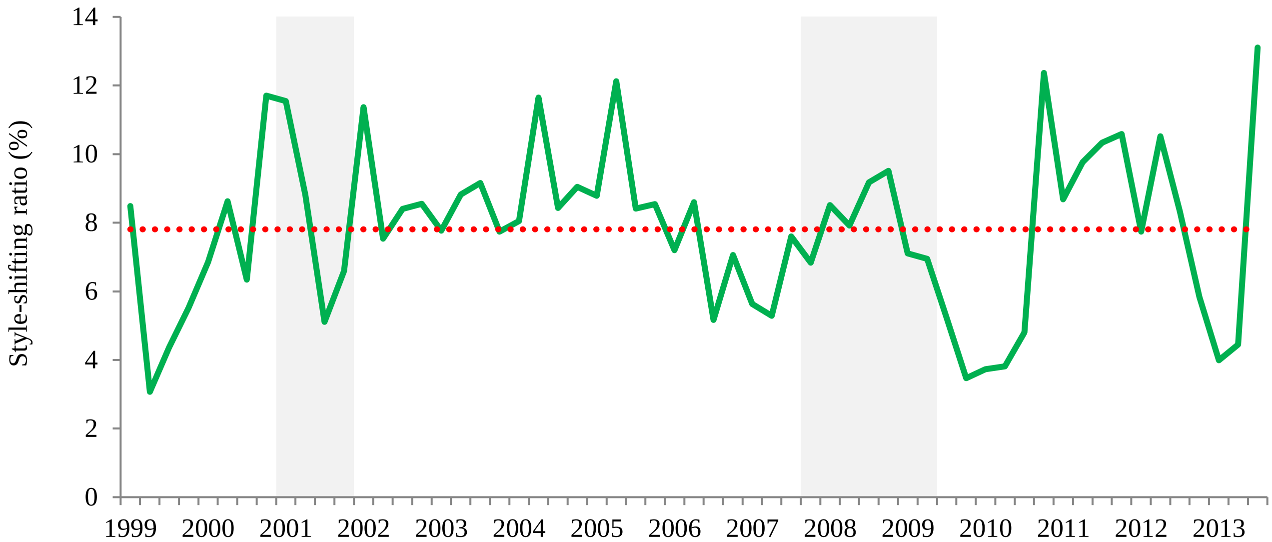


Figure 3. Time Series of Style-Shifting Ratio

This figure plots the time series of style-shifting ratio defined as the number of style-shifting funds divided by the total number of funds in each quarter. The shaded areas are the dot.com and housing crisis periods defined by NBER.



Online Appendix for

"Hedge Fund Manager Skill and Style-Shifting"

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December 2020

This appendix provides supplementary analyses and tables for the paper titled as "Hedge Fund Manager Skill and Style-Shifting" published in *Management Science*.

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A1. Style-shifting: Return-Correlation Based Style Identification

In this section, we conduct another important robustness check using the alternative procedure of fund style identification in Section 3.2.1, that is, funds' styles are identified using fund return correlations. Section A1.1 describes this identification procedure and Section A1.2 reports the empirical findings.

A1.1. Return-Correlation Based Style Identification Procedure

This style-identification procedure is applied to self-reported single-strategy hedge funds in the TASS database. As a result, we include the following styles: convertible arbitrage, emerging markets, equity market neutral, event-driven, fixed income arbitrage, global macro, long-short equity, and managed futures.[7] We end up with 2,846 individual hedge funds in eight unique styles over the sample period. We first use funds' self-reported styles to calculate the equal-weighted returns for each unique style in the first two years (eight quarters), that is, for the period from January 1994 to December 1995. Based on these self-reported style returns, we calculate the Pearson pairwise correlations of a fund's returns with the returns of each of the eight unique style indexes over the first two years, and we define the style with the highest correlation as the temporary style of the fund of interest for December 1995. Each style's return for January 1996 is updated based on the temporary styles assigned for December 1995. We calculate funds' Pearson pairwise correlations with the updated returns of each style based on observations from April (the 2nd quarter) 1994 to March 1996, and assign the style with the highest correlation as the fund's temporary style in March 1996. We repeat this procedure for the entire sample period up to December 2013, and obtain the time series of quarterly styles. To avoid spurious style identification and over-identification of style-shifting, an identified style for a fund based on the above procedure is considered as valid only if the fund maintains the same style for at least three consecutive quarters; otherwise, the style from the prior quarter is retained as the fund style.

[7] We drop dedicated short bias funds because they do not reach our minimum requirement of at least 20 individual fund observations in each month for each unique category to ensure reliable inferences.

A1.2 Alternative Style Identification Based on Return Correlation

The empirical results are reported in Tables A9 through A11 in this online appendix. The results suggest that style-shifting is not uncommon in the hedge fund industry and that style-shifting funds are forward-looking and exhibit both style timing skill and expertise in new styles. Table A9 in the Online Appendix shows that the average shifting ratio based on this identification procedure is about 6.59% per quarter, which is similar across styles (varying between 5.01% and 8.41%) and is close to the shifting ratio based on the out-of-sample PC procedure (Table 3 in the paper). We investigate whether shifting funds time new styles by testing whether a hedge fund's style-shifting decisions are positively related to the return spreads between new and old styles in the subsequent three to 12 months (Table A10). The coefficient of the style-shifting dummy variable in each regression is positive and becomes significant in the regressions of 12-month abnormal style returns. The results are consistent with but weaker than those based on the out-of-sample PC identification procedure (Table 5 in the paper). We perform linear regressions of abnormal fund returns over the subsequent three to 12 months on the style-shifting dummy variable to test whether style-shifting funds show expertise in new styles when using this identification procedure. The coefficient of the style-shifting dummy in each regression in Table A11 in this Appendix is positive and statistically significant. In sum, the results in Tables A10 and A11 are consistent with the forward-looking hypothesis for hedge funds' style-shifting decisions and suggest that our findings are robust to the style identification procedure based on fund return correlations.

Table A1: Correlation Matrix of PCs

This table reports the correlation matrix of the top 20 out-of-sample PCs, as proxies of hedge fund styles, over the sample period. The PCs are derived from (out-of-sample) monthly hedge fund returns in subsequent quarter using the (in-sample) top 20 eigenvalues estimated over the most recent 24 months. The bold numbers denote statistical significance at least at 5% level.

	Correlation matrix																		
PCs	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th	14th	15th	16th	17th	18th	19th	20th
1st	**-0.14**	0.05	0.06	0.09	**0.20**	-0.01	-0.08	**0.15**	-0.08	0.02	**0.18**	**0.15**	**0.17**	-0.13	0.23	0.05	**0.17**	0.03	0.03
2nd		-0.04	**0.22**	0.03	-0.10	-0.11	-0.09	0.11	-0.04	0.02	0.06	-0.01	0.03	0.22	-0.05	0.11	0.00	**-0.16**	-0.04
3rd			0.08	-0.03	0.03	0.04	-0.02	0.07	0.02	-0.15	-0.03	-0.05	0.06	-0.07	0.13	0.02	0.08	0.14	**0.20**
4th				0.10	-0.05	0.02	0.05	-0.02	0.10	-0.08	0.06	-0.17	0.06	-0.02	0.03	0.05	**0.16**	0.04	0.00
5th					-0.01	0.03	0.04	0.01	0.00	0.08	-0.03	-0.01	0.04	0.08	-0.15	-0.07	0.07	0.06	0.04
6th						-0.02	0.02	0.06	**-0.20**	0.06	**0.19**	**0.22**	0.04	0.11	-0.02	0.02	0.09	-0.17	0.07
7th							0.08	**0.29**	0.09	-0.01	0.08	-0.04	-0.06	-0.02	0.09	0.08	-0.05	-0.07	-0.04
8th								0.09	-0.01	**0.18**	0.06	0.06	0.03	**-0.14**	0.02	0.05	0.08	0.04	-0.13
9th									-0.09	-0.01	**0.15**	0.03	0.01	0.05	0.07	0.12	0.06	-0.07	0.03
10th										0.07	**-0.14**	-0.14	0.11	-0.04	-0.11	0.04	**-0.16**	0.08	0.13
11th											-0.05	0.01	0.05	-0.04	-0.04	0.09	-0.18	0.00	0.01
12th												0.12	0.11	0.10	0.09	0.05	0.12	**-0.14**	**-0.21**
13th													-0.02	0.10	0.09	0.10	-0.03	**-0.14**	**-0.04**
14th														0.05	0.11	-0.07	-0.03	0.03	0.08
15th															-0.03	0.11	-0.10	**-0.31**	-0.11
16th																0.11	**-0.19**	0.06	0.07
17th																	-0.07	0.04	-0.06
18th																		0.03	-0.07
19th																			0.06

TableA2. Stability Tests of Out-of-Sample PCs

This tables reports the empirical results of the stability tests of the 20 out-of-sample PCs over time and across fund subsamples. The time series stability test is conducted by estimating in-sample eigenvalues based on 24- (base case) and 36-month (alternative) rolling windows. Columns 1 and 2 report the mean and standard deviation of each PC based on the 24-month rolling window and column 3 reports the pairwise correlations of the pairwise PCs of the 24-month and 36-month rolling windows. The subsample stability test is conducted by splitting the whole hedge fund sample into two equal subsamples and examining the correlation of the pairwise PCs from the two subsamples. Columns 4-7 report the summary statistics of the out-of-sample PCs in each subsample and the last column reports the pairwise correlations of PCs. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

PCs	Whole sample			Subsample				
				1st half		2nd half		
	Mean	Stdev.	Pairwise Corr w/ alternative PC	Mean	Stdev.	Mean	Stdev.	Pairwise correlation
1st	14.98	69.47	0.99***	10.91	47.53	10.09	53.38	0.88***
2nd	3.51	41.98	0.42***	3.84	27.39	4.48	30.34	0.41***
3rd	0.93	26.77	0.50***	-0.40	19.45	2.89	17.98	0.36***
4th	1.74	23.19	0.41***	0.98	15.17	0.57	16.31	0.37***
5th	0.26	17.60	0.18***	-0.52	12.69	-0.40	13.01	0.27***
6th	1.86	15.03	0.26***	1.74	10.16	0.84	11.91	0.39***
7th	0.58	12.82	0.27***	0.80	8.69	1.81	9.84	0.12*
8th	2.16	12.06	0.22***	0.84	8.20	0.61	9.79	0.20***
9th	1.40	9.94	0.05	0.91	7.95	1.17	8.79	0.01
10th	1.52	9.15	-0.01	0.75	6.64	0.00	7.37	-0.11
11th	0.17	9.74	0.07	0.46	7.39	-0.47	7.20	0.12*
12th	0.49	8.91	0.06	0.60	7.84	0.27	7.41	0.06
13th	0.02	8.06	0.16**	0.61	6.69	1.09	7.82	0.04
14th	0.78	7.68	-0.10	0.98	6.52	0.51	6.25	0.06**
15th	0.61	8.85	-0.16**	0.12	6.88	0.28	6.28	-0.23***
16th	0.03	7.21	0.09	0.78	5.55	0.57	6.73	0.08
17th	0.16	7.72	0.20***	1.08	5.97	0.09	6.38	-0.11
18th	0.85	7.01	-0.08	0.94	5.77	-0.56	6.16	-0.05
19th	-0.62	7.65	0.24***	0.39	5.51	-0.35	7.56	0.10
20th	0.51	7.08	-0.03	0.50	6.14	0.05	6.02	0.08

Table A3: Return Correlations of Shifting Funds with Styles.

This table reports the time series averages of the cross-sectional mean correlations of shifting funds' returns with their new and old styles when they shift (columns 1-3) and the cross-sectional mean correlations of shifting funds' returns with their styles and with other styles when they do not shift (columns 4-6). The correlations of non-shifting funds' returns with their styles and with other styles are also reported. The sample period is from January 1994 to December 2013. *** indicates significance at 1% level.

	Shifting funds						Non-shifting funds		
	Shifting periods			Non-shifting periods			Whole sample period		
Styles	New style	Old style	New-Old	Own-style	Other styles	Own-other	Own-style	Other styles	Own-other
All	0.52	0.29	0.23***	0.60	0.041	0.56***	0.71	0.03	0.68***
1st	0.53	0.38	0.15***	0.66	0.044	0.62***	0.73	0.036	0.69***
2nd	0.51	0.22	0.29***	0.59	0.039	0.55***	0.60	-0.001	0.60***
3rd	0.53	0.32	0.21***	0.53	0.050	0.48***	0.54	0.033	0.51***
4th	0.52	0.23	0.29***	0.53	0.027	0.50***	0.58	0.043	0.53***
5th	0.49	0.24	0.25***	0.49	0.026	0.46***	0.49	0.018	0.47***
6th	0.49	0.23	0.26***	0.50	0.031	0.47***	0.48	0.020	0.46***
7th	0.48	0.21	0.27***	0.48	0.015	0.46***	0.50	-0.001	0.50***
8th	0.46	0.15	0.31***	0.45	0.023	0.43***	0.46	0.052	0.41***
9th	0.48	0.24	0.24***	0.49	0.031	0.45***	0.49	0.014	0.48**
10th	0.47	0.16	0.31***	0.45	0.004	0.45***	0.34	-0.029	0.37***
11th	0.49	0.24	0.25***	0.48	0.004	0.47***	0.53	0.042	0.49***
12th	0.51	0.30	0.21***	0.51	0.032	0.47***	0.55	0.040	0.51***
13th	0.48	0.25	0.23***	0.50	0.022	0.48***	0.49	0.041	0.45***
14th	0.50	0.26	0.24***	0.49	0.035	0.46***	0.40	-0.015	0.42***
15th	0.48	0.23	0.25***	0.47	0.009	0.46***	0.45	0.011	0.44***
16th	0.49	0.23	0.26***	0.48	0.012	0.47***	0.43	-0.002	0.43***
17th	0.49	0.24	0.25***	0.47	0.026	0.45***	0.53	0.048	0.48***
18th	0.47	0.23	0.24***	0.48	0.014	0.46***	0.48	0.006	0.47***
19th	0.47	0.19	0.28***	0.47	0.001	0.47***	0.47	0.014	0.46***
20th	0.48	0.20	0.28***	0.48	0.014	0.47***	0.47	-0.017	0.48***

Table A4. Style Transition Matrix

Hedge funds are sorted into style groups based on identified styles in period *t*-1. For each style, we compute the percentage of funds shifting to other styles over period *t* and the percentage of funds staying in the same style. This table reports the time series average of transition ratios for all styles and each individual style over the whole sample period. The sample period is from January 1994 to December 2013.

Initial style	Subsequent style																				Total (%)
	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th	14th	15th	16th	17th	18th	19th	20th	
1st	96.48	0.50	0.24	0.28	0.18	0.28	0.17	0.09	0.14	0.10	0.17	0.22	0.20	0.29	0.06	0.15	0.09	0.11	0.16	0.10	100
2nd	3.94	88.48	1.27	0.79	0.36	0.56	0.20	0.46	0.18	0.36	0.13	0.58	0.18	0.71	0.33	0.18	0.25	0.25	0.56	0.23	100
3rd	4.77	2.43	86.74	1.45	0.47	0.16	0.25	0.47	0.28	0.44	0.35	0.22	0.16	0.25	0.16	0.19	0.16	0.35	0.44	0.25	100
4th	4.02	0.83	1.62	87.82	0.24	0.39	0.20	0.35	0.39	0.24	0.51	0.51	0.24	0.32	0.32	0.51	0.16	0.83	0.24	0.28	100
5th	5.22	0.54	0.78	0.78	86.49	0.36	0.30	0.12	1.08	0.48	0.24	0.42	0.24	0.90	0.24	0.60	0.48	0.36	0.12	0.24	100
6th	4.41	0.91	0.79	0.54	0.30	86.76	0.60	0.18	0.24	0.30	0.67	0.73	0.06	0.73	0.67	0.18	0.54	0.67	0.30	0.42	100
7th	2.77	1.52	0.53	0.46	0.79	0.46	87.55	0.26	0.59	0.33	0.33	0.99	0.26	0.79	0.46	0.86	0.20	0.20	0.40	0.26	100
8th	1.65	2.94	0.55	1.56	0.55	1.19	1.19	85.48	0.09	0.18	0.09	0.83	0.64	0.74	0.46	0.37	0.28	0.28	0.55	0.37	100
9th	4.74	0.59	0.79	0.79	0.10	0.89	0.59	0.40	83.89	0.40	0.69	0.89	0.40	0.69	0.30	0.69	0.69	1.48	0.59	0.40	100
10th	3.92	1.50	0.58	0.92	0.33	0.50	0.67	0.58	0.58	86.00	0.83	0.33	0.42	0.58	0.75	0.25	0.42	0.17	0.58	0.08	100
11th	2.97	2.25	1.45	0.36	0.36	0.65	0.80	0.43	0.22	0.29	86.74	0.43	0.36	0.51	0.14	0.29	0.80	0.14	0.36	0.43	100
12th	4.03	0.66	1.04	0.43	0.71	0.38	0.66	0.14	0.47	0.24	0.33	87.67	0.24	0.52	0.19	0.33	0.66	0.66	0.28	0.33	100
13th	4.02	1.80	0.26	0.60	0.43	0.43	0.09	0.43	0.34	0.43	0.26	0.34	87.77	0.26	0.26	0.43	0.86	0.51	0.34	0.17	100
14th	3.28	2.38	2.75	0.58	0.32	0.32	0.42	0.21	0.32	0.42	0.16	1.11	0.11	85.98	0.11	0.21	0.48	0.32	0.21	0.32	100
15th	2.89	1.00	1.59	0.60	0.30	0.50	0.80	0.50	0.60	0.20	0.50	0.30	0.00	0.10	87.36	0.40	0.70	0.70	0.50	0.50	100
16th	4.20	0.29	1.45	0.43	0.43	0.58	0.29	0.58	0.36	0.22	0.43	0.43	0.51	0.51	0.22	87.84	0.29	0.29	0.36	0.29	100
17th	3.48	0.43	1.48	1.22	0.43	0.78	0.52	0.52	0.26	0.35	0.43	0.70	0.35	0.70	0.43	0.52	87.13	0.09	0.09	0.09	100
18th	4.50	1.29	0.75	0.48	0.34	0.27	0.54	0.68	0.75	0.20	0.68	0.68	0.41	0.82	0.68	0.27	0.34	85.49	0.48	0.34	100
19th	2.99	0.24	1.54	0.65	0.48	0.48	0.08	0.32	0.73	0.65	0.08	0.40	0.24	0.81	0.32	0.57	0.48	1.21	86.91	0.81	100
20th	2.04	0.71	1.18	0.63	0.16	0.24	0.79	0.63	1.34	0.79	0.31	0.71	0.39	0.79	0.31	0.55	0.31	0.47	0.24	87.42	100

Table A5. Market Conditions and Style-Shifting

This table reports the percentages of style-shifting funds during different market conditions. In the left panel, we divide our sample period into up and down market periods based on whether the market return is positive or negative in a given quarter. In the right panel, we divide our sample period into high and low hedge fund flow periods based on the median of aggregated quarterly flows to the hedge fund industry. In each panel, the difference in style-shifting ratio between two subperiods is also reported. ***, and ** denote statistical significance at the 1% and 5% levels, respectively. The sample period is from January 1994 to December 2013.

	Market Performance			Aggregated Fund flow		
Style	Up	Down	Up-Down	High	Low	High-Low
All funds	7.27	8.38	-1.11***	7.87	7.50	0.37**
1st	3.37	3.78	-0.41***	3.42	3.62	-0.19
2nd	7.93	17.72	-9.78***	12.29	10.80	1.50***
3rd	13.07	13.60	-0.53	13.95	12.62	1.34***
4th	11.01	14.20	-3.19***	12.95	11.45	1.50***
5th	12.19	15.79	-3.60***	13.89	13.15	0.73
6th	12.52	14.47	-1.95***	13.41	13.07	0.34
7th	10.89	15.14	-4.24***	11.32	13.50	-2.18***
8th	14.75	14.13	0.62	15.25	13.84	1.41**
9th	14.61	18.70	-4.09***	19.66	12.78	6.88***
10th	15.65	11.16	4.49***	13.91	14.09	-0.18
11th	14.03	11.92	2.12***	13.23	13.29	-0.06
12th	11.99	12.91	-0.92**	12.15	12.50	-0.34
13th	12.01	12.62	-0.61	15.34	9.32	6.02***
14th	14.21	13.68	0.53	14.33	13.72	0.61
15th	12.06	13.65	-1.59***	11.80	13.43	-1.63***
16th	10.14	15.66	-5.53***	12.84	11.53	1.32***
17th	11.38	15.44	-4.06***	12.86	12.88	-0.02
18th	14.97	13.72	1.25**	14.28	14.73	-0.44
19th	11.42	15.97	-4.55***	14.08	12.16	1.92***
20th	12.40	12.87	-0.47	11.55	13.54	-2.00***

Table A6: Impact of Sample Biases

The table reports the results of the impact of survivorship and back-filling biases in the TASS database on the analysis of hedge fund style-shifting. The analysis of the impact of survivorship bias is conducted by deleting or adding the number of hedge funds equal to the total number of funds in the sample multiplied by attrition rate. Attrition rate is the ratio of the number of defunct funds to the number of hedge funds that existed at the start of the quarter. The added or removed funds are either randomly drawn or are selected as the worst-performing funds in the sample period. The first four columns report the time series average of style-shifting ratios for the whole sample and for each style after controlling survival biases. We control for the effect of backfill bias by deleting all return observations before the date the fund is firstly added to the TASS database. The last column reports the time series average of style-shifting ratio after deleting the backfilled observations. *** denotes statistical significance at the 1% level. The sample period is from January 1994 to December 2013.

	Survivorship bias analysis				Back-filling bias analysis
	Shifting ratio with deletions		Shifting ratio after additions		
Funds in styles	Random draws	Worst funds	Random draws	Worst funds	shifting ratio after back-fills removed
All funds	7.66***	7.65***	7.63***	7.64***	6.90***
1st	3.54***	3.49***	3.51***	3.55***	3.20***
2nd	11.60***	11.40***	11.35***	11.53***	12.53***
3rd	13.22***	13.41***	13.37***	13.22***	12.53***
4th	12.48***	12.63***	12.50***	12.39***	11.64***
5th	14.07***	13.72***	13.70***	13.95***	14.04***
6th	13.31***	13.47***	13.37***	13.27***	15.12***
7th	12.28***	12.15***	12.46***	12.55***	13.65***
8th	13.93***	14.46***	14.09***	13.78***	13.79***
9th	16.61***	15.89***	15.77***	16.27***	14.92***
10th	14.48***	15.05***	14.82***	14.52***	12.78***
11th	13.45***	12.88***	12.81***	13.17***	13.89***
12th	12.48***	12.59***	12.33***	12.30***	13.86***
13th	11.97***	12.43***	12.46***	12.13***	13.36***
14th	13.53***	14.36***	14.25***	13.68***	13.84***
15th	12.36***	12.39***	12.60***	12.66***	13.86***
16th	12.33***	12.05***	11.97***	12.16***	13.91***
17th	12.56***	12.67***	13.06***	12.93***	11.98***
18th	14.25***	13.95***	14.55***	14.84***	12.68***
19th	13.44***	12.93***	12.96***	13.44***	13.02***
20th	12.30***	13.00***	12.59***	12.15***	12.77***

Table A7. Style-Timing and Style-Expertise: Long-horizon Performance

We decompose the cumulative returns of style-shifting funds over subsequent periods into passive strategy returns, the gain from timing new styles, and the gain from expertise in new styles. This table reports the time series average of cross-sectional means of the equal-weighted cumulative returns of style-shifting funds and the gains of style-timing and style expertise, respectively, over subsequent one, two, and three years. Newey-West *t*-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1994 to December 2013.

	Subsequent period		
	1-year	2-year	3-year
Fund returns	7.62***	18.00***	30.31***
	(5.49)	(6.09)	(6.75)
Style timing	0.76**	1.46*	1.18
	(2.04)	(1.87)	(0.97)
Style expertise	1.10**	4.67***	9.86***
	(2.18)	(3.50)	(4.95)

Table A8. Robustness Check: Results Based on Eight Out-of-Sample PCs

This table reports the empirical results of hedge fund style-shifting based on the top eight out-of-sample PCs. Panel A reports summary statistics of style-shifting for the whole sample and for each style, including the average number of self-reported single-strategy funds per quarter, the average number of style-shifting funds per quarter, and the average percentage of funds shifting styles each quarter. Panel B reports the time series average of cross-sectional means of returns of style-shifting funds and the gains of style-timing and style expertise, respectively. Style returns are AUM-weighted and fund returns are either equal- or AUM-weighted. Newey-West *t*-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1994 to December 2013.

Panel A: Summary Statistics of Style-Shifting

Style	Avg. no. of funds/quarter	Avg. no. of style-shifting funds/quarter	Avg. style-shifting ratio
All styles	1,200.59	81.39	6.82***
1st	730.50	24.61	3.44***
2nd	121.41	11.77	11.24***
3rd	91.11	11.50	12.89***
4th	66.86	8.57	12.82***
5th	50.23	7.00	13.57***
6th	53.63	6.43	12.36***
7th	50.93	6.59	13.05***
8th	35.93	4.93	13.34***

Panel B: Return Decomposition: Style-timing vs. Style-expertise

	1-quarter	2-quarter	1-year
	Equal-weighted shifting fund returns		
$R_{i,t+k}$	1.77***	3.57***	7.44 ***
	(4.31)	(4.44)	(5.20)
R_{t+k}^{New}	1.51***	2.98***	5.62 ***
	(4.12)	(4.13)	(4.21)
R_{t+k}^{old}	1.31***	2.77***	5.85 ***
	(3.30)	(3.80)	(4.46)
$(R_{i,t+k} - R_{t+k}^{Old})$	0.46**	0.81**	1.83 **
	(1.97)	(2.11)	(2.14)
$\left(R_{t+k}^{New} - R_{t+k}^{Old}\right)$	0.19	0.21*	0.22*
	(0.93)	(1.75)	(1.78)
$(R_{i,t+k} - R_{t+k}^{New})$	0.26*	0.60**	1.60 ***
	(1.86)	(2.05)	(2.78)
	AUM-weighted shifting fund returns		
$R_{i,t+k}$	1.73***	3.52***	7.36 ***
	(4.23)	(4.41)	(5.19)
R_{t+k}^{New}	1.51***	2.98***	5.62 ***
	(4.12)	(4.13)	(4.21)
R_{t+k}^{old}	1.31***	2.77***	5.85 ***
	(3.30)	(3.80)	(4.46)
$(R_{i,t+k} - R_{t+k}^{Old})$	0.41*	0.76*	1.73 *
	(1.82)	(2.04)	(2.09)
$\left(R_{t+k}^{New} - R_{t+k}^{Old}\right)$	0.19	0.21*	0.22 **
	(0.93)	(1.75)	(1.78)
$(R_{i,t+k} - R_{t+k}^{New})$	0.22**	0.54**	1.51 ***
	(1.72)	(1.98)	(2.71)

Table A9. Summary Statistics of Hedge Fund Style-Shifting – Return Correlation Based Approach

This table reports summary statistics of style-shifting for the whole sample of all self-reported single-strategy funds and for each unique style, including the total number of funds in our sample and the number of funds in each style based on the identification procedure of return correlation approach, the average number of funds per quarter, the average number of style-shifting funds per quarter and the average percentage of funds shifting styles each quarter. The sample period is from January 1994 to December 2013.

Fund style	No. of funds based on self-reported style	No. of funds based on our identification	Avg. no. of funds/qtr	Avg. no. of style-shifting funds/qtr	Avg. shifting ratio
Whole sample	2,846	2,846	959.37	67.07	6.59***
Convertible arbitrage	121	221	74.93	5.88	8.41***
Emerging market	313	478	104.63	8.12	7.71***
Equity market neutral	203	321	213.64	15.18	6.71***
Event-driven	330	451	106.15	5.38	7.09***
Fixed income arbitrage	162	223	64.07	5.96	8.38***
Global macro	194	107	120.08	10.15	7.96***
Long-short equity hedge	1,229	702	169.60	10.29	7.53***
Managed futures	295	343	116.26	6.11	5.01***

Table A10. Style-Shifting and Future Style Performance – Return Correlation Based Approach

This table reports the results of regressing future return spreads between the new and old styles, which equals zero if the fund does not shift style, on a style-shifting dummy variable $SF_{i,t}^{Old \to New}$ which equals one if fund *i* shifts its style in quarter *t* and zero otherwise. Control variables include the cumulative return spread between the new and old styles and the cumulative returns of style-shifting funds over the past three to 12 months. The Newey-West *t*-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1994 to December 2013.

Dependent Variable	$\Delta R_{[t+1,t+3]}^{New-Old}$		$\Delta R_{[t+1,t+6]}^{New-Old}$		$\Delta R_{[t+1,t+12]}^{New-Old}$	
Intercept (%)	0.00*	0.00*	0.00	0.00	0.00	0.00
	(1.93)	(1.83)	(0.57)	(0.62)	(1.45)	(0.57)
$SF_{i,t}^{old \to new}$	0.27	0.32	0.56	0.74	1.25***	1.60***
	(1.31)	(1.60)	(1.51)	(1.58)	(3.75)	(4.91)
$\Delta R_{[t-1,t-3]}^{New-Old}$	0.07***	0.06***	0.05	0.05	0.02	0.02
	(4.72)	(3.90)	(1.12)	(1.13)	(0.06)	(0.53)
$\Delta R_{[t-1,t-6]}^{New-Old}$	-0.07	-0.04	0.07***	0.08***	0.04	0.03
	(-0.56)	(-0.29)	(3.26)	(3.38)	(1.16)	(1.13)
$\Delta R_{[t-1,t-12]}^{New-Old}$	-0.02***	-0.02***	-0.05***	-0.06***	-0.08***	-0.08***
	(-3.19)	(-3.31)	(-5.39)	(-5.58)	(-6.12)	(-6.31)
$Ret_{i,[t-1,t-3]}^{Shifting fund}$		0.06***		0.05***		0.02
		(5.16)		(2.77)		(0.82)
$Ret_{i,[t-1,t-6]}^{Shifting fund}$		-0.02**		-0.02		-0.04**
		(-2.06)		(-1.31)		(-2.03)
$Ret_{i,[t-1,t-12]}^{Shifting fund}$		-0.01*		-0.02***		-0.03***
		(-1.84)		(-3.39)		(-3.21)
R^2 (%)	1.13	1.98	1.58	2.25	2.39	3.68

Table A11. Style-Shifting and Future Fund Performance – Return Correlation Based Approach

This table reports the results of regressing a fund's future style-adjusted (abnormal) returns ($AR_{i,[t+1,t+k]}$) on the style-shifting dummy ($SF_{i,t}^{Old \to New}$) which equals one if fund i shifts its style in quarter t and zero otherwise. Control variables include the fund return, return volatility over the past 12 months, fund size (AUM), fund flow over the past 12 months, fund age, incentive fee, management fees, a high-water mark dummy, the lengths of the lockup period and redemption notice, an indicator of leverage, and the minimum investment requirement. The associated Newey-West t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1994 to December 2013.

Dependent	$AR_{i,[t+1,t+3]}$		$AR_{i,[t+1,t+6]}$		$AR_{i,[t+1,t+12]}$	
Intercept	-0.68***	-2.08***	-1.32***	-4.07***	-2.33***	-7.92***
	(-13.02)	(-14.86)	(-18.88)	(-20.08)	(-22.31)	(-25.98)
$SF_{i,t}^{Old \to New}$	0.18**	0.16**	0.59***	0.55***	0.90***	0.78***
	(1.97)	(2.04)	(4.29)	(4.03)	(4.51)	(3.91)
Return	0.10***	0.10***	0.11***	0.11***	0.14***	0.13***
	(10.52)	(10.25)	(9.30)	(8.94)	(7.32)	(6.86)
Return volatility	0.22***	0.22***	0.43***	0.45***	0.77***	0.80***
	(13.93)	(14.08)	(21.30)	(21.56)	(25.29)	(25.66)
Log (AUM)	-0.00*	-0.00***	-0.00*	-0.00***	-0.00*	-0.00***
	(-1.93)	(-3.83)	(-1.75)	(-5.32)	(-1.94)	(-6.67)
Fund flow	0.00*	0.00*	0.00***	0.00**	0.00***	0.00**
	(1.78)	(1.88)	(2.65)	(2.00)	(2.67)	(2.17)
Flow volatility	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(-0.23)	(-0.30)	(-0.72)	(0.51)	(-0.92)	(-0.77)
Log (age)		0.00**		0.00***		0.01***
		(2.55)		(3.44)		(6.52)
Incentive fee		0.02***		0.03***		0.03***
		(3.55)		(3.65)		(3.13)
Management fee		0.28***		0.58***		1.21***
		(6.86)		(9.99)		(13.92)
High water mark		0.00***		0.00***		0.01***
		(2.87)		(4.46)		(6.41)
Lockup		0.00**		0.00***		0.00***
		(2.00)		(2.74)		(4.83)
Redemption		0.00***		0.01***		0.00***
		(6.94)		(10.11)		(13.40)
Leverage		0.00*		0.00**		0.00**
		(1.94)		(2.21)		(2.40)
Min investment		0.00***		0.00***		0.00***
		(6.19)		(8.11)		(10.32)
R^2 (%)	1.24	1.41	1.74	2.06	2.20	2.81

Table A12: Multi-Style Shifting: Summary Statistics of Sharpe Regressions

The table reports summary statistics of style weight and weight change of multi-style shifting funds identified by the quadratic Sharpe regressions. The Sharpe regression for fund i in period t is conducted as $r_{i,t} = \sum_{s=1}^{S} \beta_s r_{s,t} + \varepsilon_{i,t}$, *Subject to* $\sum \beta_s = 1, \beta_s \geq 0$ over the most recent 24 months. $r_{s,t}$ is the return of style *s* in period *t* and the number of styles *S* is set to be five and the corresponding styles are selected as those closely related to fund returns. β_s is defined as the weight of fund *i* on style *s* in period t. This table reports the time series average of cross-sectional mean of style weights and weight changes over the sample period. The sample period is from January 1994 to December 2013.

Style	Mean	Stdev.	25%tile	50%tile	75%tile	Min	Max
				Distribution of style weight			
All	20.00	25.46	0.00	9.81	31.67	0.00	100.00
1st	39.73	33.39	7.18	35.30	65.84	0.00	100.00
2nd	26.85	25.85	2.57	21.48	42.70	0.00	100.00
3rd	14.66	17.88	0.00	7.71	24.83	0.00	99.07
4th	10.41	14.91	0.00	1.79	17.37	0.00	92.97
5th	8.34	13.36	0.00	0.19	13.09	0.00	87.28
				Distribution of style weight change			
All	-0.10	13.67	-2.13	0.00	2.10	-97.30	96.22
1st	-0.11	15.25	-4.41	-0.01	4.58	-90.91	90.44
2nd	2.22	16.17	-2.45	0.02	6.95	-89.33	92.28
3rd	-0.10	13.07	-1.96	0.00	2.12	-85.92	81.23
4th	-0.92	11.39	-1.10	0.00	0.15	-86.85	68.62
5th	-1.58	11.01	-0.83	0.00	0.00	-84.25	62.84

Table A13: Robustness Check: Multi-style Shifting Based on Eight Out-of-Sample PCs

This table reports the decomposition of multi-style shifting fund i's cumulative return over future k-quarter $R_{i,[t,t+k]}$, into passive gain $\sum_{s=1}^{S} \omega_{i,s,t-1} R_{[t,t+k]}^{s}$ the style-timing gain, $\sum_{s=1}^{S} (\omega_{i,s,t} - \omega_{i,s,t-1}) R_{[t,t+K]}^{s}$, and the style expertise, $(R_{i,[t,t+k]} - \sum_{s=1}^{S} \omega_{i,s,t} R_{[t,t+k]}^{S})$, where S is set to be five and the corresponding styles are selected as those closely correlated with fund returns. All analyses are based on the top eight out-of-sample PCs. Fund's style weights are estimated using the quadratic Sharpe regression of Equation (4). Panels A 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 based on whole sample of funds. Panels B and C report the results of multi-style shifting funds defined as those funds with shifts in style weights between two consecutive quarters equal to or higher than 25% and 50%, respectively. Newey-West t-statistics are in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from January 1994 to December 2013.

	Cumulative fund performance in subsequent periods		
	1-quarter	2-quarter	1-year
Panel A: All funds			
Fund return	1.70***	3.35***	6.62***
	(2.72)	(2.89)	(3.14)
Passive	1.57***	3.01***	5.98***
	(4.02)	(4.04)	(4.51)
Style-Timing	0.002	0.04	0.08
	(0.11)	(1.60)	(1.37)
Style-Expertise	0.13	0.30	0.57
	(0.47)	(0.63)	(0.62)
Panel B: Funds with at least one style weight shift ≥25%			
Fund return	1.99***	3.78***	7.92***
	(3.82)	(3.278)	(4.34)
Passive	0.83***	1.60***	3.34***
	(3.68)	(4.44)	(5.07)
Style-Timing	0.11**	0.20*	0.14*
	(2.01)	(1.92)	(1.80)
Style-Expertise	1.05***	1.99***	4.25***
	(3.12)	(2.88)	(3.45)
Panel C: Funds with at least one style weight shift ≥50%			
Fund return	2.83***	5.09***	9.77***
	(3.42)	(3.56)	(3.60)
Passive	0.78*	1.27**	3.24***
	(1.95)	(2.17)	(3.48)
Style-Timing	0.15**	0.41**	0.29*
	(2.36)	(2.02)	(1.91)
Style-Expertise	1.89***	3.42***	6.24***
	(2.82)	(2.95)	(2.99)

Table A14. Style-Shifting and Fund Characteristics

This table reports the time series average of the cross-sectional mean of each lagged fund characteristic in each quarter for both style-shifting and non-shifting funds. Static fund characteristics include the lengths of the lockup period and redemption notice, the minimum investment requirement, a leverage dummy, incentive and management fees and a high-water mark dummy, and time-varying fund characteristics include log (AUM), log (age), fund return, Fung-Hsieh alpha, Sharpe ratio, information ratio, Sortino ratio, fund return volatility, fund flow and flow volatility. All time-varying independent variables are lagged by one quarter. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Static Characteristics

	Shifting funds	Non-shifting funds	Difference
Lockup (months)	2.95	2.61	0.34*
			(1.90)
Redemption notice (days)	35.18	33.06	2.12**
			(2.29)
Log (min investment)	0.91	0.75	0.16**
			(2.02)
Leverage	0.56	0.66	-0.10***
			(-5.04)
Incentive fee (%)	19.05	17.69	1.36***
			(8.19)
Management fee (%)	1.45	1.40	0.05*
			(1.65)
High-water mark	0.63	0.47	0.16***
			(11.08)

Panel B: Time-Varying Characteristics

	Shifting funds	Non-shifting funds	Difference
Log (AUM)	17.20	20.06	-2.86***
			(9.58)
Log (age)	2.40	2.59	-0.19***
			(-17.84)
12-mo average return (%)	0.87	0.78	0.09**
			(2.51)
F-H alpha (%)	0.74	0.55	0.19***
			(5.03)
Sharpe ratio	0.56	0.32	0.16***
			(4.32)
Information ratio	0.05	0.02	0.03**
			(2.15)
Sortino ratio	0.60	0.39	0.21***
			(5.39)
Return volatility	3.64	3.67	-0.03
			(-0.49)
12-month fund flow (%)	10.46	8.83	1.63***
			(2.91)
Flow volatility (%)	3.71	4.38	-0.67*
			(-1.74)