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INVESTMENT STYLE VOLATILITY AND MUTUAL FUND PERFORMANCE

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We develop a holdings-based statistic to measure the volatility of a fund's investment style characteristic profile over time. On average, funds with lower levels of style volatility significantly outperform more style-volatile funds on a risk-adjusted basis. We show that style volatility has a distinct impact on future fund performance compared to fund expenses or past risk-adjusted returns, with the level of indirect style volatility being the primary determinant of the overall effect. We conclude that deciding to maintain a less volatile investment style is an important aspect of the portfolio management process.

There is by now ample evidence that an equity mutual fund's investment style has become deeply ingrained in how the fund is defined and the returns it produces. Researchers and portfolio managers alike have long been aware of the benefits of forming stock portfolios that emphasize various firm-related attributes (such as price–earnings ratios, market capitalization, or return momentum). For example, Capaul *et al.* (1993), Fama and French (1998), and Chan and Lakonishok (2004) all show that portfolios of value stocks outperform portfolios of growth stocks on a long-term, risk-adjusted basis and that this "value premium" is a pervasive feature of global capital markets, despite some disagreements as to why this premium occurs. Additionally, Malkiel (1995) demonstrates that a fund's ability to outperform a benchmark such as the S&P 500 is related to its objective class, which has led other researchers (e.g., Brown and Goetzmann, 1997) to question the efficacy of traditional methods for classifying funds.

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In this study, we consider an aspect of the investment style question that has received little attention in the literature; namely, the impact on performance associated with the level of investment *style volatility* in the portfolio. Specifically, we define style volatility as the degree to which the portfolio's investment style characteristics shift over time as a result of how the manager chooses to implement the fund's style mandate; a portfolio with less (more) style volatility can be thought of as one with a more (less) predictable implementation of its style strategy. We then pose the following question: Do investors benefit from managers who maintain their designated investment strategy on a more volatile or a less volatile basis? That is, regardless of the specific investment mandate, does a manager who keeps a tighter control on the volatility of that style decision add value relative to a manager who allows the portfolio's style to drift more over time? The underlying premise of this investigation is that level of volatility resulting from how a manager implements the fund's investment mandate *should* be related to the returns it produces.

What is not necessarily clear, however, is the probable direction of this relationship. On one hand, there are several potential reasons why, ceteris paribus, portfolios with a lower level of style volatility (i.e., more style predictability) should produce superior returns. First, it is likely that less style-volatile funds exhibit less portfolio turnover and, hence, have lower transaction costs than funds that allow their style to drift. Second, it is possible that managers who act opportunistically will end up altering the risk of their portfolios in a way that leads to suboptimal performance, as shown by Huang *et al.* (2011), Cao *et al.* (2017), and Chua *et al.* (2018). Finally, it is also likely that managers with less style volatile approaches are easier for other market participants to evaluate accurately. Therefore, since better managers will want to be assessed more precisely, maintaining a less style-volatile portfolio is one way that they can signal their superior skill to potential investors.

Conversely, it is also possible that managers who adopt a strategy designed to remain close to a style benchmark or factor model loading could underperform (or at least fail to outperform) their peer group. Asness *et al.* (2000) document that, while a less volatile value-oriented strategy might produce superior returns over time, portfolios formed around growth characteristics have outperformed value-oriented portfolios by almost 30% in given holding periods. Thus, although a less style-volatile portfolio might reduce the potential for underperformance, it is also unlikely to capture the benefits that accrue to a manager who possesses the ability to accurately time these style rotations in the market; see, for example, Swinkels and Tjong-a-Tjoe (2007). It may also be true that fund managers capable of producing positive abnormal returns through superior "bottom-up" security selection skills find that they shift the investment style of their portfolios indirectly with their individual stock transactions.

We begin our investigation by describing a new approach to measuring style volatility. Specifically, we assess the volatility of the manager's style implementation decisions by examining how changes in the portfolio's security holdings over time alter its profile with respect to three specific style characteristics: market capitalization, book-to-market ratio, and return momentum. The advantage of this holdings-based style volatility metric is that it captures the essence of the actual adjustments the manager made to the portfolio's composition. Furthermore, we are also able to decompose this measure into two separate components accounting for the direct and indirect effects that a manager's portfolio adjustments have on style volatility.

Using this style volatility statistic in conjunction with a survivorship-free universe of mutual funds over the period from January 1978 to December 2009, the primary goal of our empirical investigation tests how a manager's ability to maintain a consistent investment style affects future risk-adjusted returns. We assess performance over four return intervals following the date on which we calculate the style volatility measure: one, three, six, and twelve months in the future. As part of this evaluation, we control for the influence of a number of additional factors shown to influence fund performance, including past risk-adjusted returns (i.e., the performance persistence effect), portfolio turnover, fund assets under management, and fund expense ratio. As robustness checks, we also consider a wide range of alternative estimation methodologies and approaches to volatility measurement.

The main findings document a significantly negative correlation between a fund's style volatility level and its subsequent risk-adjusted performance. This supports the conclusion that, on average, funds with the least volatile investment styles over time produce superior risk-adjusted returns compared to funds with a greater degree of style volatility. Our tests also show that the impact that style volatility has on future performance is distinct from the effects of past performance and fund expenses established elsewhere in the literature. We report additional tests re-examining these relationships after considering source characteristics (firm size, value-growth, momentum) for the aggregate style volatility measure on an individual basis. Interestingly, the correlation between a fund's performance and the consistency of its investment style does appear to depend on the predominant driver of that volatility: the negative relationship between the two variables is the most significant when market capitalization is the largest contributor and is weakest when return momentum is the dominant source of the volatility measure.

When we decompose our aggregate style volatility statistic into its direct and indirect components, we once again find differential effects on fund performance. The intuition behind this decomposition is that changes in a portfolio's overall style profile could result from explicit adjustments the manager makes (i.e., direct volatility) or indirect shifts caused by changes in the characteristics of the existing holdings themselves. We document a significant negative relationship between risk-adjusted fund performance and indirect style volatility, meaning that even managers who may not be deliberately trying to manipulate the characteristics of their portfolios need to be concerned with maintaining a stable style profile. Similarly, the overall relationship between fund performance and direct volatility remains negative, but this effect varies considerably with the style characteristic most responsible for that volatility. In fact, when the direct style volatility measure is broken down into all three dominant-source characteristics, the firm size subsample exhibits significant underperformance while the value-growth and momentum subsamples generate largely insignificant coefficients.

Our main result regarding the ability of low-style volatility funds to produce superior risk-adjusted returns proves to hold under a wide variety of methodological assumptions regarding such things as how future returns are estimated, how investment style is classified, or the way in which the style volatility measure is calculated. In particular, substituting a fund's tracking error—which can be interpreted as a *returns-based* measure of volatility relative to its style-specific benchmark—in place of our holdings-based statistic does not materially affect this connection, despite the fact that tracking error and style volatility are themselves less than perfectly correlated.

Finally, to document the economic significance of the impact that a manager's style volatility decision has on fund performance, we show that our holdings-based measure can be used by investors to increase substantially the ex ante probability of identifying a superior fund manager. Furthermore, we also demonstrate how the style volatility statistic can be integrated alongside the past performance and fund expense variables to help investors form profitable risk-adjusted trading strategies. Collectively, our results support the conclusion that investment style volatility does indeed matter and that a manager's ability to maintain a portfolio with a stable style profile is a skill that is rewarded in the market.

1 A Measure of Style Volatility

1.1 Defining style volatility

The most direct way to assess a fund's style volatility involves how the characteristics of the securities held in the portfolio vary over time. As no existing metric is suitable for this purpose, we create a new holdings-based measure employing the following multi-step procedure. First, based on Daniel *et al.* (1997), each year during the sample period (i.e., at the end of June) we used a $(5 \times 5 \times 5)$ sorting procedure to classify every potential stock position into quintiles according to three characteristics: market capitalization, book-to-market ratio, and past return momentum. Consistent with that work, for each characteristic we assign a score of 5 to a stock falling in the quintile containing the highest values of that characteristic (i.e., largest stocks, highest book-to-market ratios, highest prior-year returns) and a score of 1 to a stock in the lowest quintile.

The second step then looks at a fund's most recent holdings and computes the value-weighted average size, book-to-market, and momentum scores across the entire portfolio based on the procedure developed by Kacperczyk *et al.* (2005). For each fund, these three average characteristic-rank scores were computed on a monthly basis using the most recently reported holdings available (e.g., holdings reported at the end of September were used to calculate rankings for the portfolio in October, November, and December). For example, a manager placing two-thirds of her assets in the largest stocks (quintile 5) and one-third of her positions in quintile 4 stocks would have a size characteristic ranking of 4.67. Notice that there are three ways in which this ranking variable can change over time: (i) the relative values of the existing holdings change, which can occur monthly; (ii) the manager explicitly alters the composition of the portfolio, which can be observed quarterly; or (iii) an existing stock holding has its characteristic ranking reclassified, which can occur annually.[1]

Given these monthly indications of a manager's investment style, our style volatility statistic measures how the characteristic rankings vary over time. The third step of the process calculates the standard deviation of the manager's average ranking to each characteristic using the most recent 36 months of data. For fund manager j in month t, we calculate for each characteristic c:

$$\sigma_{c,j,t} = \left\{ \sum_{n=0}^{35} \frac{(\text{Rank}_{c,j,t-n} - \text{MRank}_{c,j})^2}{(36-1)} \right\}^{1/2} \tag{1}$$

where $\text{Rank}_{c,j,t-n}$ is the weighted average characteristic ranking in month $t-n$ and $\text{MRank}_{c,j}$ is the mean of these monthly rankings during the 36-month measurement period. Finally, the holdings-based style volatility measure (HSV) associated with the j-th manager in month t is computed as the equally weighted average of the set of $\{\sigma_{c,j,t}\}$ given in Equation (1), or:

$$\mathrm{HSV}_{j,t} = \sum_{c=1}^{3} \frac{\sigma_{c,j,t}}{3} \tag{2}$$

From this formulation, managers with a *higher* degree of stability in the style profile of their portfolios will produce *lower* HSV values over time.[2]

The intuitive appeal of Equation (2) as a proxy for a manager's ability to remain committed to an investment style is that it is based on the extent to which the actual characteristics of the underlying portfolio holdings migrate on a monthly basis. That is, it is not portfolio turnover per se that causes a fund's style to drift—although these variables may well be related—but whether a manager replaces one stock holding with another having very different attributes. Furthermore, by its construction, Equation (2) allows for a more precise delineation of the source for the style volatility (e.g., intentional rebalancing by the manager of a particular investment characteristic).[3]

1.2 Testable hypotheses

We test three specific hypotheses. The first supposition examines the relationship between style volatility and subsequent fund performance. As noted earlier, it is unclear whether this commitment in managing the portfolio will result in better performance. In fact, there are two particular reasons why *less* style-volatile portfolios might produce superior risk-adjusted returns. First, there is a negative correlation between fund expense ratios and returns (e.g., Carhart, 1997; Gil-Boaz and Ruiz-Verdu, 2009). More active management, with its attendant higher degree of information processing and trading, might increase fund expenses to the point of diminishing relative performance, in both present and future periods. Second, beyond portfolio turnover, it may also be that managers of more style-volatile funds are chronically underinvested in the "hot" sectors of the market through their more frequent tactical portfolio adjustments.[4] There is a long-standing literature suggesting that professional asset managers generally possess negative market and style timing skills; see, for example, Kon (1983) and Coggin *et al.* (1993). Conversely, it is also possible that managers are rewarded for deviating from their investment mandates in certain environments (e.g., rapidly declining equity markets). If so, more style-volatile portfolios could have periods of outperformance even if the long-term trend runs the opposite way.

Hypothesis 1: On average, funds with lower levels of style volatility (i.e., low HSV) generate higher total and relative risk-adjusted returns in the future than more style-volatile (i.e., high HSV) funds.

The second hypothesis examines the possibility that our style volatility measure, HSV, is simply a proxy for other factors that have been shown to impact a fund's future risk-adjusted performance. Given the negative association between fund expenses and performance already noted, it is important to establish how a fund implements its style decision is merely a surrogate for that portfolio being a low-cost operation. Furthermore, it is also possible that HSV just mimics a fund's past risk-adjusted performance (i.e., alpha). A recurring question in the fund performance literature has been whether managers are capable of generating abnormal returns that persist over time. Hendricks *et al.* (1993), Brown and Goetzmann (1995), and Herrmann and Scholz (2013) document a short-run, positive correlation between abnormal returns produced in successive periods. Additionally, Grinblatt and Titman (1992) find that past risk-adjusted performance is predictive of future performance for periods as long as three years. Finally, Christopherson *et al.* (1998) establish that bad performance persists after conditioning return expectations on the myriad publicly available macroeconomic information, while Ibbotson and Patel (2002) report alpha persistence adjusting for the possibility that a fund's investment style can change over time.

Hypothesis 2: The impact of style volatility on a fund's future risk-adjusted returns is distinct from the influence of past performance and fund expenses.

Our final hypothesis involves the decomposition of a fund's overall level of style volatility into its direct and indirect parts. There is no reason to believe that the impact that these two components might have on future returns will be the same. Alford *et al.* (2003) demonstrate that managers who are better at controlling incremental return volatility (relative to a benchmark) consistently produce superior risk-adjusted performance. Thus, it is likely that indirect style volatility—which we label IHSV—is negatively related to future performance. It is also possible that managers who purposely drift their portfolio's style are genuinely skillful. The basis for that skill could be either the ability to time style rotations in the market (e.g., a shift in the relative risk premia of value and growth stocks) or, as Cremers and Petajisto (2009) capture with their Active Share measure, a talent for selecting misvalued individual securities. Consequently, a measure of direct style volatility (DHSV) *could* be positively related to future performance and that relationship might also vary with the dominant source characteristic in the style volatility calculation.

Hypothesis 3: Indirect style volatility (IHSV) is negatively correlated with future risk-adjusted returns while direct style volatility (DHSV) could be either positively or negatively correlated with future performance.

2 Data, Methodology and Descriptive Statistics

2.1 Sample construction

Our data come from two primary sources: The CRSP Mutual Fund database and the CDA/Spectrum Mutual Fund Holding database. The period covered by the investigation is January 1978 to December 2009. From the CRSP survivorship bias-free database, we collect monthly information for each eligible fund on total net-of-fee returns (i.e., capital gain plus income distribution, less expenses), total net assets (TNA) under management, expense ratio, and portfolio turnover. For every fund meeting the screening criteria outlined below and for which a complete set of CRSP data was available, the CDA/Spectrum database is then used to obtain on a quarterly basis the equity holdings (i.e., share name, total shares held) in the portfolio. We exclude from consideration index funds, fixed-income funds, as well as balanced, sector, and life-cycle/asset allocation funds. Also, for funds with multiple share classes, we compute all of our fund-level variables by aggregating the relevant information across the different tranches. Finally, funds managing less than $5 million are eliminated as are funds with less than the three years of prior return history required for the estimation process.

While CRSP offers various classification schemes that provide information about a particular fund's investment style (e.g., Wiesenberger, Lipper), they do not include the system popularized by Morningstar that places each fund into one of nine style categories: large-cap value (LV), large-cap blend (LB), large-cap growth (LG), mid-cap value (MV), mid-cap blend (MB), mid-cap growth (MG), small-cap value (SV), small-cap blend (SB), and small-cap growth (SG).

Morningstar began this classification approach in 1992, roughly half way through our sample period. Thus, to classify the investment style for our funds, we adopt a multi-step sorting procedure that captures the essence the process they used at that time. At the beginning of each calendar year, we use fund returns for the previous 36 months to estimate the parameters of the four-factor version of the Fama and French–Carhart model that includes Jegadeesh and Titman's (1993) return momentum variable:

$$\begin{aligned}(R_{jt} - \mathrm{RF}_t) = a_j &+ b_{jM}(R_{Mt} - \mathrm{RF}_t) \\ &+ b_{j\mathrm{SMB}}\mathrm{SMB}_t + b_{j\mathrm{HML}}\mathrm{HML}_t \\ &+ b_{j\mathrm{UMD}}\mathrm{UMD}_t + e_{jt}. \qquad (3)\end{aligned}$$

Equation (3) employs the following factor definitions: (i) $(R_{jt} - \mathrm{RF}_t)$ and $(R_{Mt} - \mathrm{RF}_t)$ are the month t returns to fund j and the CRSP value-weighted index, respectively, in excess of the corresponding one-month U.S. Treasury bill yield; (ii) SMB_t is the difference in month t returns between small-cap and large-cap portfolios; (iii) HML_t is the difference in month t returns between portfolios of stocks with high and low book-to-market ratios; and (iv) UMD_t is the difference in month t returns between portfolios of stocks with high and low stock return performance over the preceding year.[5]

Since market capitalization and relative valuation are the characteristics defining the classification scheme, the estimated values of b_{SMB} and b_{HML} from Equation (3) are the relevant parameters to consider. Using these factor loading estimates, fund investment style is determined as follows: (i) at the beginning of every year, each fund is ranked by its b_{SMB} coefficient from most negative (i.e., large-cap orientation) to most positive (i.e., small-cap orientation); and (ii) based on this ranking, funds are divided into large-, mid-, and small-cap categories so that they account for 58%, 23%, and 19%, respectively, of the size distribution; (iii) within each of these three firm size groupings, funds are further divided into value, blend, and growth categories in the respective proportions of 30%, 33%, and 37% by a ranking of their b_{HML} parameters from most positive (i.e., value orientation) to most negative (i.e., growth orientation); and (iv) the entire sorting process, starting with a re-estimation of Equation (3) for every available fund, is repeated each January during the sample period as new funds satisfy the selection criteria.[6]

2.2 *Descriptive statistics*

The top part of Table 1 summarizes the total number of funds in each style category for every year of the sample period. Given the assignment process, the earliest style category year possible is 1981, with all funds reported for this period having returns dating to January 1978. The final column documents the steady increase during most of the period in the total number of funds available for style classification; from 251 portfolios in 1981, the sample grew at an annual rate of about 6% to 1,142 funds in 2009. The bottom of the display lists descriptive statistics for annual total return, return standard deviation, assets under management, expense ratio, and portfolio turnover. The reported figures confirm much of the conventional wisdom about investment style and fund performance. For instance, value-oriented funds in the large-cap category produce average annual returns that are consistently higher than those for growth-oriented portfolios, but only marginally so for small-cap funds and not at all for mid-cap portfolios. Alternatively, controlling for the book-to-market ratio, small-cap funds outperform large-cap funds by an

Table 1 Mutual fund style sample by year.

	Mutual fund style category									
Year	LV	LB	LG	MV	MB	MG	SV	SB	SG	Total
1981	43	48	55	17	19	22	14	15	18	251
1982	43	48	54	17	19	22	14	15	18	250
1983	47	53	59	18	21	24	15	17	20	274
1984	50	56	63	20	22	25	16	18	21	291
1985	55	60	69	21	24	28	18	19	23	317
1986	60	67	75	24	26	30	19	21	25	347
1987	69	75	86	27	30	34	22	25	28	396
1988	73	81	91	29	32	36	23	26	30	421
1989	78	86	97	31	34	39	25	28	32	450
1990	80	88	99	31	35	39	26	28	33	459
1991	83	92	103	33	36	41	27	29	34	478
1992	84	93	105	33	37	42	27	30	35	486
1993	89	98	110	35	38	44	29	32	36	511
1994	110	121	137	43	48	55	36	39	45	634
1995	130	144	161	51	57	65	42	47	53	750
1996	149	164	185	59	65	73	48	54	61	858
1997	172	190	213	68	75	85	56	62	70	991
1998	206	227	255	81	90	101	67	74	84	1185
1999	232	255	287	91	101	114	75	84	94	1333
2000	225	248	279	89	98	110	73	81	92	1295
2001	231	254	285	91	101	113	75	83	94	1327
2002	233	257	288	92	102	115	76	84	94	1341
2003	236	259	292	93	103	116	77	84	96	1356
2004	240	265	298	95	105	118	78	87	97	1383
2005	234	258	290	93	102	115	76	84	95	1347
2006	231	255	286	92	101	114	75	83	94	1331
2007	221	243	274	87	96	109	72	79	90	1271
2008	222	244	275	88	97	109	72	80	90	1277
2009	198	219	246	78	87	98	64	72	80	1142
Averages: (1981–2009)										
Ann Rtn–%	10.88	10.08	10.04	12.04	11.39	12.32	12.99	12.45	12.97	—
Std Dev-%	14.27	14.14	16.62	15.61	16.37	19.89	19.09	19.07	22.39	—
TNA-$MM	1,319	1,301	1,231	670	696	695	371	383	486	—
Exp Ratio-%	1.18	1.11	1.20	1.29	1.29	1.30	1.40	1.35	1.45	—
Turnover-%	73.41	85.20	94.15	80.91	90.80	106.66	78.79	95.89	114.94	—

This table reports the number of mutual funds included in each style objective category by year from January 1981 to December 2009. The numbers listed represent those funds with at least 36 months of return history prior to the given date. The following style classifications are used: large-cap value (LV), large-cap blend (LB), large-cap growth (LG), mid-cap value (MV), mid-cap blend (MB), mid-cap growth (MG), small-cap value (SV), small-cap blend (SB), and small-cap growth (SG). Averages (rounded to the nearest fund) are also listed for two non-overlapping subsets of the 29-year sample period. The last five rows of the display report sample period-wide category averages for annual fund returns, annual return standard deviation, total net assets (TNA), annual fund expense ratios, and annual fund turnover.

average of between 2.11% and 2.93% per year, albeit with higher total standard deviations.

These summary statistics also reveal that portfolios in different style categories appear to be managed differently. Over the entire sample period, growth funds have higher turnover ratios than value funds (e.g., SG turnover exceeds SV turnover by 114.94% to 78.79%) and large-cap funds have lower turnover ratios than small-cap funds (e.g., LG turnover is 20.74 percentage points lower than SG turnover). Additionally, small-cap and growth funds have higher expense ratios than large-cap and value funds, respectively. Finally, large-cap funds consistently hold more assets than small-cap funds.

These results imply that it may be quite difficult to compare directly the return performance of two funds that have contrasting investment styles. Fund investment prowess is more appropriately viewed on a relative basis within style categories; this is the tournament approach that Brown *et al.* (1996) and Chevalier and Ellison (1997) adopt, where a manager's performance and compensation are determined compared to peers within a style class. Of course, this industry practice is driven by investors who concentrate on a fund's past total returns when making their investment decisions (e.g., Sirri and Tufano, 1998). Consequently, in the subsequent analysis, we consider the role that investment style volatility exerts on fund performance in the context of the nine style tournaments defined by the size- and valuation ratio-based categories.

2.3 Style volatility behavior

For this initial analysis, we calculate fund HSV values for each year for all nine style classes, using returns for the prior three years. Funds are then rank ordered and sorted into low style volatility and high style volatility subsamples by median value for the objective class. Table 2 summarizes the characteristics of funds split into these style volatility bins and lists sub-group median values for the following statistics: HSV, end-of-year total net assets, peer group ranking (i.e., the fund's relative position in the annual performance tournament, based on total return), annual total return, return standard deviation, annual tracking error (TE) relative to a style-specific benchmark portfolio, portfolio turnover, and expense ratio.[7] To produce the reported numbers, we sort the funds annually into HSV groups to produce the base levels of the various statistics and these values are then averaged to produce the display.

The findings indicate that large-cap funds demonstrate less investment style volatility than do small- or mid-cap funds. For instance, the median HSV value for the low volatility portion of the three large-cap style categories is 0.47. By contrast, the low-style volatility portions of the small- and mid-cap objectives yield a median HSV value of 0.61. Comparable results obtain for the high-style volatility groupings: The median large-cap HSV is 0.86 with the analogous value for the other two size-based categories being 1.03. Additionally, the median low-HSV fund always has a lower tracking error to its benchmark than its high-HSV counterpart.

Table 2 also supports the conjecture that less style-volatile funds are managed in a significantly different manner than more style-volatile ones. Based on a simple comparison of median turnover ratios, it is apparent that low-HSV funds do less trading than otherwise comparable high-HSV portfolios in all nine style groups. Furthermore, low-HSV funds also have lower average expense ratios and appear to produce higher total and relative returns for virtually all of the style categories. The median annual fund returns produced by low-HSV funds are larger than those for high-HSV managers in eight of the nine style categories (MG being the exception), but with lower return

Table 2 Mutual fund style volatility by category.

Style group	Style volatility	Median HSV	Median fund TNA ($MM)	Median peer group ranking	Median annual fund return (%)	Median Fund Std. Dev. (%)	Median Tracking Error (%)	Median Fund Turnover (%)	Median Fund Expense Ratio
Large value (LV)	Low	0.47	437	52.26	11.03	13.36	5.21	42.42	1.00
	High	0.92	222	46.72	9.95	14.33	8.36	63.69	1.24
Large blend (LB)	Low	0.43	369	50.43	10.33	13.79	4.51	47.02	0.96
	High	0.75	210	48.40	10.03	14.30	6.68	77.59	1.14
Large growth (LG)	Low	0.53	350	50.78	10.13	15.63	5.31	61.41	1.04
	High	0.86	268	48.72	9.81	16.56	7.28	84.80	1.16
Mid value (MV)	Low	0.59	346	51.09	11.33	14.84	6.63	47.70	1.10
	High	1.07	154	47.24	11.29	15.61	9.19	67.73	1.31
Mid blend (MB)	Low	0.55	282	49.84	11.36	15.68	6.44	59.06	1.11
	High	0.95	186	48.53	11.17	16.39	8.35	84.53	1.27
Mid growth (MG)	Low	0.63	279	50.09	11.81	18.96	8.18	70.00	1.16
	High	1.00	212	47.52	11.84	20.00	9.71	105.71	1.25
Small value (SV)	Low	0.67	231	53.38	13.81	16.21	8.78	52.66	1.28
	High	1.26	145	48.28	11.20	20.74	14.80	67.40	1.45
Small blend (SB)	Low	0.54	252	51.97	12.64	18.21	7.43	62.79	1.19
	High	0.96	135	46.79	11.21	18.97	9.51	97.10	1.39
Small growth (SG)	Low	0.67	229	51.90	12.76	21.12	8.37	78.76	1.28
	High	1.03	175	46.79	12.38	22.49	10.59	100.94	1.41

This table reports style volatility statistics for the mutual fund sample over the period January 1981–December 2009. Funds within a style objective are grouped by average style characteristic volatility of the fund's security holdings (HSV), as calculated by Equation (2). For each style group, funds are separated into "low" volatility and "high" volatility groups relative to the category-wide median values of HSV. Style volatility rankings are based on holdings and fund returns for the 36-month period preceding the year for which the reported characteristics are produced. Results are shown for the following statistics: HSV, fund total net assets, peer group ranking (i.e., the fund's relative position in the annual performance tournament, based on total return), annual total return, return standard deviation, fund tracking error relative to its style-specific benchmark, portfolio turnover, and expense ratio. The numbers reported represent aggregated values of these statistics; the funds were sorted annually into volatility groups to produce the base levels of the various statistics and these values were then averaged to produce the display.

standard deviations in all nine cases. Additionally, the managers of less style-volatile portfolios produce a higher median style group ranking in all nine style groups.

2.4 Relative contributions to style volatility

The style volatility measure in Equation (2) averages the standard deviations of the fund's mean ranking with respect to three style factors: market capitalization, book-to-market ratio, and return momentum. Thus, for any fund on a given assessment date, it is possible to measure the overall level of style volatility as well as the amount each characteristic contributes to the total. We would not expect a priori that each style factor will add equally to a fund's overall HSV score. Instead, it is likely that active portfolio managers using style timing strategies may increase the dispersion in their ranking to different factors at different points in time.

To understand this process better, for every fund j in our sample on each measurement date t we calculate the proportion of HSV contributed by the c-th style characteristic as $[\sigma_{c,j,t} \div (3 * \mathrm{HSV}_{j,t})]$, which is just the style factor-specific score in Equation (1) divided by the numerator of Equation (2). We then calculate cross-sectional averages of these contribution proportions on a yearly basis from 1981 to 2009, based on the year-end values of $\sigma_{c,j,t}$ and $\mathrm{HSV}_{j,t}$.

Figure 1 illustrates how the relative contributions to HSV from the three style characteristics evolved over time. Most striking is the substantial role that return momentum plays in determining the overall level of a fund's investment style volatility. Indeed, variation in the momentum factor contributes roughly as much as the size and value-growth factors combined. The numbers underlying the graph bear this out: The time-series average contribution proportion for the momentum factor is 48.1% while the size and value-growth factors account for 22.0% and 29.9%, respectively, of the variation in HSV. Furthermore, the annual contribution proportions for the momentum style characteristic range from 43.1% to 55.4%.

One explanation for this outcome is that fund managers are often constrained by investors with regard to the decisions they make on the size and value-growth dimensions of their portfolios. Therefore, altering a portfolio by either of those two characteristics is likely to be far more of a visible event than if the return momentum characteristic is altered. Of course, the fact that momentum is the largest contributor to HSV does not mean that it will be the most useful style factor in explaining future fund performance, which is a topic we examine in the next section.

3 Main Empirical Results

3.1 Overall tests

3.1.1 Panel regression results

Collectively, our first two hypotheses hold that: (i) the volatility of a fund's investment style will be negatively related to the manager's ability to produce superior risk-adjusted returns in the future, and (ii) this style volatility effect is distinct from the impact associated with the persistence of past fund performance or fund expenses. To test this combined prediction over the entire sample period, we estimate a series of panel regression equations with the following methodology:

(i) Starting at the beginning of our sample period, for each fund we estimated the parameters of Equation (4) using the previous 36 months of returns. This estimation produces the intercept term—i.e., ALPHA—that we use as our proxy for past abnormal investment performance. The HSV statistic is calculated over this same 36-month window according to Equation (2).

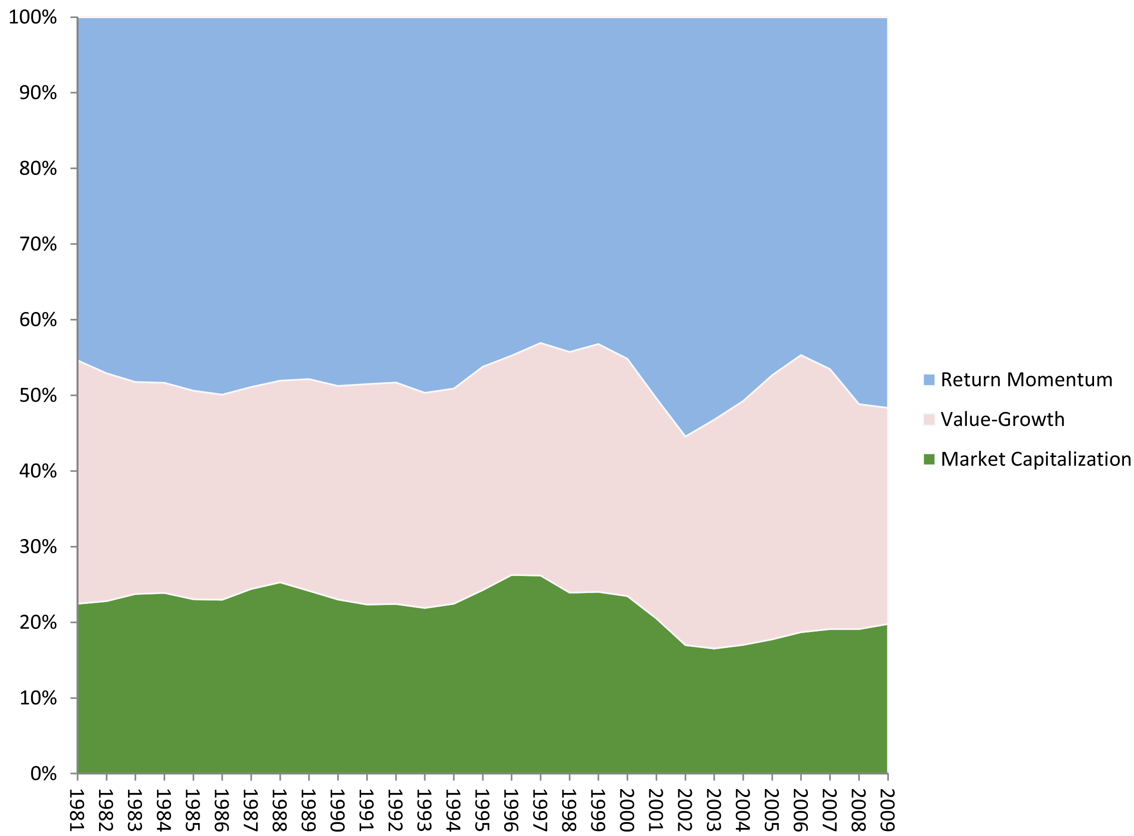

Figure 1 Relative contributions to the investment style volatility (HSV) measure. This figure shows the percentage contribution of three separate investment style characteristics—market capitalization (i.e., firm size), book-to-market ratio (i.e., value-growth), return momentum—to HSV, the overall measure of style volatility. The reported percentages are recalculated annually as cross-sectional averages over the 1981–2009 sample period.

(ii) At this same point in time, we calculate each fund's risk-adjusted return over the subsequent n-month period. For this task, using a forward-looking alpha coefficient relative to a factor model such as Equation (4) with "stale" parameter estimates can lead to suboptimal inference; see Cremers *et al.* (2012). Instead, since fund complexes and managers act as if they compete in more narrowly defined style-specific tournaments, we convert a fund's total return over a given horizon to a z-score by standardizing within the portfolio's style classification.[8] This value is our primary measure of future performance.

(iii) We specify four values of n: one (i.e., the fund's next month return), three (i.e., next quarter return), six (i.e., next two-quarter return), and 12 (i.e., next year return). These performance statistics represent risk-adjusted *future* returns because they are calculated over a different time period than the style volatility and past performance variables we use to explain them. To create a complete time series for each fund, we repeat the previous steps by sequentially rolling the 36-month estimation window forward n months at a time, where the value for n once again defines the length of the future return forecast period.

(iv) In separate estimations, we then regress the one-, three-, six-, or twelve-month tournament returns on the prior levels of ALPHA and HSV using all available data for each sample fund. To assess their combined influence on future risk-adjusted returns, we also consider an interaction term defined as the product of ALPHA and HSV. In various forms of this regression, we include the following control variables: portfolio turnover (TURN), fund size (TNA), measured by the assets under management at the end of the estimation period, and fund expense ratio (EXPR).

(v) Each version of these panel regressions is estimated with year fixed-effects to control for unobserved heterogeneity in the cross-section of funds caused by the passage of time.

Table 3 reports these regression results. The findings in Panels A, B, C, and D use one-, three-, six-, and twelve-month future risk-adjusted returns as a dependent variable, respectively. We estimate parameters for seven different combinations of the independent variables, starting with a simple model involving ALPHA alone (Model 1), which provides a baseline analysis of the persistence phenomenon. The positive coefficient values in all four panels of the display indicate that relative performance did indeed persist throughout the sample period. This alpha persistence effect proves to be reliable even though the return-generating model used to measure risk-adjusted returns includes a return momentum factor, despite Carhart's (1997) earlier findings.

The remaining six models in Table 3 (Models 2–7) then examine the role that investment style volatility plays in predicting future risk-adjusted fund performance. Overall, the results strongly support the conclusion that these two variables are inversely and meaningfully related. The coefficients estimated for HSV are always in the predicted negative direction (i.e., higher past style volatility, lower future risk-adjusted performance) and are always statistically significant. For instance, Model 2 tests the simplest form of the relationship between subsequent returns and HSV. Across the four panels, all of the return forecast periods produce highly significant coefficient values of the appropriate sign: −0.009 for one-month returns, −0.025 for three-month returns, −0.031 for six-month returns, and −0.028 for 12-month returns. Additionally, notice that like ALPHA, the influence of HSV appears to peak for the three-, six-, and twelve-month future return prediction periods.[9]

The findings for the four variations of Model 3—which includes HSV with ALPHA as regressors—show that the style volatility variable is not a simple surrogate for ALPHA. In fact, the coefficient levels for HSV remain statistically significant and either do not change in value or actually increase with the addition of the past performance metric. Furthermore, there is some evidence that the style volatility and persistence variables combine in a way that produces a meaningful effect; the various coefficients for the [ALPHA*HSV] interaction term in Models 4 are negative but generally less significant and the inclusion of this term has virtually no impact on the influence exerted by either ALPHA or HSV separately. Accordingly, these results confirm the uniqueness of style volatility as a determinant of future risk-adjusted returns.

Models 5–7 explore these relationships further by controlling for other mitigating influences. The results for Models 5 and 6, which include TURN and TNA, show that adding portfolio turnover and fund size does nothing to diminish the magnitude of the style volatility variable. Therefore, it also appears that HSV is not merely a proxy for TURN. Finally, the connection between style volatility and future risk-adjusted performance is

Table 3 Style volatility and fund performance regression results: unconditional panel tests.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Panel A. One-month future returns as dependent variable							
Intercept	0.000	0.002	0.002	0.001	0.001	0.001	0.001
	(1.00)	(0.32)	(0.41)	(0.40)	(0.62)	(0.63)	(0.68)
ALPHA	0.044		0.043	0.045	0.043	0.043	0.043
	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HSV		−0.009	−0.009	−0.009	−0.011	−0.011	−0.007
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
[ALPHA*HSV]				−0.003			−0.003
				(0.08)			(0.05)
TURN					0.009	0.009	0.012
					(0.00)	(0.00)	(0.00)
TNA						0.001	−0.003
						(0.56)	(0.10)
EXPR							−0.021
							(0.00)
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001
# of observations				233,944			
Panel B. Three-month future returns as dependent variable							
Intercept	−0.000	0.003	0.002	0.002	0.001	0.001	0.001
	(0.92)	(0.94)	(0.48)	(0.47)	(0.73)	(0.74)	(0.82)
ALPHA	0.066		0.064	0.068	0.062	0.062	0.063
	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HSV		−0.025	−0.026	−0.025	−0.027	−0.027	−0.020
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
[ALPHA*				−0.008			−0.007
HSV]				(0.01)			(0.01)
TURN					0.009	0.009	0.013
					(0.02)	(0.02)	(0.00)
TNA						0.002	−0.005
						(0.55)	(0.14)
EXPR							−0.034
							(0.00)
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.003	0.001	0.003	0.003	0.003	0.003	0.004
# of observations				77,061			

Table 3 (*Continued*)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Panel C. Six-month future returns as dependent variable							
Intercept	−0.001	0.005	0.003	0.004	0.002	0.002	0.001
	(0.86)	(0.32)	(0.46)	(0.46)	(0.65)	(0.67)	(0.77)
ALPHA	0.067		0.068	0.076	0.064	0.064	0.068
	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HSV		−0.031	−0.032	−0.031	−0.033	−0.032	−0.023
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
[ALPHA * HSV]				−0.013			−0.013
				(0.00)			(0.00)
TURN					0.009	0.009	0.015
					(0.09)	(0.08)	(0.00)
TNA						0.004	−0.006
						(0.38)	(0.21)
EXPR							−0.049
							(0.00)
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.003	0.001	0.004	0.004	0.003	0.003	0.006
# of observations				38,072			
Panel D. 12-Month future returns as dependent variable							
Intercept	−0.002	0.005	0.003	0.003	0.001	0.001	−0.000
	(0.82)	(0.48)	(0.65)	(0.63)	(0.84)	(0.87)	(1.00)
ALPHA	0.063		0.062	0.068	0.065	0.064	0.064
	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HSV		−0.028	−0.030	−0.029	−0.031	−0.030	−0.018
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)
[ALPHA * HSV]				−0.009			−0.008
				(0.10)			(0.16)
TURN					0.012	0.012	0.020
					(0.14)	(0.12)	(0.01)
TNA						0.007	−0.008
						(0.36)	(0.27)
EXPR							−0.068
							(0.00)
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.004	0.001	0.005	0.005	0.005	0.005	0.009
# of observations				17,679			

This table reports results for the 1981–2009 sample period of the regression of future fund performance on past abnormal returns (ALPHA) and investment style volatility (HSV). ALPHA is estimated over a 36-month period by Carhart's four-factor version of Equation (3); HSV is estimated over a comparable period by Equation (2). Future risk-adjusted returns are measured for the n-month period following a given 36-month estimation window; Panels A, B C, and D report future return values for $n = 1$, $n = 3$, $n = 6$, and $n = 12$, respectively. ALPHA is the only regressor used in Model 1 as a base case; HSV is then included in Models 2–7. Also used as a regressor is an interaction variable formed by the product of ALPHA and the style volatility measure (HSV). Additional control regressors include portfolio turnover (TURN), total net fund assets (TNA), and fund expense ratio (EXPR). All variables are standardized by year and fund style class. P-values are listed parenthetically beneath each coefficient and year fixed-effects are included.

only slightly affected once fund expense ratios are added as a regressor (i.e., Model 7), with the parameters on HSV diminishing in magnitude but remaining statistically significant. Viewed as a whole, the findings in Table 3 provide strong support for the proposition that the volatility of a fund's investment style does impact its future performance in a distinctive manner.[10]

3.1.2 Fama–MacBeth cross-sectional results

Although the tests just presented control for time fixed effects, it is still possible that the residuals are correlated across funds during a given period. To mitigate this concern, we adopt the methodology of Fama and MacBeth (1993) to test for the roles that style volatility and performance persistence play in predicting future returns on a cross-sectional basis. Specifically, for every fund on a given month, we use the prior 36-month data to calculate values of past performance (ALPHA) and the style volatility score (HSV). Next, we compute risk-adjusted tournament returns for each fund over the subsequent one-, three-, six-, and twelve-month periods, which then become the dependent variables in four separate cross-sectional regressions in which ALPHA, HSV, and the other controls are the independent variables. Finally, repeating the first two steps for a series of different months that are rolled forward on a periodic n-month basis generates the requisite time series of parameter estimates.

For each set of future returns, Panels A–D of Table 4 list averages of the time series of these estimated coefficients, along with p-values based on the means of those coefficients. All four panels confirm the general conclusions discussed above and underscore that they are neither spurious nor driven by large samples. First, the positive correlation between past and future risk-adjusted fund returns suggests the existence of performance persistence in the fund sample. Second, there is also a strong inverse connection between a fund's style volatility and its future risk-adjusted

Table 4 Style volatility and fund performance regression results: Fama–Macbeth regressions.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Panel A. One-month future returns as dependent variable							
ALPHA	0.045		0.041	0.044	0.042	0.042	0.043
	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HSV		−0.016	−0.014	−0.014	−0.018	−0.018	−0.014
		(0.04)	(0.05)	(0.05)	(0.01)	(0.02)	(0.04)
[ALPHA*HSV]				−0.003			−0.004
				(0.49)			(0.40)
TURN					0.016	0.016	0.018
					(0.01)	(0.01)	(0.00)
TNA						0.000	−0.006
						(0.91)	(0.82)
EXPR							−0.024
							(0.00)
Adj. R^2	0.021	0.018	0.035	0.042	0.045	0.047	0.056
# of observations				348			

Table 4 (*Continued*)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Panel B. Three-month future returns as dependent variable							
ALPHA	0.068		0.062	0.065	0.060	0.060	0.059
	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HSV		−0.037	−0.033	−0.031	−0.041	−0.041	−0.031
		(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
[ALPHA * HSV]				−0.005			−0.004
				(0.43)			(0.52)
TURN					0.022	0.022	0.025
					(0.03)	(0.03)	(0.02)
TNA						0.001	−0.008
						(0.85)	(0.16)
EXPR							−0.039
							(0.00)
Adj. R^2	0.022	0.019	0.036	0.041	0.045	0.046	0.055
# of observations				115			
Panel C. Six-month future returns as dependent variable							
ALPHA	0.067		0.063	0.070	0.062	0.061	0.064
	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HSV		−0.051	−0.048	−0.045	−0.056	−0.055	−0.043
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
[ALPHA*HSV]				−0.013			−0.014
				(0.15)			(0.13)
TURN					0.025	0.026	0.029
					(0.06)	(0.06)	(0.04)
TNA						0.004	−0.008
						(0.60)	(0.32)
EXPR							−0.050
							(0.00)
Adj. R^2	0.019	0.021	0.035	0.039	0.042	0.042	0.051
# of observations				57			

performance, with the strongest relationship for three- and six-month future returns. Third, [ALPHA*HSV] remains negative but becomes highly insignificant and its inclusion does little to reduce the influence of the past performance and style volatility variables taken separately. Fourth, TNA is still an unreliable explanatory variable, whereas the coefficient on TURN remains significantly positive, albeit at attenuated levels. Finally, the fund's expense ratio is still strongly negatively correlated with future risk-adjusted performance and this relationship dissipates the impact of ALPHA and HSV to a minor extent.

Table 4 (*Continued*)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Panel D. 12-month future returns as dependent variable							
ALPHA	0.052		0.044	0.052	0.051	0.049	0.049
	(0.07)		(0.09)	(0.04)	(0.07)	(0.08)	(0.06)
HSV		−0.050	−0.048	−0.043	−0.063	−0.061	−0.047
		(0.06)	(0.05)	(0.06)	(0.01)	(0.02)	(0.07)
[ALPHA*HSV]				−0.010			−0.009
				(0.50)			(0.54)
TURN					0.054	0.054	0.060
					(0.01)	(0.01)	(0.00)
TNA						0.007	−0.009
						(0.50)	(0.46)
EXPR							−0.066
							(0.00)
Adj. R^2	0.026	0.018	0.034	0.040	0.045	0.045	0.059
# of observation				29			

This table reports mean time-series values for a series of regression parameters estimated cross-sectionally using the three-step Fama–MacBeth procedure. In the first step, values for past fund performance (ALPHA) and investment style volatility (HSV) are estimated for each fund on a given date, starting in 1981, using Equations (2) and (3)). Second, four different sets of subsequent ($n = 1$, $n = 3$, $n = 6$, and $n = 12$) risk-adjusted returns are calculated for each fund by style tournament. This cross section of future returns is regressed against the estimated values of ALPHA, HSV, the interaction between past performance and style volatility (ALPHA*HSV), and controls for portfolio turnover (TURN), fund size (TNA), and expense ratio (EXPR). Third, the first two steps are repeated by rolling the estimation month forward on a periodic basis through the end of 2009. P-values are listed parenthetically beneath each reported parameter estimate and intercepts are not listed for expositional convenience. Panels A, B, C, and D report results for one-, three-, six-, and twelve-month future returns, respectively.

3.2 The characteristics of style volatility and fund performance

Figure 1 illustrated that the three separate style characteristics—size, value-growth, and momentum—are not represented equally in the HSV statistic. Thus, it is possible that the contributions of these characteristics might also differ in how they correlate with the fund's future risk-adjusted returns. We replicate the panel regression analysis in Table 3 using three non-overlapping regressors associated with the style characteristic volatility statistics (i.e., $\sigma_{c,j,t}$) defined in Equation (1) that forms the component parts of the aggregate HSV measure. Table 5 summarizes these findings, listing the estimated parameters from an appropriately modified version of Model 7 in Table 3 (i.e., the "full control" specification) for all four forecast horizons. The findings show the dramatic difference that the source characteristic makes in how style volatility impacts future fund performance. In particular, the overall negative correlation between HSV and subsequent risk-adjusted returns is not a uniform result across the coefficients reported for the component volatility source variables. For style volatility related to market capitalization (i.e., σ_{size}), the reported parameter values are negative and highly statistically significant, regardless of the return forecast period. For the value-growth component, estimated coefficients remain negative for all four prediction periods,

Table 5 The dominant source of style volatility and fund performance: Panel regression results.

Variable	One-month predicted returns	Three-month predicted returns	Six-month predicted returns	12-Month predicted returns
Intercept	0.001	0.001	0.003	0.002
	(0.71)	(0.82)	(0.54)	(0.77)
ALPHA	0.043	0.064	0.071	0.059
	(0.00)	(0.00)	(0.00)	(0.00)
σ_{size}	−0.008	−0.015	−0.020	−0.030
	(0.00)	(0.00)	(0.00)	(0.00)
σ_{vg}	−0.002	−0.009	−0.009	−0.000
	(0.32)	(0.03)	(0.13)	(0.96)
σ_{mom}	0.002	−0.004	−0.001	−0.000
	(0.51)	(0.34)	(0.86)	(0.87)
[ALPHA*HSV]	−0.003	−0.007	−0.013	−0.003
	(0.07)	(0.02)	(0.01)	(0.57)
TURN	0.012	0.015	0.017	0.027
	(0.00)	(0.00)	(0.00)	(0.00)
TNA	−0.004	−0.006	−0.006	−0.002
	(0.08)	(0.01)	(0.24)	(0.74)
EXPR	−0.021	−0.034	−0.048	−0.063
	(0.00)	(0.00)	(0.00)	(0.00)
Year fixed-effects?	Yes	Yes	Yes	Yes
Adj. R^2	0.002	0.005	0.008	0.009
# of observations	233,944	77,061	38,072	17,679

This table reports results for the 1981–2009 sample period of the regression of future fund performance on past abnormal returns (ALPHA) and investment style volatility (HSV), segmented into its three component parts (i.e., market capitalization, value-growth, return momentum) according to the characteristic volatility measures (σ_c) defined by Equation (1). ALPHA is estimated over a 36-month period by Carhart's four-factor version of Equation (3); HSV is estimated over a comparable period by Equation (2). HSV is multiplied by an indicator variable assuming the value of one if the particular style factor is the primary contributor to a fund's overall style volatility and zero otherwise. Future risk-adjusted returns are measured for the n-month period following a given 36-month estimation window, where $n = 1$, $n = 3$, $n = 6$, and $n = 12$. Also used as regressors are an interaction variable formed by the product of ALPHA and the style volatility measure (HSV), portfolio turnover (TURN), total net fund assets (TNA), and fund expense ratio (EXPR). All variables are standardized by year and fund style class. P-values are listed parenthetically beneath each coefficient and year fixed-effects are included.

but are only statistically reliable for the three-month forecast horizons. Conversely, when the return momentum contribution is isolated, the relationship between style volatility and future performance is completely insignificant.

The immediate implication is that when style volatility is driven primarily by the market capitalization factor, it leads to a significant relative reduction in the fund's future risk-adjusted returns. Style volatility driven by the value-growth characteristic has a comparable effect, although apparently not as reliable. On the other hand, style volatility borne of the decision to alter the portfolio's return momentum does not lead to a diminution of future relative performance. The surprising thing about this situation is that although the firm size characteristic makes the smallest contribution to the style volatility of the average portfolio—the time-series mean of [$\sigma_{\text{size}} \div$ HSV] is just 22%—when it is the dominant source of variation for a specific fund, it is an extremely destructive force. Variations in the value-growth factor are also destructive to future performance but to a far lesser extent. Finally, portfolios varying in their return momentum characteristic, which is the source of most style volatility, apparently do not suffer because of it.

4 Decomposing Style Volatility

4.1 Measuring direct and indirect style volatility effects

A logical extension of the preceding analysis asks to what extent is a portfolio's level of style volatility related to direct managerial actions as opposed to changes that might have occurred without the manager's awareness? Accordingly, we extract from HSV two supplementary measures that capture: (i) the *direct* style volatility resulting from explicit adjustments to portfolio holdings; and (ii) the *indirect* style volatility in the portfolio that manifests implicitly whenever the style characteristics of the existing holdings change over time.

To understand the difference between these components, notice that managers who actively attempt to adjust the investment style of their portfolios can do so in two ways. First, they can make security-specific trades that, while based on relative valuation judgments, nevertheless have the effect of altering style characteristics in the fund. Second, managers can make trades in an attempt to time perceived rotations in the style factors directly (e.g., increase holdings of large-cap stocks, decrease holdings of small-cap stocks). Regardless of the reason, these explicit adjustments will be reflected in changes in the portfolio share holdings over time which, assuming the characteristic rankings of stocks in the portfolio remain fixed, become the source of any style variation that managers intended to implement. So, for any fund in month t, the *direct holdings-based style volatility (DHSV)* score is given by the following standard deviation computation:

$$\text{DHSV}_t = \sigma\left\{\sum_{i=1}^{n} w_{i,t}\cdot\overline{S_i},\ \sum_{i=1}^{n} w_{i,t-1}\cdot\overline{S_i},\ \ldots,\ \sum_{i=1}^{n} w_{i,t-35}\cdot\overline{S_i}\right\} \quad (4)$$

where $w_{i,t}$ is the weight of the i-th stock in the portfolio and $\overline{S}$ is the average style characteristic ranking of Stock i over the prior 36-month period.

It is also possible for a fund's investment style to change over time even without the manager making any direct adjustments to portfolio holdings, if the characteristics of their existing holdings shift appreciably. Alternatively, it could also be the case that the style characteristics of the stocks in the managed portfolio remain constant in an absolute sense (e.g., the book-to-market ratio does not change) but the characteristics of the stocks in the benchmark index shift causing style volatility in the portfolio on a relative basis. In either case, the subsequent increase in HSV was clearly unintended by the manager. To capture this dimension, we calculate an *indirect holdings-based style volatility (IHSV)* score for each fund, assuming that the most recent (i.e., month t) set of share holdings was constant over the prior 36-month period. With this "fixed share" assumption, we compute the IHSV measure as:

$$\text{IHSV}_t = \sigma\left\{\sum_{i=1}^{n} w_{i,t}^{t}\cdot S_t,\ \sum_{i=1}^{n} w_{i,t-1}^{t}\cdot S_{t-1},\ \ldots,\ \sum_{i=1}^{n} w_{i,t-35}^{t}\cdot S_{t-35}\right\} \quad (5)$$

Table 6 Direct vs. indirect style volatility and fund performance: Panel regression results.

Variable	One-month predicted returns			Three-month predicted returns			Six-month predicted returns			12-Month predicted returns		
Panel A. Direct component of style volatility as independent variable												
Intercept	0.001	0.001	0.005	0.000	0.000	0.006	0.003	0.003	0.009	0.002	0.002	0.009
	(0.79)	(0.79)	(0.03)	(0.95)	(0.95)	(0.12)	(0.55)	(0.54)	(0.12)	(0.75)	(0.75)	(0.26)
ALPHA	0.041	0.041	0.041	0.061	0.062	0.062	0.065	0.065	0.065	0.058	0.058	0.058
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
DHSV	−0.001			−0.007			−0.014			−0.020		
	(0.81)			(0.09)			(0.01)			(0.01)		
$[D\sigma]_{\text{size}}$		−0.004	−0.003		−0.007	−0.006		−0.007	−0.006		−0.017	−0.014
		(0.10)	(0.21)		(0.08)	(0.15)		(0.21)	(0.32)		(0.04)	(0.09)
$[D\sigma]_{\text{vg}}$		0.002	0.002		−0.002	−0.001		−0.001	−0.001		0.008	0.010
		(0.49)	(0.42)		(0.68)	(0.75)		(0.84)	(0.93)		(0.35)	(0.24)
$[D\sigma]_{\text{mom}}$		0.002	0.001		−0.000	−0.001		−0.012	−0.012		−0.015	−0.014
		(0.46)	(0.56)		(0.99)	(0.89)		(0.05)	(0.04)		(0.07)	(0.08)
[ALPHA*HSV]	−0.000	−0.000	−0.000	−0.006	−0.006	−0.006	−0.006	−0.006	−0.006	−0.007	−0.007	−0.007
	(0.89)	(0.86)	(0.80)	(0.04)	(0.04)	(0.04)	(0.13)	(0.13)	(0.12)	(0.26)	(0.25)	(0.23)
TURN	0.010	0.010		0.012	0.013		0.015	0.015		0.026	0.026	
	(0.00)	(0.00)		(0.00)	(0.00)		(0.01)	(0.01)		(0.00)	(0.00)	
TURN-Low20			−0.023			−0.030			−0.030			−0.034
			(0.00)			(0.00)			(0.03)			(0.07)
TNA	−0.003	−0.003	−0.002	−0.004	−0.004	−0.004	−0.005	−0.004	−0.004	−0.001	−0.001	−0.001
	(0.21)	(0.20)	(0.24)	(0.25)	(0.23)	(0.27)	(0.37)	(0.38)	(0.40)	(0.84)	(0.89)	(0.88)
EXPR	−0.023	−0.023	−0.022	−0.037	−0.036	−0.035	−0.050	−0.050	−0.048	−0.065	−0.065	−0.062
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year FE?		Yes			Yes			Yes			Yes	
Adj. R^2	0.003	0.003	0.003	0.006	0.006	0.006	0.008	0.008	0.008	0.009	0.009	0.009
# of observations		233,303			76,758			38,117			19,357	

Table 6 (*Continued*)

Variable	One-month predicted returns			Three-month predicted returns			Six-month predicted returns			12-Month predicted returns		
Panel B. Indirect component of style volatility as independent variable												
Intercept	0.001	0.001	0.005	0.001	0.001	0.007	0.004	0.004	0.009	0.003	0.003	0.009
	(0.73)	(0.73)	(0.02)	(0.77)	(0.77)	(0.09)	(0.45)	(0.45)	(0.12)	(0.66)	(0.66)	(0.24)
ALPHA	0.042	0.042	0.042	0.065	0.065	0.065	0.068	0.069	0.069	0.063	0.064	0.063
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
IHSV	−0.012			−0.028			−0.039			−0.032		
	(0.00)			(0.00)			(0.00)			(0.00)		
$[\mathrm{I}\sigma]_{\mathrm{size}}$		−0.006	−0.006		−0.016	−0.016		−0.028	−0.028		−0.034	−0.033
		(0.01)	(0.01)		(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
$[\mathrm{I}\sigma]_{\mathrm{vg}}$		−0.004	−0.004		−0.009	−0.008		−0.004	−0.003		0.003	0.004
		(0.07)	(0.10)		(0.02)	(0.03)		(0.50)	(0.54)		(0.66)	(0.62)
$[\mathrm{I}\sigma]_{\mathrm{mom}}$		−0.004	−0.003		−0.011	−0.010		−0.020	−0.019		−0.007	−0.006
		(0.11)	(0.19)		(0.01)	(0.01)		(0.00)	(0.00)		(0.33)	(0.40)
[ALPHA*HSV]	−0.001	−0.001	−0.001	−0.006	−0.006	−0.007	−0.005	−0.005	−0.005	−0.007	−0.007	−0.008
	(0.46)	(0.37)	(0.33)	(0.03)	(0.02)	(0.02)	(0.24)	(0.21)	(0.20)	(0.19)	(0.16)	(0.15)
TURN	0.011	0.011		0.012	0.012		0.013	0.013		0.023	0.023	
	(0.00)	(0.00)		(0.00)	(0.00)		(0.02)	(0.01)		(0.00)	(0.00)	
TURN-Low20			−0.024			−0.029			−0.025			−0.032
			(0.00)			(0.00)			(0.06)			(0.08)
TNA	−0.003	−0.003	−0.003	−0.005	−0.005	−0.005	−0.005	−0.005	−0.005	−0.001	−0.001	−0.002
	(0.14)	(0.14)	(0.16)	(0.18)	(0.16)	(0.18)	(0.32)	(0.29)	(0.29)	(0.88)	(0.83)	(0.80)
EXPR	−0.021	−0.021	−0.020	−0.033	−0.033	0.032	−0.046	−0.046	0.044	−0.063	−0.063	−0.060
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year FE?		Yes			Yes			Yes			Yes	
Adj. R^2	0.002	0.002	0.002	0.005	0.005	0.005	0.007	0.007	0.007	0.008	0.008	0.008
# of observations		233,303			76,758			38,117			19,357	

This table reports results for the 1981–2009 sample period of the regression of future risk-adjusted fund returns on past style volatility decomposed into its direct (DHSV) and indirect (IHSV) parts according to Equations (4) and (5), respectively. In Panels A and B, respectively, both direct and indirect HSV are also segmented into their three component parts by style characteristic (i.e., market capitalization, value-growth, momentum). Future fund tournament returns are measured for one-, three-, six-, and twelve-month intervals following a given 36-month estimation window. Also used as control variables are past risk-adjusted fund performance (ALPHA), an interaction variable formed by the product of ALPHA and HSV, portfolio turnover (TURN), an indicator variable for funds in the lowest turnover quintile (TURN-Low20), total net fund assets (TNA), and fund expense ratio (EXPR).

where:

$$w_{i,s}^{t} = \frac{\text{share}_{i,t} \cdot \text{price}_{i,s}}{\sum_i \text{share}_{i,t} \cdot \text{price}_{i,s}}$$

$$\text{for } s = t, t-1, \ldots, t-35.$$

In Equation (5), it is the manager's share decision that remains constant while the style characteristics of the underlying "fixed" holdings are allowed to change over time.[11]

4.2 *Direct and indirect style volatility and fund performance*

Table 6 produces the "full control" version of the panel regression model in Table 3 with some appropriate modifications to the HSV variable. For each of the four return forecast periods, specifications are estimated using the direct and indirect components of the aggregate style volatility regressor: (i) DHSV in Panel A and (ii) IHSV in Panel B.[12] Additionally, in a manner comparable to Table 5, we also segment the DHSV and IHSV variables by the three source characteristics of style volatility, which we label as $[D\sigma]_c$ and $[I\sigma]_c$, respectively, relative to the c-th characteristic.[13] The breakdown of DHSV by the contributing source of overall style volatility permits an examination of whether managers who attempt to produce abnormal returns by timing each style factor are able to do so.

Looking at the overall effect of direct and indirect style volatility first, in Panels A and B the left-hand columns for each of the return forecast horizons report the estimated parameters for the DHSV and IHSV variables, respectively. In all four cases for each measures, the coefficients are negative and range in value from −0.001 (one-month returns) to −0.020 (12-month returns) for DHSV and from −0.012 (one-month returns) to −0.039 (six-month returns) for IHSV. Furthermore, all of these parameters are statistically significant, with the exception of one-month return forecasts for DHSV. The magnitude of the coefficients on IHSV is roughly two-to-four times larger than those for DHSV, regardless of the forecast horizon. Finally, the inclusion of these modified measures does nothing to alter the influence of the other control variables (e.g., ALPHA and EXPR also remain statistically reliable).

The primary interpretation of these findings is unambiguous and consistent with our third hypothesis: Managers who allow the investment style of their portfolios to drift over time by indirect means will experience lower relative risk-adjusted returns in the future. Thus, even purely passive managers—presumably those who are just trying to capture index returns consistent with the fund's risk exposure—might still fall short of that goal if the style characteristics of their existing holdings shift appreciably from month to month. This implies that fund managers with no intention of trying to produce abnormal returns through security selection or tactical allocation still need to maintain a stable and predictable investment style to prevent the loss of value relative to their peers. Beyond that, the relative size of the parameter estimates for the DHSV variable suggests that managers who do manipulate the investment style of their portfolios directly are not as likely to impact future performance in an adverse manner as those managers whose style volatility is unintentional.

Given our findings in the previous section, we also consider whether the impact of direct and indirect style volatility varies by style component. The middle columns of each return forecast period in Table 6 list the estimated coefficients for the set of $[D\sigma]_c$ and $[I\sigma]_c$ variables described earlier. The results are quite similar to those for the characteristic segmentation of the aggregate HSV measure in Table 5. The firm size characteristic is negatively correlated with subsequent performance for both DHSV and IHSV, although this relationship is considerably stronger when we look at the indirect component of style volatility. Thus, managers who attempt to outperform expectations by either explicitly or implicitly adjusting the firm size style characteristic in their portfolio will substantially inhibit future performance. By contrast, the coefficients for both ($[D\sigma]_{\text{vg}}$, $[I\sigma]_{\text{vg}}$) and ($[D\sigma]_{\text{mom}}$, $[I\sigma]_{\text{mom}}$) are far less statistically reliable and occasionally assume insignificantly positive values. Therefore, with certain exceptions (e.g., the six-month forecast horizon), alterations in the other two style characteristics seem to have little impact on the portfolio's future risk-adjusted performance.

Finally, we also examine the possibility that active managers following an extremely low turnover strategy will exhibit greater levels of IHSV when overall market volatility increases. In such conditions, holding on to high-conviction stock positions in the fund for long periods of time (e.g., several years) may manifest in substantially larger levels of style-related volatility, which is unlikely to be an intentional action. Although portfolio turnover is represented as a control variable in the preceding regressions, it is possible that the construction of TURN does not fully capture the potential impact of these "hyper-low" turnover strategies. To address this issue, we replace the sample-wide TURN control with an indicator variable assuming the value of one if a fund is in the low turnover quintile in a given year, zero otherwise. Both panels of Table 6 show the findings using this alternative turnover control—labeled as TURN-Low20—which are listed in the right-hand columns for each respective forecasted return period. In particular, the results in Panel B indicate that the relationships between each of the components of IHSV and future risk-adjusted returns remain unchanged, meaning that they are robust with respect to this more severe characterization of low fund turnover. Notice also that the significantly negative coefficient for TURN-Low20 is consistent with the earlier outcome that portfolios with the highest turnover levels tend to produce slightly larger levels of future risk-adjusted performance.[14]

5 Additional Robustness Tests

5.1 Style volatility and the role of active security selection

Cremers and Petajisto (2009) introduce a measure of how managers intentionally manipulate their portfolio weights to be different than those in the benchmark index. Their Active Share (AS) statistic for fund j at month t is calculated for the N securities in the investable universe as:

$$\text{AS}_{j,t} = \frac{1}{2}\sum_{i=1}^{N} |\text{w}_{j,i,t} - w_{\text{Index},i,t}| \qquad (6)$$

AS should capture the part of HSV related to deliberate security selection strategies. While earlier findings show that indirect style volatility was an important predictor of future fund performance, it nevertheless may be the case that HSV simply mimics the explanatory power of AS.

To see if this is true, we replicate the full version of our main panel regression using AS as an additional control variable. Specifically, in addition to the Russell index return data described earlier, we obtain the requisite index holdings data (i.e., constituent securities and investment weights) from 1980 to 2009 from the Frank Russell Company. We then compute the AS measure relative to the style group-specific indexes following Equation (6).[15] These regression results are summarized in Table 7. The most important thing to note is that the coefficients on the overall HSV variable remain negative for all four prediction intervals and are statistically significant for all but the 12-month future returns. In fact, in comparison to the baseline findings presented in Table 3, it is clear that the magnitude of the contribution of HSV is not diminished at all by including AS as a regressor, which can also be said for the other controls such as ALPHA and EXPR. Therefore, we can conclude that HSV is indeed a distinctive explanatory factor relative to the information contained in the active selection variable.

5.2 *An alternative style classification method*

As explained in Section 2, we chose the factor loading-based method of classifying funds into nine investment style categories due to its consistency with both market practice and past academic research (e.g., Chan *et al.*, 2002). However, it is useful to consider how our findings could be sensitive to these style class definitions. While some of the previous robustness checks suggest that modifications *within* the factor loading-based scheme make no difference, it is nevertheless possible that a completely separate alternative to the present style classification system might.

Rather than using the estimated factor betas from Equation (3), a fund's style could be inferred directly from characteristics of its portfolio holdings. Once again relying on Kacpercyzk *et al.* (2005), for each fund in our sample at a given point in time, we use the most recently reported set of holdings to calculate the average characteristic score to each of the three style characteristics (i.e., market capitalization, book-to-market ratio, and return momentum). Dividing the range of scores for each characteristic into terciles, we then use a ($3 \times 3 \times 3$) sorting process to place each fund into its appropriate style category "bin" for the purpose of normalizing its future risk-adjusted return measures. While this holdings-based classification procedure using three style characteristics is not typical of how investment style is categorized within the mutual fund industry, it is somewhat more analogous to how we define our style volatility measure.

To see whether this affected our style volatility measure's ability to predict future risk-adjusted returns, we again replicate the full version of our main panel regression with the amended process. The results, which are listed in Table 8, show that the alternative classification scheme had little overall effect on HSV's importance as an explanatory variable. The estimated coefficients for HSV remain negative for each of the four future return prediction periods and statistically significant in all but the 12-month interval. Furthermore, none of the explanatory factors are affected by the alternative categorization process (with the exception of TNA, which is now statistically significant for the three shortest future return prediction periods). Thus, how a fund's investment style is classified does not appear to be responsible for our original conclusions.

5.3 *A returns-based style volatility measure*

As we have emphasized, our HSV measure of style volatility is based on an examination of how the portfolio holdings in a mutual fund change over time. The implicit assumption in this choice is that a style volatility measure based on portfolio returns rather than holdings would not be as informative, representing at best the "fingerprints" of the manager's decision-making prowess. On the other hand, returns can typically be measured over much shorter time periods than holdings (e.g., daily) and more currently, which is a great advantage to an investor trying to discriminate between the actual and self-reported style of a given fund.

As a final robustness check, we examine the relationship between the consistency of a portfolio's investment style and its future performance using a returns-based measure of style volatility. As Ammann and Zimmerman (2001) note, tracking error (TE) is a natural way to use fund returns for this purpose, since TE measures the variance of the return differential between a fund and

Table 7 Style volatility and fund performance panel regression results: Controlling for active share.

Variable	One-month predicted returns	Three-month predicted returns	Six-month predicted returns	12-Month predicted returns
Intercept	0.001	0.001	0.003	0.005
	(0.64)	(0.75)	(0.72)	(0.58)
ALPHA	0.039	0.060	0.062	0.044
	(0.00)	(0.00)	(0.00)	(0.00)
HSV	−0.004	−0.018	−0.024	−0.014
	(0.08)	(0.00)	(0.00)	(0.14)
AS	0.002	0.001	0.002	0.017
	(0.46)	(0.77)	(0.72)	(0.06)
[ALPHA*HSV]	−0.002	−0.007	−0.015	−0.001
	(0.22)	(0.01)	(0.00)	(0.85)
TURN	0.013	0.009	0.015	0.041
	(0.00)	(0.03)	(0.02)	(0.00)
TNA	−0.002	−0.006	−0.003	0.002
	(0.30)	(0.14)	(0.52)	(0.79)
EXPR	−0.022	−0.035	−0.050	−0.061
	(0.00)	(0.00)	(0.00)	(0.00)
Year fixed-effects?	Yes	Yes	Yes	Yes
Adj. R^2	0.001	0.003	0.004	0.004
# of observations	188,152	62,182	30,800	14,917

This table reports results for the 1981–2009 sample period of the regression of future risk-adjusted fund returns on past abnormal returns (ALPHA) and investment style volatility (HSV), after controlling for the active share (AS) measure. ALPHA is estimated over a 36-month period by Equation (3), with HSV measured over a comparable period by Equation (2). AS is estimated at a particular month t by Equation (6) using the fund's reported portfolio weights compared to the weights of the Russell index for the corresponding style group. Future fund tournament returns are measured for one-, three-, six-, and twelve-month intervals following a given 36-month estimation window. Also used as a regressor is an interaction variable formed by the product of ALPHA and the HSV. Additional control variables include portfolio turnover (TURN), total net fund assets (TNA), and fund expense ratio (EXPR). All variables are standardized by year and fund style class. P-values are listed parenthetically beneath each coefficient and year fixed-effects are included.

its style-specific index. So, at each point during the 1981–2009 sample period when we measure HSV, we also calculate the portfolio's TE statistic using the prior 36 months of return data. We then replicate the complete analysis in Section 3 using TE as our style volatility measure in lieu of HSV. Table 9 presents a condensed version of these findings, reporting the estimated coefficients for the unconditional panel regression model containing the full set of controls.

Before discussing the findings, it is worth mentioning that the unconditional correlation coefficient, aggregated cross-sectionally and across time, between HSV and TE is 0.5796. Thus, we would expect the two measures to provide comparable, but not exact, results when used as regressors in the fund performance forecast equation. Generally speaking, that is indeed what the findings indicate. The coefficient on TE is significantly negative for all four return

Table 8 Style volatility and fund performance panel regression results: Alternative investment style classification.

Variable	One-month predicted returns	Three-month predicted returns	Six-month predicted returns	12-Month predicted returns
Intercept	−0.001	−0.002	−0.002	−0.003
	(0.71)	(0.64)	(0.68)	(0.67)
ALPHA	0.039	0.062	0.066	0.045
	(0.00)	(0.00)	(0.00)	(0.00)
HSV	−0.004	−0.012	−0.020	−0.020
	(0.05)	(0.00)	(0.00)	(0.10)
[ALPHA*HSV]	−0.004	−0.013	−0.007	−0.008
	(0.02)	(0.00)	(0.10)	(0.18)
TURN	0.009	0.015	0.018	0.031
	(0.00)	(0.00)	(0.00)	(0.00)
TNA	−0.008	−0.011	−0.012	−0.009
	(0.00)	(0.00)	(0.02)	(0.23)
EXPR	−0.023	−0.035	−0.045	−0.058
	(0.00)	(0.00)	(0.00)	(0.00)
Year Fixed-Effects?	Yes	Yes	Yes	Yes
Adj. R^2	0.001	0.005	0.007	0.006
# of observations	233,944	77,061	38,072	17,679

This table reports results for the 1981–2009 sample period of the regression of future risk-adjusted fund returns on past abnormal returns (ALPHA) and investment style volatility (HSV), using the holdings-based method described in Section 5.2 as an alternative means of classifying a fund's investment style. ALPHA is estimated over a 36-month period by Equation (3), with HSV measured over a comparable period by Equation (2). Future fund tournament returns are measured for one-, three-, six-, and twelve-month intervals following a given 36-month estimation window. Also used as a regressor is an interaction variable formed by the product of ALPHA and the HSV. Additional control variables include portfolio turnover (TURN), total net fund assets (TNA), and fund expense ratio (EXPR). All variables are standardized by year and fund style class. *P*-values are listed parenthetically beneath each coefficient and year fixed-effects are included.

forecast periods (including the 12-month horizon), which is consistent with the hypothesis that funds with a greater degree of past variability relative to their style benchmark produce lower risk-adjusted returns in the future. An interpretation of the additional control variables—especially ALPHA—also remains the same, as does the significantly negative coefficient on the interaction term between ALPHA and TE. Consequently, the relationship between a fund's style volatility and future investment performance is not likely to be an artifact of how the former variable is measured.

6 Economic Significance

To assess the economic significance of style volatility investing, we ask: Controlling for portfolio expenses and past performance, would investors be able to exploit the return differential (if any) generated by less or more style-volatile portfolios? To address this issue, we calculate the returns to several hypothetical portfolios sorted by combinations of HSV, ALPHA, and EXPR. Beginning in January 1981, funds are divided into one of two portfolios according to high and low values of the relevant sorting variables. These portfolios are then rebalanced on a quarterly basis and investment performance statistics are calculated through December 2009.

Table 10 documents the investment performance for six different pairs of portfolios. For the first three of these portfolio pairs, funds are defined using just one of the sorting variables at a time. This allows for a comparison of the differential impact that expense ratio, past performance, and style volatility have when considered separately. The next two—[Lo EXPR, Lo HSV] vs. [Hi EXPR, Hi HSV] and [Hi ALPHA, Lo HSV] vs. [Lo ALPHA, Hi HSV]—provide comparisons of the synergies that exist when investors select managers that have either low expense ratios or superior past performance along with a less style-volatile investment approach. The final comparison examines the difference between [Lo EXPR, Hi ALPHA, Lo HSV] and [Hi EXPR, Lo ALPHA, Hi HSV] managers controlling for all three factors. High and low values of the sorting variables were defined by the upper and lower quartiles of the respective distributions.

Without regard to past performance or style volatility issues, investing with managers who run

Table 9 Returns-based style volatility and fund performance: Panel regression tests.

Variable	One-month predicted returns	Three-month predicted returns	Six-month predicted returns	12-Month predicted returns
Intercept	−0.002	−0.003	0.001	−0.003
	(0.34)	(0.32)	(0.77)	(0.64)
ALPHA	0.044	0.068	0.068	0.056
	(0.00)	(0.00)	(0.00)	(0.00)
TE	−0.014	−0.030	−0.023	−0.018
	(0.00)	(0.00)	(0.00)	(0.02)
[ALPHA*TE]	−0.002	−0.007	−0.013	−0.013
	(0.12)	(0.00)	(0.00)	(0.00)
TURN	0.011	0.010	0.015	0.032
	(0.00)	(0.00)	(0.00)	(0.00)
TNA	−0.003	−0.004	−0.006	−0.005
	(0.16)	(0.22)	(0.21)	(0.50)
EXPR	−0.021	−0.032	−0.049	−0.059
	(0.00)	(0.00)	(0.00)	(0.003)
Year fixed-effects?	Yes	Yes	Yes	Yes
Adj. R^2	0.001	0.005	0.006	0.006
# of observations	233,944	77,061	38,072	17,679

This table reports results for the 1981–2009 sample period of the regression of future fund performance on past abnormal returns (ALPHA) and past style volatility measured with the returns-based tracking error (TE) statistic. ALPHA is estimated over a 36-month period by Carhart's four-factor version of Equation (3); TE is estimated over a comparable period. Future risk-adjusted returns are measured for the n-month period following a given 36-month estimation window, where future return values for $n = 1$, $n = 3$, $n = 6$, and $n = 12$ are used. Also specified as a regressor is an interaction variable formed by the product of ALPHA and the style volatility measure (TE). Additional control regressors include portfolio turnover (TURN), total net fund assets (TNA), and fund expense ratio (EXPR). All variables are standardized by year and fund style class. P-values are listed parenthetically beneath each coefficient and year fixed-effects are included.

low-expense portfolios generates an annual return premium of 102 basis points (i.e., 10.91% vs. 9.89%) and with a lower level of portfolio standard deviation. Furthermore, investments based on just past fund performance levels show an even more pronounced increase in annual return (i.e., 11.47% to 9.24%) with a roughly comparable level of return standard deviation. Finally, portfolios sorted unconditionally on the style volatility variable produce a 90 basis point return premium for the Lo HSV investment, but with a risk level that was almost 60 basis points *lower* than that for the Hi HSV portfolio. The comparative Sharpe ratios listed in the last column are always larger for the respective upper quartile sort, showing that lower expense, higher past performance, and less style volatile investments always outperformed their counterparts on a risk-adjusted basis.[16]

The last three pair-wise comparisons document how the performance advantage associated with the style volatility decision is embellished by managers with low expense-high past performance operations. When Lo HSV and Hi HSV portfolios are modified to include extreme values of ALPHA in the sorting procedure, the return premium increases from 90 basis points to 165 basis points (i.e., 11.08% vs. 9.43%). The synergy between EXPR and HSV is larger still; adding this variable increases the Lo HSV vs. Hi HSV return premium from 90 to 268 basis points. Lastly, when funds are sorted on all three variables, the result is a return differential of 344 basis points with a reduction in overall risk. As before, the Sharpe ratios for each of the Lo HSV-based portfolios exceed those for the comparable Hi HSV portfolios by a sizeable margin.

Table 10 Style volatility and mutual fund investment performance: Economic significance.

Portfolio formation variables: EXPR	ALPHA	HSV	Cumulative value of \$1 invested	Average Annual Return (%)	Return Differential (bp)	Annual Standard Deviation (%)	Sharpe Ratio
Lo	—	—	15.579	10.91	102	15.67	0.357
Hi	—	—	11.557	9.89		15.90	0.287
—	Hi	—	18.077	11.47	224	16.09	0.383
—	Lo	—	9.454	9.24		16.17	0.242
—	—	Lo	15.121	10.75	90	15.48	0.351
—	—	Hi	11.348	9.85		16.06	0.282
Lo	—	Lo	18.670	11.51	268	15.51	0.399
Hi	—	Hi	8.342	8.83		16.21	0.217
—	Hi	Lo	16.652	11.08	165	15.41	0.374
—	Lo	Hi	10.116	9.43		16.03	0.257
Lo	Hi	Lo	17.994	11.38	344	15.44	0.393
Hi	Lo	Hi	6.538	7.94		15.91	0.165

This table considers the economic significance of the relationship between future mutual fund performance and style volatility. The display reports the cumulative value of a one dollar investment in various portfolios of mutual funds established in January 1981 and then rebalanced on a quarterly basis through the end of 2009. Also listed are the average annual return, standard deviation, and Sharpe ratio of those portfolios. Portfolios were formed based on fund expense ratio (EXPR), past risk-adjusted fund performance (ALPHA), and style volatility (HSV). Statistics are given for portfolios formed with the following characteristics: (i) Lo EXPR vs. Hi EXPR; (ii) Hi ALPHA vs, Lo ALPHA; (ii) Lo HSV vs. Hi HSV; (iv) [Lo EXPR, Lo HSV] vs. [Hi EXPR, Hi HSV]; (v) [Hi ALPHA, Lo HSV] vs. [Lo ALPHA, Hi HSV]; and (vi) [Lo EXPR, Hi ALPHA, Lo HSV] vs. [Hi EXPR, Lo ALPHA, Hi HSV]. Portfolios were formed with high and low values defined relative to the upper and lower quartiles, respectively, of each variable.

The main conclusion implied by these findings is that each of the contributions of a fund manager that we consider—running a low-expense operation, demonstrating superior past performance, and managing in a low style volatility manner—appears to have the potential to benefit investors. Beyond the independent contributions they make, there also appears to be a considerable amount of synergy possible between these effects. Of course, given that the benefits of investing with managers who control their expense ratios and persistently produce superior risk-adjusted returns are well documented, the extension provided by these results is to offer some perspective on the economic consequences of the manager's style volatility choice.

7 Concluding Comments

One of the more intriguing developments in professional asset management during the past few decades has been the evolution in how a portfolio's investment style is defined and the role that this style decision plays in determining fund returns. While considerable effort has been put toward establishing whether a manager's selection of a particular set of style characteristics influences performance, relatively little is known about whether the manager's ability to maintain that style mandate also has a significant impact on investment returns.

Does investment style volatility matter? The results of this study strongly suggest that the answer is "yes". Using a new measure of style volatility linked to fund holdings, we test three specific hypotheses related to this issue, namely that: (i) a negative relationship exists between portfolio style volatility and future risk-adjusted performance, (ii) the relationship between style volatility and future performance is separate and distinct from the roles played by past performance and fund expenses, and (iii) the direct and indirect components of style volatility will have different impacts on future performance. Based on a survivorship bias-free sample of equity mutual funds drawn from nine distinct style groups over 1978–2009, the data provide strong support for all three propositions under a wide variety of test conditions and alternative possibilities.

First, the typical low-style volatility fund does indeed tend to produce higher risk-adjusted returns over subsequent holding periods ranging from one month to one year into the future. Second, we also confirm that the connection between style volatility and future fund returns is distinct from—and of comparable magnitude to—those related to past performance (i.e., alpha), fund turnover, fund size, and fund expense ratio. Third, both the direct and indirect components of style volatility retain a strong negative connection to future performance, and the firm size characteristic appears to be to predominant source of those relationships. Furthermore, we also show that the relationship between style volatility and future fund returns does not change appreciably when a returns-based volatility metric replaces our holdings-based statistic. Finally, the style volatility measure proved useful in forming trading strategies capable of generating measurable levels of outperformance.

These findings evoke several implications and extensions. Most notably, it appears that the ability for portfolio managers to sustain a preferred degree of predictability to their designated investment styles is a valuable skill. In fact, maintaining a low and observable level of volatility in their investment style is one of the ways in which superior managers can signal their prowess to investors. Furthermore, although our results do not negate the possibility that managers who follow an explicit tactical style timing strategy can be successful, they do suggest that indirect style volatility can lead to inferior relative performance; the decision to maintain a stable and predictable style profile may be more useful in helping managers avoid chronically poor performance than in creating an environment that fosters persistent superior relative returns. At the very least, it seems clear that style volatility is another element that must be factored into the on-going debate of whether mutual fund performance is predictable over time.

Appendix: Relative Measures of Investment Style Volatility

By its design, the style volatility measure (i.e., HSV) summarized by Equation (2) captures the extent to which the aggregate equity style position of a particular fund varies relative to its own average location. In this sense, HSV can be viewed as an *absolute* volatility statistic. Another way to view the problem is to consider how a fund's style position varies in relation to the benchmark against which its performance is measured, suggesting that a *relative* volatility statistic may be appropriate. In this Appendix, we create two different versions of a relative style volatility measure (i.e., RHSV) that is consistent with the holdings-based approach outlined in Section 1.1 for our original metric. We then reproduce our main empirical findings in Table 3 using RHSV instead of HSV as an independent variable in order to establish the extent to which a manager's sensitivity to a benchmark might affect the overall results.

Table A.1 Benchmark-relative style volatility and fund performance.

Variable	One-month predicted returns		Three-month predicted returns		Six-month predicted returns		12-Month predicted returns	
Panel A. HSV vs. RHSV1								
Intercept	0.001	0.001	0.001	0.002	0.001	0.004	−0.000	0.001
	(0.68)	(0.68)	(0.82)	(0.68)	(0.77)	(0.53)	(1.00)	(0.95)
ALPHA	0.043	0.040	0.063	0.060	0.068	0.068	0.064	0.052
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HSV	−0.007		−0.020		−0.023		−0.018	
	(0.00)		(0.00)		(0.00)		(0.03)	
RHSV1		−0.005		−0.017		−0.023		−0.008
		(0.07)		(0.00)		(0.00)		(0.41)
[ALPHA * HSV]	−0.003		−0.007		−0.013		−0.008	
	(0.05)		(0.01)		(0.00)		(0.16)	
[ALPHA * RHSV1]		−0.001		−0.007		−0.015		−0.007
		(0.48)		(0.02)		(0.00)		(0.28)
TURN	0.012	0.012	0.013	0.009	0.015	0.015	0.020	0.015
	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.01)	(0.01)	(0.09)
TNA	−0.003	−0.003	−0.005	−0.006	−0.006	−0.004	−0.008	−0.008
	(0.10)	(0.26)	(0.14)	(0.12)	(0.21)	(0.46)	(0.27)	(0.33)
EXPR	−0.021	−0.021	−0.034	−0.035	−0.049	−0.049	−0.068	−0.081
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.001	0.001	0.004	0.004	0.006	0.005	0.009	0.008
# of observations	233,944	179,238	77,061	59,060	38,072	29,158	17,679	13,535

Table A.1 (*Continued*)

Variable	One-month predicted returns		Three-month predicted returns		Six-month predicted returns		12-Month predicted returns	
Panel B. HSV vs. RHSV2								
Intercept	0.001	−0.002	0.001	−0.004	0.001	−0.003	−0.000	−0.002
	(0.68)	(0.34)	(0.82)	(0.29)	(0.77)	(0.57)	(1.00)	(0.78)
ALPHA	0.043	0.037	0.063	0.056	0.068	0.063	0.064	0.068
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HSV	−0.007		−0.020		−0.023		−0.018	
	(0.00)		(0.00)		(0.00)		(0.03)	
RHSV2		−0.002		−0.014		−0.021		−0.019
		(0.52)		(0.00)		(0.00)		(0.03)
[ALPHA * HSV]	−0.003		−0.007		−0.013		−0.008	
	(0.05)		(0.01)		(0.00)		(0.16)	
[ALPHA * RHSV2]		0.003		0.001		−0.004		−0.002
		(0.06)		(0.70)		(0.32)		(0.76)
TURN	0.012	0.008	0.013	0.005	0.015	0.008	0.020	0.019
	(0.00)	(0.00)	(0.00)	(0.28)	(0.00)	(0.18)	(0.01)	(0.04)
TNA	−0.003	−0.003	−0.005	−0.005	−0.006	−0.006	−0.008	−0.007
	(0.10)	(0.17)	(0.14)	(0.19)	(0.21)	(0.30)	(0.27)	(0.37)
EXPR	−0.021	−0.025	−0.034	−0.040	−0.049	−0.055	−0.068	−0.069
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.001	0.002	0.004	0.005	0.006	0.007	0.009	0.008
# of observations	233,944	195,394	77,061	63,969	38,072	31,465	17,679	14,474

This table reports results for regressions of future fund performance and investment style volatility, measured either in absolute terms (HSV) or relative to two versions of a style-specific benchmark (RHSV). Panel A lists results for RHSV1 calculated by Equation (A.1) while Panel B shows findings for RHSV2 calculated by Equation (A.2). Future risk-adjusted returns are measured for the n-month period following a given 36-month estimation window using $n = 1$, $n = 3$, $n = 6$, and $n = 12$, respectively. Control variables include fund past abnormal performance (ALPHA), an interaction variable formed by the product of ALPHA and the respective style volatility measure (HSV or RHSV), portfolio turnover (TURN), total net fund assets (TNA), and fund expense ratio (EXPR). P-values are listed parenthetically beneath each coefficient and year fixed-effects are included.

The first, and most computationally streamlined, version of a relative style volatility statistic is computed for any period t as the simple difference between the HSV statistic for the j-th fund and its style-specific benchmark, b:

$$\text{RHSV1}_{j,t} = \text{HSV}_{j,t} - \text{HSV}_{b,t} \qquad \text{(A.1)}$$

where HSV is once again computed for both the fund and the benchmark portfolio in the same manner as before. Notice that since each fund classified into the same style category is assumed to have the same benchmark, deploying the statistic in Equation (A.1) should be comparable to using a style fixed effect in the regression analysis, a process that we already have in place.

The second version of a relative style volatility measure we consider computes the standard deviation of how the j-th fund's style score varies over the 36-month interval ending at period t compared to that of the benchmark portfolio:

$$\text{RHSV2}_{j,t} = \sigma\{[\text{Style Score}]_j - [\text{Style Score}]_b\} \quad \text{(A.2)}$$

Here [Style Score] is calculated for each portfolio at each period as a weighted average of the characteristic ranking values (i.e., $\text{Rank}_{c,j,t}$) of the underlying holdings, as described by Equation (1). Although more computationally challenging, RHSV2 has the advantage of incorporating relative variations into a fund's equity position directly into our holdings-based approach for measuring style volatility.

We recreated a complete set of our unconditional panel regression tests in Table 3 using both versions of RHSV instead of HSV as a direct regressor, as well as in combination with the fund's past performance variable (i.e., [ALPHA*RHSV]). As noted in Section 5.1, one limitation to this analysis is that holdings data for the Russell benchmarks are only available for the LV, LB, LG, SV, SB, and SG style indexes, which led to a reduction in the sample size of approximately 18–24% compared to our original estimations, depending on which version of the relative style volatility measure was used. We estimated separate sets of regression parameters using both RHSV1 and RHSV2.

To facilitate the most meaningful comparison of the impact associated with both the absolute and relative style volatility measures, Table A.1 lists findings for the "full control" versions of these regressions of future fund performance on past abnormal returns and style volatility, which correspond to the findings shown for Model 7 of Table 3 using the HSV statistic. (We computed a comparable set of results for each of the seven regression models shown in Table 3, but for brevity the findings for Models 1–6 are suppressed here and are available upon request.) In this new display, Panels A and B report results using the RHSV1 and RHSV2 statistics, respectively. As before, predicted risk-adjusted returns for each fund are computed over one-, three-, six-, and twelve-month intervals. For comparative ease, each panel of this display also reproduces the results from Table 3 for every return forecast period using the original HSV variable.

The main outcome of this analysis is that switching from an absolute measure of style volatility to a benchmark-relative one does little to diminish the strength of the relationship between the style volatility of a fund and its future risk-adjusted returns. That is, although slightly attenuated in size, the estimated parameters for the RSHV statistics remain properly signed and, for the most part, statistically reliable. The two exceptions to that conclusion are the one-month predicted return results for RHSV2 and the 12-month return forecast results for RHSV1, which do exhibit negative coefficient estimates, but ones that are not statistically significant. However, the RHSV2 measure interacted with ALPHA does produce a statistically meaningful coefficient for the 12-month predicted returns. Furthermore, recall that these new findings are generated with substantially smaller sample sizes, which makes the similarity in the reported coefficients that much more striking. Based on this collective evidence, we once again conclude that there is a meaningful relationship between the stability of a fund's investment style and its future performance, which is robust with respect to whether the style volatility statistic is calculated on an absolute or a relative basis.

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Notes

1 During most of our sample period, funds were required by law to disclose their holdings semi-annually. About 79% of the observations are from the most recent quarter and only 3% of the holdings are more than two quarters old.

2 Meier and Rombouts (2009) examine a related concept involving how fund style rotates over time using the proprietary scores that Morningstar began producing for funds in May 2002. However, since their measure is not directly based on the fund holdings themselves, it is difficult to compare it with Equation (2). Wermers (2012) proposes an alternative style drift measure which for each investment attribute takes the absolute difference in a fund's characteristic ranking at two points in time (i.e., the current date and the previous year) and sums those absolute differences across the three attributes. Thus, that statistic views style drift over a single year, whereas HSV measures the total volatility generated by the manager's style decisions over a three-year period.

3 This HSV statistic can be viewed as an *absolute* style volatility measure in that it marks changes in investment style in terms of a fund's own average position. In the Appendix, we also consider two versions of a *relative* style volatility statistic that replaces Equation (2) with a measure that assesses movements in the fund's investment style compared to that of a style-specific benchmark index.

4 Barberis and Shleifer (2003) model an economy where some investors shift assets between style portfolios to exploit perceived contrarian and momentum opportunities. However, without knowledge of the style currently in favor, they argue that arbitrage is not riskless and that no consistent profits are available. Nevertheless, Frijns *et al.* (2016) document that more than three-quarters of mutual fund managers engage in some form of style-based feedback trading. Wahal and Yavuz (2012) document the empirical relationship that exists between momentum profits and comovement with investment style; see also Barberis *et al.* (2005).

5 When using the estimated parameters on SMB and HML to sort funds into style classes (as explained below), we used versions of the model both with and without UMD. The inclusion of UMD made virtually no difference in the relative values of the coefficients for SMB and HML and hence made no difference in the way funds were classified. The results reported in subsequent sections are based on style group categorizations from the three-factor model.

6 The percentages used in this classification process reflect the *actual* style cell proportions for those funds in our sample that Morningstar did classify during the 1992–2009 subperiod. To insure that this approach did not bias the findings, we also replicated our analysis after sorting fund style by two different schemes. First, we classified funds into style groups each year according to the proportions that Morningstar employs for *their* sample: (70%, 20%, 10%) for the market capitalization dimension and equal weightings for the relative valuation dimension. (Notice that applying these proportions on a *different* sample would likely lead to an arbitrary outcome if the characteristics inherent in that sample did not coincidentally match.) Second, for the subperiod starting in 1992, we also used Morningstar's *actual* style group assignments for the funds in our sample. Neither of these alternative classification schemes produces results that are materially different in any way from those reported herein and they are available upon request; see also Chan *et al.* (2002) for a variation on this style classification scheme.

7 We estimate a fund's tracking error as the volatility over time of the difference between its return and that to the style class benchmark using 36 months of past returns and the following style-specific indexes: Russell 1000-Value (LV), Russell 1000-Blend (LB), Russell 1000-Growth (LG), Russell Mid-Cap-Value (MV), Russell Mid-Cap-Blend (MB), Russell Mid-Cap-Growth (MG), Russell 2000-Value (SV), Russell 2000-Blend (SB), and Russell 2000-Growth (SG). The return data for these indexes came directly from Frank Russell Company.

8 We replicate our entire set of results using three separate measures of future risk-adjusted fund returns,

which differ primarily in how fund risk is estimated. Chiefly because of its out-of-sample nature, throughout the study we report findings based on the following design: Each fund's total return is normalized within its relevant style class (i.e., tournament) by subtracting the return to its style-specific benchmark portfolio and then dividing this difference by the cross-sectional standard deviation of the funds in that style class, or $\frac{(R_{j,s,(t+1,\ldots,t+n)} - R_{b,s,(t+1,\ldots,t+n)})}{\sigma_{s,(t+1,\ldots,t+n)}}$. We also estimate two alternative measures where (i) risk is measured by the historical standard deviation of Fund j's returns over the 36-month period ending just before month t, and (ii) Fund j's historical standard deviation is indexed to the historical standard deviation of the benchmark for style class s. Our main findings are invariant to these adjustments, which are available upon request.

9 To provide some economic intuition for these parameters, recall that the dependent variable is the fund's net-of-benchmark return divided by the cross-sectional standard deviation of the returns to all of the peer funds in the style group. So, focusing on the 12-month forecast parameter of -0.028 and noting that the average cross-sectional style group standard deviation is about 20%, this implies an increase in a fund's style-adjusted annual excess return of 56 basis points (i.e., $-0.028 \times 20\%$) for each one standard deviation decline in the HSV measure.

10 Recall that a non-negligible portion of our fund sample (i.e., 21%) does not report holdings in the most recent quarter, which could create an unintended bias when measuring HSV using monthly data. To address this concern, as a robustness check we reproduced the results in Panels B–D in Table 3 using HSV statistics based on 12 quarters of data instead of the comparable 36-month month period specified in Equation (2). We label this quarterly version of the HSV measure as HSVQ. (Note that it is only possible to reproduce the three-, six-, and twelve-month forecasted return results with a quarterly style volatility measure.) Although parameter values were slightly reduced in magnitude, this adjustment did not change either the strength or the pervasiveness of the hypothesized relationship between predicted returns and style volatility. With Model 4 as an example, the estimated parameters for HSVQ (versus HSV in Table 3) are: -0.023 (-0.025) for three-month forecasted returns, -0.024 (-0.031) for six-month forecasted returns, and -0.020 (-0.029) for 12-month forecasted returns. All of these new estimates remain statistically significant with P-values of 0.00, despite the substantially smaller sample sizes associated with using quarterly data. A full set of findings for the revised Table 3 using HSVQ is available upon request.

11 An alternative assumption that could be used in the calculation of Equation (5) is that the manager keeps the security *weights*, rather than the actual shares, fixed over time. Of course, holding these weights constant implies that the manager rebalances the portfolio periodically. With this "fixed weight" assumption the indirect measure of style volatility becomes: $\sigma\{\sum_{i=1}^{n} w_{i,t} \cdot S_t, \sum_{i=1}^{n} w_{i,t} \cdot S_{t-1}, \ldots, \sum_{i=1}^{n} w_{i,t} \cdot S_{t-35}\}$. We have estimated the empirical analysis described below using both definitions of IHSV, but we only report those findings based on the "fixed share" measure since that best reflects the position of a hypothetical buy-and-hold investor. The findings using the "fixed weight" alternative are available upon request.

12 Due to its non-linear nature as a variance statistic, HSV is not simply the sum of DHSV and IHSV. Consequently, analysis based on the relative magnitudes of the direct and indirect volatility measures (e.g., DHSV $\div$ HSV) is not feasible. Furthermore, for the funds in our sample, the correlation between the full HSV measure and its direct (DHSV) component is 0.71, indicating that high-style volatility portfolios tend to be attributable to direct managerial action.

13 In calculating $[D\sigma]_c$ for a fund on Date t, we compute the average characteristic score (and price) of each stock over the prior 36 months and, holding this average score and price constant, we then calculate the weighted average characteristic scores of the fund for the same interval (i.e., only the share holdings are allowed to change). $[D\sigma]$ is the standard deviation of this monthly characteristic score series. For $[I\sigma]_c$, we hold the recently disclosed share holdings for a fund constant and allow the price and characteristic scores of each stock to change. We then compute the average characteristic score over the prior 36 months and calculate $[I\sigma]$ as the standard deviation of this series.

14 Given that our definition of a "hyper-low" turnover fund as one falling in the bottom quintile may not be standard, we replicated these results using bottom decile and tercile indicator variables (i.e., TURN-Low10 and TURN-Low33, respectively) instead of TURN-Low20. These alternative estimations, which are not show in Table 6, did nothing to alter our main conclusions, although the relationship between the most extreme low turnover funds (i.e., lowest decile) and future predicted returns did become statistically insignificant for the longest two forecast horizons.

[15] Holdings data are not available for the mid-cap value (MV), mid-cap blend (MB), and mid-cap growth (MG) style indexes, which reduce slightly the sample size relative to the analysis reported previously.

[16] Sharpe ratios are calculated for each portfolio as the difference between its average annual return and the average annual risk-free rate divided by the portfolio's annualized standard deviation. The average annual risk-free rate for 1981–2009 is 5.32%, which is established by annualizing the average of the monthly Treasury bill yields listed in the Fama–French database.

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