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Do fund managers time momentum? Evidence from mutual fund and hedge fund returns

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Abstract

By examining fund returns we find strong evidence that both hedge funds and mutual funds trade on momentum. Moreover, the average hedge fund has modest momentum timing skill, trading more aggressively when momentum profits are higher, while the average mutual fund does not. Momentum trading alone does not translate into superior performance. However, funds with momentum timing ability significantly outperform and the risk-adjusted-return-difference between the top and the bottom timers is around 1.7% (1.3%) per year for hedge (mutual) funds. We provide further evidence that dynamic momentum strategies enhance fund performance, and momentum timing skills vary considerably with fund investment styles.

KEYWORDS
hedge funds, momentum timing, momentum trading, mutual funds

JEL CLASSIFICATION
G10, G11, G23

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1 | INTRODUCTION

The momentum anomaly, that is, past winners significantly outperform past losers over intermediate horizons, is a premier anomaly in the finance literature. The momentum effect persists after its original discovery and is present across a wide range of asset classes (Asness et al., 2013; Jegadeesh & Titman, 2001). There is extensive literature to investigate whether institutional investors arbitrage against the anomaly, but the findings are surprisingly mixed. Using institutions' stockholdings, Grinblatt et al. (1995), Bennett et al. (2003), and Griffin and Xu (2009) find significant evidence of momentum trading, while Falkenstein (1996), Gompers and Metrick (2001), and Lewellen (2011) find no such evidence. Lakonishok et al. (1992), Wermers (1999), Badrinath and Wahal (2002), and Yan and Zhang (2009) find evidence of institutional momentum trading, but limited only to small stocks, past losers, entry trades, and short-term institutions, respectively. More recently, Grinblatt et al. (2020) find that mutual funds trade on momentum, whereas hedge funds follow contrarian strategies. This last finding is puzzling because hedge fund managers are generally considered more sophisticated than mutual fund managers.

Another important issue that has been largely overlooked in the literature is whether institutional investors are able to time momentum returns. Recent studies show that the momentum profits vary substantially with market conditions and occasionally exhibit crashes (Daniel & Moskowitz, 2016). For example, it has been documented that momentum profits are higher subsequent to high market returns (Cooper et al., 2004) and during periods of high investor sentiment (Stambaugh et al., 2012). Existing studies also find that the momentum profits tend to be lower in January (Jegadeesh & Titman, 2001) and are more likely to have crashes following high momentum volatility (Barroso & Santa-Clara 2015). These studies suggest that adjusting portfolio's exposure to momentum based on these conditioning variables should lead to greater investment performance. However, little research has examined whether institutional investors are aware of the predictability of the momentum returns and engage in momentum timing.

In this paper, we perform a first comprehensive analysis based on a large sample of hedge funds and mutual funds to investigate (1) whether fund managers actively trade on momentum; (2) whether fund managers possess momentum timing skills; (3) to what extent the momentum trading and timing skills improve fund performance.

We focus on hedge funds and mutual funds in this paper for three reasons. First, hedge funds and mutual funds are dominant players in the asset management industry. Second, data on fund returns are readily available for hedge funds and mutual funds. Third, hedge funds and mutual funds are widely considered as sophisticated investors who are likely to exploit market mispricing. Hedge funds, in particular, are regarded as the closest to the ideal rational arbitrageurs among all investors (Brunnermeier & Nagel, 2004).

We extend the literature on institutional investor momentum trading by focusing on fund returns instead of stockholdings. Although stockholdings data may inform us about institutional investors' trading behaviour, such data (i.e., the 13F filings) have a number of limitations. First of all, 13F filings do not report short positions. This omission is particularly problematic for hedge funds and for the analysis of long-short trading strategies. Second, quarterly holdings do not capture intra-quarter trades. Previous studies (e.g., Puckett & Yan, 2011) have shown that interim trading by institutional investors can be particularly informative. More importantly, intra-quarter trades are crucial for one to analyze fund managers' momentum timing skills. Third, 13F reports are not mandatory for fund companies managing less than $100 million or for holdings less than $200,000 or 10,000 shares. Finally, quarter-end institutional holdings may present a biased view of institutions' actual holdings during the quarter because of window dressing (Lakonishok et al., 1991). Therefore, we take a different approach in this paper. We use fund returns to examine whether institutional investors trade on the momentum anomalies and whether they exploit the predictability of the momentum returns. Intuitively, if fund managers trade on momentum, we would expect fund returns to be positively related to the long-short returns of momentum strategies. Furthermore, if fund managers can time momentum, we would expect the momentum loadings to be higher (lower) when the momentum profits are higher (lower).

We begin our empirical analysis by examining whether hedge funds and mutual funds, in the aggregate, trade on momentum. We follow Fama and French (2010) and construct average returns across all hedge funds or mutual funds. We then regress aggregate fund returns on the long-short returns of the momentum strategy. We find that aggregate fund returns load positively and significantly on momentum. This evidence holds after controlling for Fung and Hsieh (2004) seven factors for hedge funds and Fama and French (1996) three factors for mutual funds. The results are robust to equal or value weighting and are stronger for hedge funds than for mutual funds. In short, we find significant evidence that both hedge funds and mutual funds, in the aggregate, follow momentum strategies.

We then use aggregate fund returns to examine whether hedge funds and mutual funds possess momentum timing skills. We modify the standard market timing models of Treynor and Mazuy (1966) and Henriksson and Merton (1981) by replacing market returns with momentum returns. Regardless which model we use, we find that the average hedge fund has some momentum timing ability. That is, the average hedge fund trades more aggressively on momentum when momentum strategies are more profitable. In contrast, we find little evidence that the average mutual fund can time momentum returns based on standard timing models.

Next, we examine momentum trading and momentum timing at the fund level by using individual fund returns. The results are largely consistent with those obtained from aggregate fund returns. Specifically, we find that fund-level momentum loadings are disproportionately positive for both hedge funds and mutual funds. For example, the 95th percentile of *t*-statistics on momentum loading is 4.21 across all hedge funds. In comparison, the 5th percentile is only −2.21, much smaller in magnitude than its right-tail counterpart. Mutual funds exhibit *t*-statistics that are also positively skewed, consistent with momentum trading. In contrast to the significant evidence on momentum trading, we find that the *t*-statistics on the momentum timing coefficient are much smaller in magnitude. The distribution of the *t*-statistics is slightly skewed to the right for hedge funds, while displaying little asymmetry among mutual funds. This result is broadly consistent with our earlier finding based on aggregate fund returns that the average hedge fund possesses modest timing ability while the average mutual fund does not.

We also examine if the momentum loadings vary with market conditioning variables (i.e., market states, investor sentiment, calendar month and past momentum volatilities). Consistent with momentum timing ability, we find that both hedge funds and mutual funds decrease the momentum loading following high prior momentum volatility. However, mutual funds trade in the wrong direction in January, that is, they engage in more momentum trading in January, despite the evidence of negative momentum returns in those months. Hedge funds, in contrast, decrease their level of momentum trading in January. Neither hedge funds nor mutual funds significantly change their momentum loadings during periods of high investor sentiment.

To explore whether funds with different investment styles exhibit different trading patterns on momentum, we classify sample funds based on their investment objectives and conduct the main analyses for subsamples of funds. We uncover a large variation in both momentum trading and momentum timing skills across different investment styles. For hedge funds, *Long-short Equity* funds and *Multistrategy* funds trade more aggressively on momentum, and they also have better momentum timing abilities. For mutual funds, *Aggressive-Growth* funds have the highest return loadings on momentum while *Growth and Income* funds load negatively on momentum. However, none of the three investment styles of mutual funds exhibit significant momentum timing skills, which is also consistent with the aggregate results for mutual funds.

Momentum strategies are high-turnover strategies, and the literature is ambiguous about whether momentum profits survive trading costs (e.g., Asness et al., 2014; Korajczyk & Sadka, 2004; Lesmond et al., 2004; and Patton & Weller, 2020). Therefore, it is not clear whether hedge funds and mutual funds that engage in momentum trading can deliver superior performance to fund investors. To investigate this issue, we sort all hedge funds or mutual funds into decile portfolios based on momentum trading or momentum timing skills. We find little evidence that momentum trading translates into superior fund performance. However, we find significant evidence that funds with high momentum timing ability outperform funds with low momentum timing ability. The magnitude of this outperformance is economically meaningful, around 1.7% per year for hedge funds and 1.3% per year for mutual funds, and statistically significant. Our results suggest that it is momentum timing, not momentum trading per se, that enhances fund performance.

During our sample period 1984–2020, the maximum drawdown to the momentum strategy is almost 70%, and the longest duration of drawdowns is more than 12 years. That is, investors who follow static momentum strategies could suffer significant losses that may take years to recoup. To obtain more insights into the value of adjusting portfolio exposure to momentum, we conduct two additional analyses. In the first analysis, we use a rolling window to estimate the momentum loadings for each fund, and we compute the standard deviation of the loadings over time. For funds which follow a static momentum trading strategy, the loading variation over time should be small. Based on the standard deviation of the loadings, we sort hedge funds or mutual funds into decile portfolios. We find that the portfolio returns increase with the momentum loading variations. That is, funds which vary the intensity of momentum trading more actively over time tend to have better performance.

In the second analysis, we focus on the fund managers' skills to avoid momentum crashes. Specifically, we define a dummy variable for momentum crash when the monthly momentum return is lower than −5%, and then we use a modified timing model to see whether funds' momentum loadings are substantially decreased in the event of momentum crashes. Using the same portfolio approach, we find evidence that funds with the highest ability to time momentum crashes outperform funds with the lowest ability to time crashes. This finding confirms that managing the risk of the momentum strategy leads to substantial economic gains (Barroso & Santa-Clara, 2015).

In our final empirical analyses, we examine the cross-sectional relation between fund momentum-timing skills and various fund characteristics. This analysis would help investors pick more successful momentum timers. For hedge funds, we find that larger funds, older funds, and funds with higher incentive fees and longer redemption notice periods are more likely to have momentum timing skills. For mutual funds, momentum timers tend to have longer histories, smaller size, and higher expense ratios.

Our paper adds to the literature on institutional momentum trading. Most prior studies in this literature use quarterly stockholdings (i.e., 13F data) and find mixed evidence on whether institutions trade on momentum. The 13F data, however, have several limitations. In contrast, we rely on fund returns to draw inferences on momentum trading.[1] In so doing, we provide an alternative and complementary view on momentum trading by institutional investors.

Our study also contributes to the literature on fund managers' timing skills. The existing studies have traditionally focused on managers' ability to time market returns, market volatility or market liquidity (see e.g., Busse, 1999; Bollen & Busse, 2001; Cao et al., 2013). In this paper, we examine the timing issues from a new perspective. To the best of our knowledge, this is the first paper to examine whether fund managers time momentum returns and whether such timing ability enhances fund performance. The issue is of particular importance in light of the recent evidence on momentum crashes (Daniel & Moskowitz, 2016). Despite the strong positive average returns of the momentum strategy, those large momentum crashes may take investors years to recover from. We show that the average hedge fund possesses modest momentum timing ability, trading more aggressively on momentum when it is more profitable. Moreover, we find evidence that funds alter the intensity of momentum trading based on market state and prior momentum volatility, which have been shown by the previous literature to predict momentum returns. Finally, we find that funds with momentum timing abilities deliver better fund performance.

The closest paper to ours is Grinblatt et al. (2020), who use the 13F data to show that mutual funds are momentum traders, whereas hedge funds are contrarian traders. Their evidence on mutual funds is consistent with ours, while their finding on hedge funds is contrary to ours. We note that we rely primarily on fund returns to infer momentum trading. As stated earlier, window dressing concerns and the lack of coverage on short positions in the 13F data may bias the inference on momentum trading. Finally, Grinblatt et al. (2020) do not examine the issues of momentum timing.

The rest of the paper proceeds as follows. Section 2 describes the data, sample, and summary statistics. Section 3 presents the empirical results. Section 4 concludes.

2 | DATA, SAMPLE, AND SUMMARY STATISTICS

2.1 | Momentum portfolios

We obtain daily and monthly stock returns from the Center for Research in Security Prices (CRSP). We include only common stocks (with a share code of 10 or 11) in our sample. To construct momentum portfolios, we sort all sample stocks into equal-weighted decile portfolios based on past returns over the period from $t-12$ to $t-1$, where t is the portfolio formation month. We follow Fama and French (1996) and skip a month to avoid market microstructure effects. We form long-short portfolios by buying past winners and selling past losers. We rebalance every month and hold the portfolios for 1 month. We follow Jegadeesh and Titman (2001) and remove all stocks with a price less than \$5 at formation or with a market

[1]We acknowledge that hedge fund returns are self-reported and may suffer from survivorship, backfill, and other reporting biases. Although these data issues may bias the level of hedge fund performance, a priori it is not clear how they bias the inference on momentum trading by hedge funds. Nevertheless, we mitigate these data biases by using standard approaches in the hedge fund literature (see Section 2.2).

capitalisation ranked in the smallest NYSE decile from our sample. We obtain Fama and French (1996) three factors from Kenneth French's website.[2]

2.2 | Hedge funds

We obtain hedge fund data from Lipper TASS and Hedge Fund Research (HFR), which are two of the most widely used hedge fund databases in the academic literature.[3] We follow the database merging approach of Joenväärä et al. (2021) and create an aggregate database by consolidating Lipper TASS and HFR databases. The aggregate database allows us to exploit all available information from the individual databases and mitigate the effects of data biases.

The consolidated database contains both live funds and defunct funds and covers hedge fund returns and various fund characteristics including fund assets under management (AUM), minimum investment, fee structure, the use of high-water mark (HWM), and share restriction provisions. The sample period for the hedge fund data is 1994–2020. We begin our sample in 1994 because the data before 1994 are subject to a survivorship bias (Fung & Hsieh, 1997; Liang, 2000).

Following the previous literature, we mitigate the backfilling bias in the hedge fund data by removing the first 12 months of observations for each fund from the sample (e.g., Teo, 2011). We also exclude funds before their assets under management exceed $10 million. In addition, we only consider funds that report net returns on a monthly basis in US dollars. We keep both live and defunct funds in the sample to remove survivorship bias, and we require each sample fund to have at least 12 monthly returns.

We harmonise database-specific investment styles into the broad styles in SEC Form PF by following the style mapping rule of Joenväärä et al. (2021). We remove the *Credit*, *Managed Futures/CTA* and *Other* categories from the sample to focus on equity-oriented funds. Our final sample contains 11,365 hedge funds in six style categories—*Equity*,[4] *Event Driven, Fund of Funds, Macro, Multistrategy*, and *Relative Value*. We obtain Fung and Hsieh (2004) seven factors from David Hsieh's website.[5]

2.3 | Mutual funds

We obtain monthly mutual fund returns, total net assets (TNA), expense ratio, turnover rate, and other fund characteristics from the CRSP Survivor-Bias-Free Mutual Fund Database. The sample period for the mutual fund data is 1984–2020. We begin the sample in 1984 because Fama and French (2010) show that the monthly return data before 1984 are biased upward. Many funds have multiple share classes, which typically differ only in fee structure (expense ratio, 12b-1 fee, and load charges). We combine these different share classes into a single fund. In particular, we calculate the TNA for each fund as the sum of the TNA of each share class and calculate fund age as the age of its oldest share class. For all other fund characteristics, for example, expense ratio, we use the TNA-weighted average across all share classes.

[2]https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[3]According to Joenväärä et al. (2021), 79% of the academic papers use Lipper TASS and 40% use HFR, and they are also among the highest-quality commercial databases for hedge funds.
[4]Most funds in this category are long-short equity funds.
[5]https://faculty.fuqua.duke.edu/~dah7/HFData.htm

We limit our analysis to US domestic actively managed equity mutual funds. We follow the procedures of Doshi et al. (2015) and rely on the CRSP investment object code to identify such funds. We exclude international, balanced, sector, bond, money market, and index funds from our sample. We also exclude funds that have less than 80% of their holdings in common stocks. Following Busse (1999), we then classify mutual funds into three broad categories based on their investment objectives, namely *Aggressive Growth*, *Growth*, and *Growth and Income*.[6]

To mitigate the effect of incubation bias, we follow prior studies and include a fund only after its TNA has surpassed $15 million (Elton et al., 2001; Fama & French, 2010). Once a fund enters our sample, we do not exclude it even if its TNA drops below $15 million. We further exclude observations before the first offer date of the fund (i.e., the date of organisation). We require a minimum of 12 monthly returns for a fund to be included in our sample. Our final sample includes 2940 distinct mutual funds.

2.4 | Hedge funds versus mutual funds

Hedge funds employ dynamic trading strategies, typically take both long and short positions, can borrow, and make extensive use of derivatives (Stulz, 2007). Hedge funds focus on arbitrage opportunities and pursue absolute returns rather than returns in excess of a benchmark. Mutual funds are more limited in their ability to hedge their positions through short-sales and derivatives use, and they are subject to diversification restrictions that constrain their ability to exploit perceived opportunities. Mutual funds must also redeem shares on a daily basis; therefore, it is risky for mutual funds to invest in strategies that may take time to become profitable, because adverse developments in the short run may lead investors to withdraw their money. The hedge fund industry, because of its higher compensation and autonomy, also attracts better talent than the mutual fund industry. In summary, we hypothesise that hedge funds are more capable of exploiting the momentum anomaly than mutual funds.

2.5 | Summary statistics for sample funds

Panel A of Table 1 presents the summary statistics of sample hedge funds.[7] The average total assets under management of our sample hedge funds is $181.44 million, while the median is only $53.12 million. The average fund is about 71 months old. The average hedge fund requires a minimum investment of $1.25 million and charges 1.42% management fee and 15.57% incentive fee. Twenty-eight percent of the hedge funds have a lock-up provision, and 77% of the funds use high-water-mark. Finally, the average redemption notice period is 42 days.

Panel B presents the summary statistics of our sample mutual funds. The average TNA is $670.72 million, while the median is $166.96 million, suggesting that fund size is skewed to the right. Also, compared to the average hedge fund, the average mutual fund is much larger. The average mutual fund is about 9 years old and has an expense ratio of 1.22% and a turnover rate of nearly 87% per year. The average total load (front-end load plus back-end load) is 1.09%.

[6]In the *Growth and Income* category, 13% of the funds are pure income funds. We do not have a separate category for them because the number of these funds is relatively small.

[7]The summary statistics for each investment style can be found in the appendix.

TABLE 1 Summary statistics: mutual funds and hedge funds

This table reports summary statistics of sample fund characteristics. Hedge fund data are from the Lipper TASS and Hedge Fund Research (HFR) databases. Mutual fund data are from CRSP mutual fund database. For hedge funds, we follow the database merging approach of Joenväärä et al. (2021) and create an aggregate database by consolidating Lipper TASS and HFR. We remove the first 12 months of observations for each fund. We also remove all observations before a fund reaches $10 million in total net assets. We only retain funds that invest in equity markets and report net returns on a monthly basis in US dollars. We exclude managed futures/CTA funds, and funds with missing or undefined investment style. For mutual funds, we limit our analysis to US domestic actively managed equity mutual funds. We exclude international, balanced, sector, bond, money market, index funds and funds with missing investment style from our sample. We also exclude funds that have less than 80% of their holdings in common stocks. We combine these different share classes into a single fund. We include a fund only after its TNA has surpassed $15 million. We further exclude observations before the first offer date of the fund. We require a minimum of 12 monthly bias-free returns for a fund to be included in our sample. Our final sample includes 11,365 hedge funds and 2940 mutual funds. The sample period is 1994–2020 for hedge funds and 1984–2020 for mutual funds.

Panel A: Hedge funds				
	Mean	**Median**	**P10**	**P90**
Fund_AUM ($ million)	181.44	53.12	12.20	382.74
Fund_Age (month)	70.77	56.31	22.00	138.55
Management fee (%)	1.42	1.50	1.00	2.00
Incentive fee (%)	15.57	20.00	0.00	20.00
Minimum investment ($ million)	1.25	0.50	0.05	2.00
Lock-up	0.28	0.00	0.00	1.00
Lock-up period (month)	3.64	0.00	0.00	12.00
Redemption notice period (days)	41.99	30.00	3.00	90.00
High water mark	0.77	1.00	0.00	1.00
Panel B: Mutual funds				
	Mean	**Median**	**P10**	**P90**
Fund_AUM ($ million)	670.72	166.96	22.64	1461.16
Fund_Age (month)	107.09	90.66	33.42	184.79
Turn_ratio (%)	87.49	71.10	26.29	153.05
Exp_ratio (%)	1.22	1.18	0.75	1.78
Load (%)	1.09	0.15	0.00	3.16

3 | EMPIRICAL RESULTS

3.1 | Momentum returns

Table 2 presents the summary statistics of momentum returns over the sample period 1984–2020. Panel A shows that the average momentum return is 1.04% per month (t-statistic = 3.35), similar in magnitude to those documented in Jegadeesh and Titman

TABLE 2 Summary statistics of momentum returns

This table reports summary statistics of momentum strategy. We obtain stock data from the CRSP database and Fama and French (1996) three factors from Kenneth French's website. Our sample consists of NYSE, AMEX, and NASDAQ common stocks (with a CRSP share code of 10 or 11). We exclude financial stocks and stocks with a price lower than \$5. We also remove stocks whose market capitalisation is ranked in the lowest NYSE decile at the portfolio formation date. We sort all sample stocks into deciles each month based on past 11 months' returns (after skipping a month) and construct equal-weighted portfolios by buying past winners and shorting past losers. Panel A reports the raw momentum return, Fama-French 3-factor alpha, maximum drawdown, and the maximum duration of drawdown. Panel B reports the regression results of the determinants of momentum returns while controlling for Fama-French three factors. UP state is a dummy variable which is equal to 1 when past 36-month cumulative market return is positive. Sentiment data is from Baker and Wurgler (2006). We define high sentiment as one if the sentiment is above median. January is a dummy variable to measure the January effect. Momentum volatility is the volatility of momentum daily returns over the past 6 months. The sample period is 1984–2020. Numbers in parentheses are *t*-statistics. Momentum returns, Fama and French three-factor returns, and momentum volatility are expressed in percent.

Panel A: Momentum returns

Average momentum return	Fama-French 3-factor alpha	Maximum drawdown	Maximum duration of drawdown
1.04% (3.35)	1.31% (4.43)	69.90%	150 months

Panel B: Predicting momentum returns

	(1)	(2)	(3)	(4)
Intercept	−0.52	0.80	1.41	2.84
	(−0.62)	(1.85)	(4.56)	(4.76)
MKTRF	−0.30	−0.27	−0.30	−0.31
	(−4.45)	(−3.74)	(−4.41)	(−4.69)
SMB	0.23	0.25	0.21	0.25
	(2.31)	(2.40)	(2.11)	(2.50)
HML	−0.61	−0.61	−0.61	−0.59
	(−6.01)	(−5.42)	(−6.06)	(−5.87)
UP state	2.08			
	(2.35)			
High sentiment		1.19		
		(1.96)		
January			−1.19	
			(−1.12)	
Momentum volatility				−1.57
				(−2.95)
R^2	12.49%	10.69%	11.64%	13.11%

(1993, 2001). The Fama–French three-factor alpha is 1.31% per month (*t*-statistic = 4.43), suggesting that the Fama and French three-factor model exacerbates the momentum anomaly, rather than explaining it.

We find that the maximum drawdown to the momentum strategy over our sample period is nearly 70%, which occurred between June 2008 and January 2010, consistent with the evidence documented in Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016). We also show that the maximum duration of drawdowns is 150 months, that is, over twelve years. In other words, investors who follow traditional, static momentum strategies may experience significant losses that take years to recoup. Unreported results indicate that momentum crashes are not one-off events. For example, during our sample period of 1984–2020, the second largest drawdown (not overlapped with the largest) is 47%, while the third largest drawdown is 38%.

In Panel B we examine the predictive ability of momentum returns. Previous studies have shown that momentum returns are significantly higher subsequent to high market returns (Cooper et al., 2004) and high investor sentiment (Stambaugh et al., 2012), and significantly lower in January (Jegadeesh & Titman, 2001) and following high momentum volatility (Barroso & Santa-Clara, 2015). To check whether the above findings hold in our sample period, we regress momentum returns on market state, sentiment, January dummy, and prior momentum volatility, while controlling for Fama and French three factors. We measure market state by using past 36-month cumulative market returns, and define UP state as 1 if the past 36-month cumulative market return is positive and 0 otherwise. For investor sentiment, we use the Baker and Wurgler's (2006) measure. We follow Stambaugh et al. (2012) and define those months with above median sentiment as high-sentiment period. Finally, we follow Barroso and Santa-Clara (2015) and compute prior momentum volatility by using past 6 months of daily momentum returns.

Overall, we find evidence consistent with the previous literature. The coefficient estimates are positive on market state and sentiment, and negative on the January dummy and prior momentum volatility. The results are economically large. For example, the coefficient on the UP state dummy indicates that momentum profits are 2.08% per month higher during UP state. The results are statistically significant for all variables except the January dummy. The lack of statistical significance on the January dummy is primarily due to low statistical power rather than a lack of economic significance. Indeed, the coefficient on the January dummy indicates that the momentum returns are 1.19% lower in January than the other months of the year. In summary, we confirm the predictive ability of these variables for momentum returns during our sample period.

3.2 | Aggregate fund returns

3.2.1 | Momentum loading

We follow Fama and French (2010) and compute equal-weighted average returns across all hedge funds (mutual funds).[8] Effectively we are treating all hedge funds (or mutual funds) as a single fund. We then regress aggregate fund excess returns on the long-short returns of the momentum strategy, while controlling for standard asset pricing factors, that is, Fung and

[8]Our results are robust when we use TNA-weighted average returns.

Hsieh (2004) seven factors for hedge funds and Fama and French (1996) three factors for mutual funds. If funds follow momentum trading strategies, that is, buying winners and selling losers, then we would expect fund returns to load positively on momentum returns.

We report the regression results in Table 3. We report the results for all funds, and for each investment style. We find strong evidence that aggregate hedge fund and mutual fund returns load positively on momentum. For hedge funds (Panel A of Table 3), the coefficient on the momentum return is 0.05 (t-statistic = 5.57). The evidence of momentum trading is weaker for mutual funds (Panel B of Table 3), but remains statistically significant. For all funds, the coefficient on the momentum factor is 0.01 (t-statistic = 2.48).

Figure 1 plots the aggregate fund loading on momentum over time for hedge funds and mutual funds. We find that the loadings on the momentum return are predominantly positive for both hedge funds and mutual funds. Negative loadings are infrequent and generally small in magnitude. Overall, we find significant evidence that, in the aggregate, both hedge funds and mutual funds follow momentum strategies. Moreover, hedge funds appear to trade more aggressively on momentum than mutual funds do. These findings are in stark contrast to Grinblatt et al. (2020), who use quarterly stockholdings and show that mutual funds are momentum traders, whereas hedge funds are contrarian traders.

We also examine the aggregate loadings on momentum for each investment style. We compute the equal-weighted average returns across funds with the same investment style and regress the average returns on the long-short returns of the momentum strategy while controlling for the standard risk factors. Detailed regression results are also reported in Table 3. For hedge funds, we find that *Equity*, *Fund of Funds*, and *Multistrategy* funds trade more aggressively on momentum as their momentum loadings are both economically and statistically significant. The momentum loadings for *Macro*, *Event Driven* and *Relative Value* funds are also positive but statistically insignificant. For mutual funds, *Aggressive Growth* funds have the highest loadings on the momentum strategy while *Growth and Income* funds load negatively on momentum. This finding is not surprising because *Aggressive Growth* funds mainly invest in glamour stocks with superior past performance and growth potential (i.e., the long-leg stocks of the momentum strategy). In contrast, income funds in the *Growth and Income* category invest in stocks with regular and established dividend history. These funds aim to offer regular and consistent income to investors rather than capital gains or short-term trading profits. Therefore, these funds prefer value-styled stocks, which are likely to have relatively poor recent performance (i.e., the short-leg stocks of the momentum strategy). Overall, the different trading patterns on momentum across funds are consistent with their investment styles.

3.2.2 | Momentum timing

We estimate momentum timing skills by using two models motivated by prior market timing models. Our primary model is adapted from Henriksson and Merton (1981) market timing model by replacing market returns with momentum returns.

$$r_t = \alpha + \beta_1 MOM_t + \beta_2 \max(MOM_t, 0) + \boldsymbol{\gamma}'\mathbf{X}_t + e_t. \quad (1)$$

Here, r_t is the aggregate hedge fund or mutual fund excess return, and MOM_t is the long-short return to the momentum strategy. The vector $\mathbf{X}_t$ contains an indicator variable for positive momentum return and a set of asset pricing factors, namely, Fung and Hsieh (2004) seven factors for hedge funds and Fama and French (1996) three factors for mutual funds. A positive

TABLE 3 Momentum trading: aggregate evidence

This table reports results for regressions of aggregate hedge fund and mutual fund returns on momentum returns. Hedge fund data are from the consolidated database of Lipper TASS and Hedge Fund Research (HFR). Mutual fund data are from CRSP mutual fund database. We classify hedge funds into six groups based on their investment styles: *Equity*, *Event-Driven*, *Fund of Funds*, *Macro*, *Multistrategy*, and *Relative Value*. We classify mutual funds into three groups based on their investment styles: *Aggressive Growth*, *Growth*, and *Growth and Income*. We compute the equal-weighted monthly returns across sample funds and regress aggregate fund returns on the time-series of momentum returns and control variables. The regression model is $r_t = \alpha + \beta_1 MOM_t + \boldsymbol{\gamma}'\boldsymbol{X_t} + e_t$, where MOM_t is momentum return. For hedge funds, control variables $\mathbf{X}_t$ include Fung and Hsieh (2004) seven factors. For mutual funds, control variables $\mathbf{X}_t$ include Fama and French (1996) three factors. The sample period is 1994–2020 for hedge funds and 1984–2020 for mutual funds. Numbers in parentheses are *t*-statistics. Fund returns and Momentum returns are expressed in percent.

Panel A. Hedge fund				
	Intercept	$\mathbf{MOM}_t$	$\mathbf{X}_t$	R^2
All funds	0.15	0.05	Included	0.72
	(2.57)	(5.57)		
Equity	0.15	0.06	Included	0.81
	(2.14)	(6.50)		
Event Driven	0.30	0.01	Included	0.69
	(5.16)	(1.49)		
Fund of Funds	0.03	0.05	Included	0.53
	(0.41)	(5.43)		
Macro	0.23	0.02	Included	0.33
	(2.25)	(1.52)		
Multistrategy	0.35	0.04	Included	0.60
	(5.15)	(4.15)		
Relative Value	0.24	0.01	Included	0.60
	(4.49)	(1.45)		
Panel B. Mutual fund				
	Intercept	$\mathbf{MOM}_t$	$\mathbf{X}_t$	R^2
All funds	−0.10	0.01	Included	0.98
	(−3.22)	(2.48)		
Aggressive Growth	−0.11	0.03	Included	0.98
	(−2.66)	(4.70)		
Growth	−0.09	0.01	Included	0.99
	(−3.69)	(2.35)		
Growth and Income	−0.08	−0.01	Included	0.98
	(−2.41)	(−1.45)		

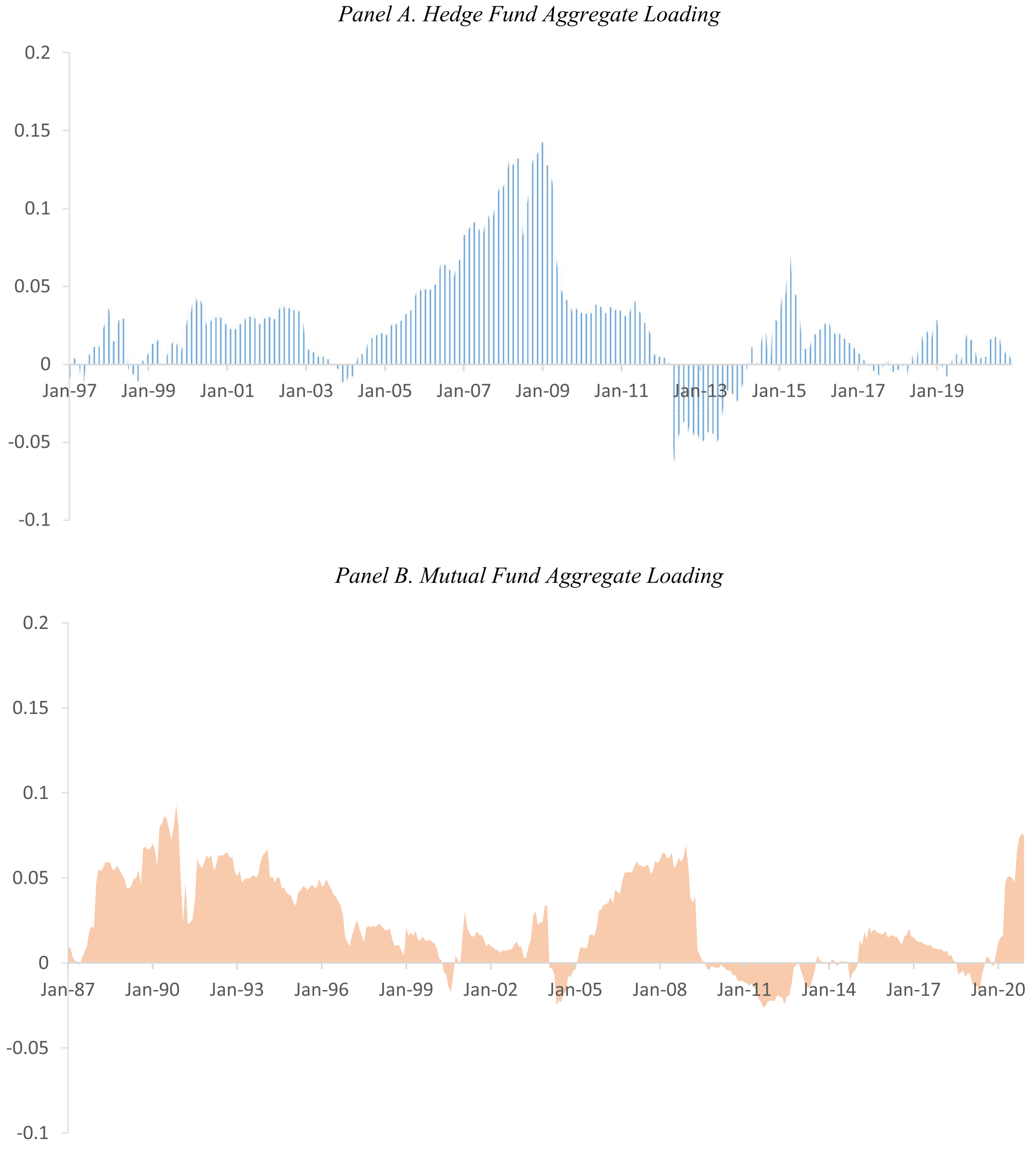

FIGURE 1 Time-varying aggregate fund return loadings on momentum. This figure plots the aggregate fund return loadings on momentum over time. We regress aggregate fund returns on momentum returns using a rolling window of 36 months to obtain loadings on momentum. For hedge funds, control variables include Fung and Hsieh (2004) seven-factors. For mutual funds, control variables include Fama and French (1996) three factors. The sample period is 1994–2020 for hedge funds and 1984–2020 for mutual funds. [Color figure can be viewed at wileyonlinelibrary.com]

and significant β_2 indicates momentum timing ability, that is, higher momentum loadings when momentum return is positive.

We present the results for regression Equation (1) in Panel A of Table 4. For hedge funds, we find that the coefficient on $\max(MOM_t, 0)$ is positive and statistically significant, indicating that funds increase the intensity of momentum trading when momentum returns are positive. This is

TABLE 4 Momentum timing: aggregate evidence

This table reports the momentum timing skills based on the aggregate hedge fund and mutual fund returns. We compute the equal-weighted monthly returns across sample funds and regress aggregate fund returns on the time-series of momentum returns and control variables. We classify hedge funds into six groups based on their investment styles: *Equity*, *Event-Driven*, *Fund of Funds*, *Macro*, *Multistrategy*, and *Relative Value*. We classify mutual funds into three groups based on their investment styles: *Aggressive Growth*, *Growth*, and *Growth and Income*. Panel A reports the regression results based on the Henriksson and Merton (1981) model using equation $r_t = \alpha + \beta_1 MOM_t + \beta_2 \max(MOM_t, 0) + \boldsymbol{\gamma}'\mathbf{X_t} + e_t$. Panel B reports the regression results based on the Treynor and Mazuy (1966) model using equation $r_t = \alpha + \beta_1 MOM_t + \beta_2 MOM_t^2 + \boldsymbol{\gamma}'\mathbf{X_t} + e_t$. The sample period is 1994–2020 for hedge funds and 1984–2020 for mutual funds. Fund returns and Momentum returns are expressed in percent. The estimated coefficient for MOM_t^2 is multiplied by 100. Numbers in parentheses are t-statistics.

Panel A. Henriksson and Merton (1981) model								
	Intercept		**MOM_t**		**max (MOM_t, 0)**		**X_t**	**R^2**
Hedge fund								
All funds	0.07	(0.58)	0.03	(1.91)	0.03	(1.67)	Included	0.72
Equity	0.05	(0.32)	0.04	(2.08)	0.06	(2.44)	Included	0.81
Event Driven	0.34	(2.73)	0.02	(1.05)	−0.00	(−0.09)	Included	0.69
Fund of Funds	0.01	(0.08)	0.05	(2.55)	0.02	(0.67)	Included	0.53
Macro	−0.00	(−0.01)	0.00	(0.05)	0.01	(0.29)	Included	0.34
Multistrategy	0.26	(1.79)	0.02	(0.88)	0.06	(2.39)	Included	0.61
Relative Value	0.08	(0.70)	−0.01	(−0.76)	0.03	(1.67)	Included	0.61
Mutual fund								
All funds	−0.17	(−2.74)	0.00	(0.49)	0.00	(0.07)	Included	0.98
Aggressive Growth	−0.20	(−2.28)	0.02	(1.58)	0.01	(0.50)	Included	0.98
Growth	−0.16	(−3.05)	0.00	(0.33)	0.00	(0.16)	Included	0.99
Growth and Income	−0.16	(−2.27)	−0.01	(−1.19)	−0.01	(−0.68)	Included	0.98
Panel B. Treynor and Mazuy (1966)								
	Intercept		**MOM_t**		**MOM_t^2**		**X_t**	**R^2**
Hedge fund								
All funds	0.11	(1.84)	0.05	(5.73)	0.07	(1.89)	Included	0.72
Equity	0.08	(1.14)	0.06	(6.81)	0.12	(2.91)	Included	0.81
Event-Driven	0.30	(5.00)	0.01	(1.46)	−0.01	(−0.36)	Included	0.69
Fund of Funds	0.01	(0.13)	0.05	(5.47)	0.03	(0.80)	Included	0.53
Macro	0.24	(2.20)	0.02	(1.49)	−0.01	(−0.21)	Included	0.33
Multistrategy	0.30	(4.18)	0.04	(4.36)	0.09	(2.33)	Included	0.61
Relative Value	0.22	(3.83)	0.01	(1.55)	0.04	(1.35)	Included	0.61

TABLE 4 (Continued)

Panel B. Treynor and Mazuy (1966)								
	Intercept		**MOM_t**		**MOM_t^2**		**X_t**	**R^2**
Mutual fund								
All funds	−0.09	(−2.73)	0.01	(2.41)	−0.02	(−0.98)	Included	0.98
Aggressive Growth	−0.10	(−2.34)	0.03	(4.70)	−0.02	(−0.52)	Included	0.98
Growth	−0.09	(−3.41)	0.01	(2.33)	−0.00	(−0.25)	Included	0.99
Growth and Income	−0.06	(−1.57)	−0.01	(−1.62)	−0.06	(−2.24)	Included	0.98

consistent with momentum timing. Since the equal-weighted average hedge return represents the performance of an average hedge fund, so our finding suggests that the average hedge fund has some momentum timing ability. The mutual funds, in contrast, exhibit little momentum timing skill as the coefficient on $\max(MOM_t, 0)$ is small and statistically insignificant.

We also examine the momentum timing abilities for each category of funds and we find that the timing skills vary with investment styles, especially for hedge funds. More specifically, the timing coefficient for *Equity* hedge funds and *Multistrategy* hedge funds are economically large and statistically significant. In contrast, the average hedge fund in the *Event Driven*, *Fund of Funds*, and *Macro* categories seem to have little momentum timing abilities as the timing coefficient is not statistically different from zero. When we examine mutual funds, none of the three investment styles exhibit significant timing abilities, which is consistent with the prior literature that hedge fund managers are better skilled than mutual fund managers.[9]

For robustness, we also estimate a model similar to Treynor and Mazuy's (1966) market timing model by including a quadratic term of momentum returns:

$$r_t = \alpha + \beta_1 MOM_t + \beta_2 MOM_t^2 + \boldsymbol{\gamma}'\mathbf{X_t} + e_t. \tag{2}$$

Here, a positive and significant β_2 suggests that the fund return–momentum return relationship is convex, consistent with momentum timing ability.

We present the results for regression Equation (2) in Panel B of Table 4. We find that the coefficient on the squared momentum return is significantly positive for hedge funds, especially for funds in the *Equity* and *Multistrategy* categories. This finding is similar to the results in Panel A and suggests that the average hedge fund has momentum timing ability. When we use the same model for mutual funds, we find that at the aggregate level, the timing coefficients are negative and statistically insignificant, indicating that mutual funds on average possess little momentum timing ability.

3.2.3 | Momentum timing with conditioning variables

Using standard timing models, we find evidence of momentum timing ability for the average hedge fund and little evidence of such ability for mutual funds. In this section, we test for

[9]For hedge fund and mutual fund performance, see for example, Kosowski et al. (2007) and Barras et al. (2010).

momentum timing ability by using conditioning variables that prior studies have shown to predict momentum returns. Specifically, prior studies have shown that momentum returns vary predictably with market state, investor sentiment, calendar month, and prior momentum volatility (Barroso & Santa-Clara, 2015; Cooper et al., 2004; Stambaugh et al., 2012; Jegadeesh & Titman, 2001), and we have confirmed these findings for our sample period in Table 2. We now examine whether fund managers exploit the predictability of momentum returns based on these conditioning variables by estimating the following regression:

$$r_t = \alpha + \beta_1 MOM_t + \beta_2 MOM_t \times Z_t + \beta_3 Z_t + \boldsymbol{\gamma}'\mathbf{X}_t + e_t, \quad (3)$$

where r_t is aggregate hedge fund or mutual fund excess return and $\mathbf{X}_t$ contains the standard asset pricing factors, that is, Fung and Hsieh (2004) seven factors for hedge funds and Fama and French (1996) three factors for mutual funds. Z_t is the conditioning variable, that is, UP state, high investor sentiment dummy, January dummy, or prior momentum volatility. The central independent variable of interest is the interaction term between momentum return and the conditioning variable. A positive coefficient on the interaction term between momentum return and UP state, for example, suggests that fund managers increase the intensity of momentum trading during UP state, consistent with momentum timing ability. Similarly, a *positive* coefficient on the interaction term between the momentum return and the high-sentiment dummy and a *negative* coefficient on interaction term between the momentum return and the January dummy or prior momentum volatility would also be consistent with momentum timing ability.

We present the results for regression Equation (3) in Table 5. We organise the results into four panels by conditioning variables. Looking at Panel A, that is, the results for market state, we find that the coefficient on the interaction term between momentum return and UP state is positive for both hedge funds and mutual funds, suggesting that funds trade more aggressively on momentum during UP state. The results, however, are only marginally significant for the aggregate mutual fund returns.

Panel B presents the results for investor sentiment. We find that the coefficient on the interaction term between momentum return and the high-sentiment dummy are mostly negative and statistically insignificant, which suggests that fund managers do not appear to exploit the predictability of momentum returns based on investor sentiment.

In Panel C, we examine whether fund managers adjust their momentum trading intensity during January, when momentum return is known to be negative. We find that hedge funds reduce their exposure to momentum during January, consistent with momentum timing ability. The results are economically meaningful with the coefficient of −0.03, but statistically marginal with *t*-statistics of −1.62. The lack of statistical significance is in part due to low statistical power because the number of Januarys is relatively small. The results for mutual funds are the opposite of those for hedge funds. We find that mutual funds significantly increase their intensity of momentum trading during January as the *t*-statistics on the coefficient of the interaction term is 2.44. This evidence represents perverse momentum timing ability by mutual funds. We conjecture that such finding is in part driven by investor flows at the beginning of year rather than a conscious effort on the part of mutual fund managers.

Panel D presents the results on prior momentum volatility. Consistent with the presence of momentum timing ability, we find the coefficient on the interaction term between momentum return and prior 6-month momentum volatility is negative across most of the regressions.

TABLE 5 Momentum timing with conditioning variables

This table reports momentum timing skills with conditioning variables. To measure managers' timing skill, we add a conditioning variable and the interaction between the conditioning variable and the momentum return to the regression model. MOM_t is momentum return. UP is a dummy variable which is equal to 1 if past 36-month cumulative market return is positive. We obtain the sentiment data from Jeffery Wurgler's website. HighSent is a dummy variable that equals one if the investor sentiment is above the median during the sample period. January is a dummy variable for the month of January. Momentum volatility is the volatility of momentum daily returns over the past 6 months. The sample period is 1994–2020 for hedge funds and 1984–2020 for mutual funds. Fund returns, momentum returns, and momentum volatility are expressed in percent. The estimated coefficient for $MOMVOL_t \times MOM_t$ is multiplied by 100. Numbers in parentheses are t-statistics.

Panel A: Market state

	Intercept	MOM_t	$UP_t \times MOM_t$	UP_t	X_t	R^2
Hedge fund						
All funds	0.24 (2.03)	0.03 (2.32)	0.01 (0.41)	−0.15 (−1.10)	Included	0.76
Equity	0.20 (1.37)	0.03 (1.97)	0.02 (1.10)	−0.08 (−0.51)	Included	0.83
Event Driven	0.40 (3.23)	0.03 (1.73)	−0.03 (−1.52)	−0.16(−1.19)	Included	0.74
Fund of Funds	0.11 (0.74)	0.06 (3.17)	−0.01(−0.37)	−0.11 (−0.70)	Included	0.59
Macro	0.49 (2.35)	0.02 (0.63)	0.01 (0.38)	−0.41 (−1.79)	Included	0.34
Multistrategy	0.47 (3.44)	0.02 (1.28)	0.02 (1.13)	−0.23 (−1.50)	Included	0.64
Relative Value	0.49 (4.51)	0.01 (0.76)	−0.00 (−0.02)	−0.33 (−2.73)	Included	0.68
Mutual fund						
All funds	−0.13 (−1.55)	−0.00 (−0.38)	0.02 (1.73)	0.03 (0.35)	Included	0.98
Aggressive Growth	−0.21 (−1.82)	0.00 (0.04)	0.04 (2.42)	0.10 (0.84)	Included	0.98
Growth	−0.14 (−2.01)	−0.01 (−0.63)	0.02 (1.93)	0.05 (0.66)	Included	0.99
Growth and Income	−0.01 (−0.11)	−0.01 (−0.59)	−0.00 (−0.05)	−0.08 (−0.82)	Included	0.98

Panel B: Sentiment

	Intercept	MOM_t	$HighSent_t \times MOM_t$	$HighSent_t$	X_t	R^2
Hedge fund						
All funds	0.13 (1.92)	0.04 (4.12)	−0.00 (−0.24)	−0.02 (−0.21)	Included	0.72
Equity	0.16 (1.89)	0.06 (4.60)	−0.01 (−0.28)	−0.08 (−0.66)	Included	0.80
Event-Driven	0.26 (3.69)	0.01 (1.06)	−0.01 (−0.41)	0.01 (0.10)	Included	0.69
Fund of Funds	−0.02 (−0.29)	0.06 (4.29)	−0.01 (−0.30)	0.06 (0.49)	Included	0.54
Macro	0.18 (1.50)	0.02 (1.07)	0.01 (0.39)	−0.01 (−0.04)	Included	0.34
Multistrategy	0.25 (3.05)	0.05 (3.87)	−0.02 (−1.07)	0.13 (1.09)	Included	0.60
Relative Value	0.27 (4.34)	0.00 (0.34)	0.01 (0.91)	−0.12 (−1.29)	Included	0.60
Mutual Fund						
All funds	−0.10 (−2.50)	0.01 (1.71)	−0.01 (−0.69)	0.06 (1.00)	Included	0.98
Aggressive Growth	−0.10 (−1.70)	0.03 (2.83)	−0.00 (−0.19)	0.03 (0.37)	Included	0.98

(Continues)

TABLE 5 (Continued)

Panel B: Sentiment	Intercept	MOM_t	$HighSent_t \times MOM_t$	$HighSent_t$	X_t	R^2
Growth	−0.10 (−2.90)	0.02 (2.66)	−0.02 (−2.00)	0.05 (1.12)	Included	0.99
Growth and Income	−0.10 (−2.21)	−0.01 (−1.39)	0.00 (0.02)	0.08 (1.24)	Included	0.98

Panel C: January	Intercept	MOM_t	$January_t \times MOM_t$	$January_t$	X_t	R^2
Hedge fund						
All funds	0.09 (1.69)	0.04 (5.72)	−0.03 (−1.62)	0.41 (2.31)	Included	0.76
Equity	0.10 (1.66)	0.06 (6.33)	−0.05 (−1.84)	0.33 (1.59)	Included	0.83
Event-Driven	0.21 (3.99)	0.01 (0.68)	0.00 (0.02)	0.54 (2.99)	Included	0.75
Fund of Funds	−0.02 (−0.29)	0.05 (5.95)	−0.03 (−1.32)	0.34 (1.64)	Included	0.59
Macro	0.11 (1.20)	0.03 (2.03)	−0.03 (−0.87)	0.49 (1.58)	Included	0.34
Multistrategy	0.25 (4.13)	0.04 (4.55)	−0.02 (−0.77)	0.49 (2.41)	Included	0.65
Relative Value	0.17 (3.75)	0.01 (1.47)	−0.02 (−0.79)	0.48 (3.02)	Included	0.68
Mutual fund						
All funds	−0.08 (−2.50)	0.01 (1.32)	0.03 (2.44)	−0.17 (−1.61)	Included	0.98
Aggressive Growth	−0.07 (−1.66)	0.03 (3.59)	0.03 (1.78)	−0.41 (−2.78)	Included	0.98
Growth	−0.09 (−3.28)	0.00 (1.06)	0.03 (2.99)	−0.02 (−0.28)	Included	0.99
Growth and Income	−0.07 (−1.94)	−0.01 (−2.16)	0.03 (2.05)	−0.10 (−0.85)	Included	0.98

Panel D: Momentum volatility	Intercept	MOM_t	$MOMVOL_t \times MOM_t$	$MOMVOL_t$	X_t	R^2
Hedge fund						
All funds	−0.02 (−0.14)	0.06 (3.31)	−1.24 (−1.21)	0.12 (1.30)	Included	0.76
Equity	−0.06 (−0.44)	0.08 (3.69)	−1.65 (−1.35)	0.16 (1.50)	Included	0.83
Event-Driven	0.20 (1.71)	−0.00 (−0.14)	0.53 (0.49)	0.05 (0.58)	Included	0.74
Fund of Funds	−0.12 (−0.85)	0.07 (3.03)	−0.94 (−0.76)	0.11 (1.01)	Included	0.59
Macro	−0.01 (−0.05)	0.08 (2.73)	−3.87 (−2.15)	0.12 (0.76)	Included	0.34
Multistrategy	0.23 (1.78)	0.07 (3.41)	−2.08 (−1.76)	0.04 (0.35)	Included	0.64
Relative Value	0.05 (0.52)	0.02 (1.25)	−0.68 (−0.72)	0.14 (1.73)	Included	0.67
Mutual fund						
All funds	−0.16 (−2.62)	0.05 (4.58)	−2.41 (−3.85)	0.04 (0.79)	Included	0.98
Aggressive Growth	−0.22 (−2.52)	0.07 (4.86)	−2.75 (−3.08)	0.08 (1.08)	Included	0.98
Growth	−0.10 (−2.05)	0.05 (5.44)	−2.63 (−4.94)	−0.01 (−0.29)	Included	0.99
Growth and Income	−0.18 (−2.62)	0.02 (1.82)	−1.92 (−2.64)	0.08 (1.39)	Included	0.98

The overall results are highly significant for mutual funds. This finding suggests that fund managers scale back their momentum trading when prior momentum volatility is high.

Overall, we find some evidence that hedge funds and mutual funds increase the intensity of their momentum trading during UP state and when prior momentum volatility is low, consistent with momentum timing ability. However, mutual funds appear to trade in the wrong direction in January, that is, they trade more aggressively on momentum in January, despite the significant evidence of negative momentum returns in January. In contrast, hedge funds engage in less momentum trading during January, consistent with momentum timing ability.

3.3 | Fund-level returns

3.3.1 | Momentum trading and timing

In this section, we examine momentum trading and momentum timing at the fund level by using individual fund returns. Specifically, we repeat all of the momentum trading and timing analyses fund by fund. For brevity, we present the distribution of regression coefficient *t*-statistics at selected percentiles. We report the results for all funds, and funds in different categories.

Panel A of Table 6 reports the results for momentum trading. The results are largely consistent with those obtained from aggregate fund returns. We find that fund-level momentum loadings are disproportionately positive. For example, the 99th percentile of *t*-statistics on momentum loading is 6.22 across all hedge funds. In comparison, the 1st percentile is only −3.76, significantly smaller in magnitude than the 99th percentile. Mutual funds exhibit more extreme values of *t*-statistics than hedge funds, but we continue to find that the 99th percentile (9.04) is larger than the 1st percentile (−6.91) in magnitude. In addition, we find that the median *t*-statistics are positive for both hedge funds and mutual funds. These results are consistent with our earlier finding based on aggregate fund returns that hedge funds and mutual funds on average are momentum traders.

Panel B of Table 6 presents the results for the momentum timing test based on regression Equation (1), that is, the model adapted from Henriksson and Merton (1981). In contrast to the large *t*-statistics on momentum loading, we find that the *t*-statistics on momentum timing are much smaller in magnitude. For example, the 99th percentile of *t*-statistics on momentum timing is 3.12 across all hedge funds, while the 1st percentile is −2.44. For mutual funds, the 99th percentile of *t*-statistics on momentum timing is 3.41 and the 1st percentile is −3.27. The distribution for hedge funds is slightly skewed to the right, while the distribution for mutual funds is largely symmetric. This finding is somewhat consistent with our previous finding that the average hedge fund has some momentum timing skills, while mutual funds display little such skill.

Figure 2 plots the distribution of fund-level momentum loading and timing coefficients. In each panel, we compare the actual distribution of the loading or timing coefficients with normal distribution. The normal distribution has a mean equal to zero and the same standard deviation as the actual distribution. By comparing the actual distribution with the normal distribution, we are able to assess (1) whether the loading or timing coefficient is on average positive or negative; (2) whether the coefficient is skewed to the left or right; and (3) whether

TABLE 6 Momentum trading and momentum timing: distribution of *t*-statistics at the fund level

This table reports the distribution of fund managers' momentum trading and timing skills. We classify hedge funds into six groups based on their investment styles: *Equity*, *Event-Driven*, *Fund of Funds*, *Macro*, *Multistrategy*, and *Relative Value*. We classify mutual funds into three groups based on their investment styles: *Aggressive Growth*, *Growth*, and *Growth and Income*. For momentum trading, we estimate the regression model: $r_t = \alpha + \beta_1 MOM_t + \boldsymbol{\gamma}'\mathbf{X_t} + e_t$. For momentum timing, we estimate the Henriksson and Merton (1981) model. We require that funds have at least 24 months' observations. For fund-level analyses, the number of hedge funds is 9,315 and the number of mutual funds is 2863. We present the distribution of the *t*-statistics of trading coefficients in Panel A and the distribution of the *t*-statistics of timing coefficients in Panel B. The sample period is 1994–2020 for hedge funds and 1984–2020 for mutual funds.

	P1	P5	P10	P50	P90	P95	P99
Panel A. Momentum trading							
Hedge fund							
All funds	−3.76	−2.21	−1.48	0.65	3.38	4.21	6.22
Equity	−4.36	−2.79	−2.01	0.47	3.33	4.14	6.80
Event Driven	−3.66	−2.16	−1.54	0.23	1.85	2.48	3.49
Fund of Funds	−1.96	−0.99	−0.36	1.84	4.37	5.12	6.98
Macro	−3.25	−2.03	−1.47	0.24	1.90	2.47	3.65
Multistrategy	−5.68	−1.93	−1.41	0.62	3.25	3.92	4.95
Relative Value	−3.46	−2.11	−1.51	0.08	1.73	2.22	3.48
Mutual fund							
All funds	−6.91	−4.75	−3.55	0.31	4.75	6.06	9.04
Aggressive Growth	−6.79	−4.20	−2.97	1.35	5.58	7.47	9.76
Growth	−6.03	−4.38	−3.26	0.28	4.42	5.54	8.83
Growth and Income	−7.66	−5.65	−4.31	−0.44	3.86	5.12	8.06
Panel B. Momentum timing							
	P1	**P5**	**P10**	**P50**	**P90**	**P95**	**P99**
Hedge fund							
All funds	−2.44	−1.59	−1.21	0.18	1.63	2.09	3.12
Equity	−2.47	−1.59	−1.26	0.23	1.76	2.22	3.31
Event-Driven	−2.69	−1.82	−1.33	0.14	1.61	2.01	2.86
Fund of Funds	−2.39	−1.57	−1.23	0.06	1.37	1.73	2.64
Macro	−2.40	−1.61	−1.20	0.08	1.43	1.84	2.61
Multistrategy	−2.27	−1.52	−1.19	0.44	1.73	2.27	2.81
Relative Value	−2.30	−1.44	−1.02	0.44	1.97	2.55	4.32
Mutual fund							
All funds	−3.27	−2.25	−1.70	0.08	1.72	2.28	3.41
Aggressive Growth	−3.35	−2.29	−1.74	−0.03	1.77	2.47	3.68

TABLE 6 (Continued)

Panel B. Momentum timing	P1	P5	P10	P50	P90	P95	P99
Growth	−2.94	−2.07	−1.61	0.16	1.87	2.35	3.37
Growth and Income	−3.83	−2.40	−1.80	0.06	1.55	1.89	3.23

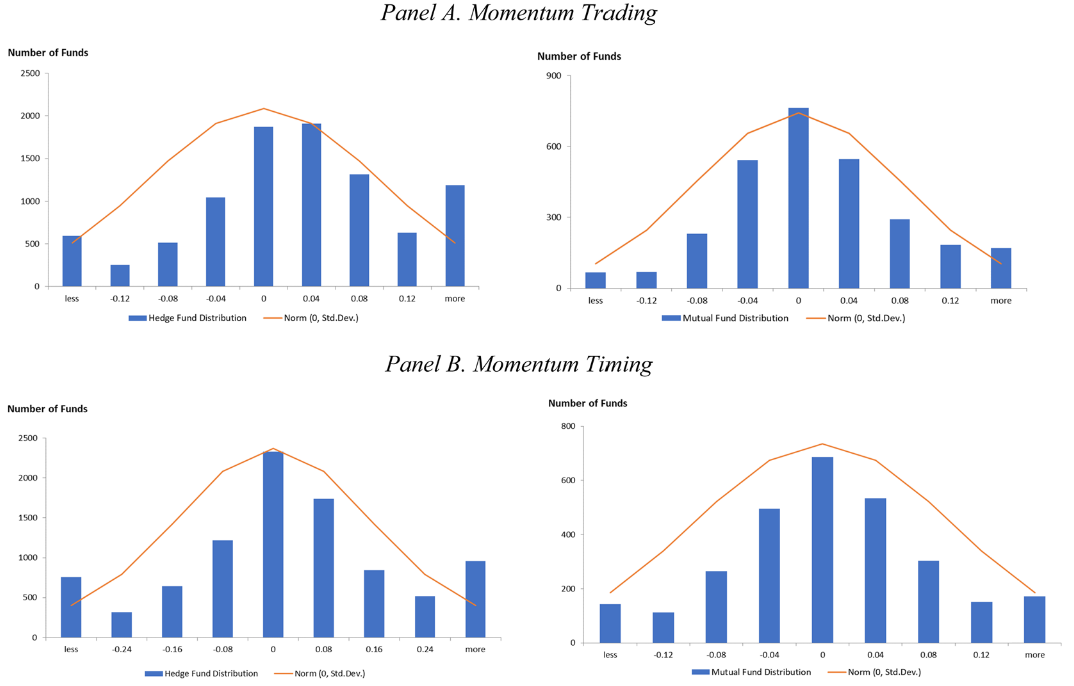

FIGURE 2 Distribution of fund-level trading and timing. This figure plots the distribution of fund managers' momentum trading and timing coefficients across sample funds. For momentum trading, we estimate the regression equation: $r_t = \alpha + \beta_1 MOM_t + \boldsymbol{\gamma}'\mathbf{X_t} + e_t$. For momentum timing, we estimate the regression equation: $r_t = \alpha + \beta_1 MOM_t + \beta_2 \max(MOM_t, 0) + \boldsymbol{\gamma}'\mathbf{X_t} + e_t$. The sample period is 1994–2020 for hedge funds and 1984–2020 for mutual funds. [Color figure can be viewed at wileyonlinelibrary.com]

the coefficient has fatter or thinner tails relative to the normal distribution. Consistent with the results in Table 6, we find that the distribution of the momentum loading coefficient is highly dispersed and has a positive mean. In comparison, the distribution of the momentum timing coefficient is more concentrated and centred around zero.

In Figure 3, we calculate the percentage of funds with positive momentum loadings and the percentage of funds with negative momentum loadings within each investment style. As shown in Panel A of the figure, 84% of the *Fund of Funds* load positively on momentum, and the corresponding number for *Equity* funds and *Multistrategy* funds is 60% and 67% respectively. When we examine mutual funds, the percentage of positive momentum loadings decreases significantly across investment styles from 65% for *Aggressive Growth* funds to 44% for *Growth and Income* funds. Overall, the fund-level results confirm that the momentum trading pattern varies considerably with fund investment styles. We also calculate the percentage of funds with positive/negative timing coefficients for each style and the results are presented in Panel B of Figure 3. Again, certain categories of hedge funds seem to have momentum timing skills as the percentages of funds with positive timing coefficients are much higher than 50%. In contrast, the percentage of funds with positive timing coefficient is close to 50% for mutual funds, which suggests that mutual funds on average do not seem to possess momentum timing skills.

In Table 7, we examine whether the intensity of momentum trading at the fund level is related to market state, investor sentiment, January, and prior momentum volatility. As in Table 6, we report the distribution of regression coefficient *t*-statistics at selected percentiles. The fund-level distribution confirms the results from aggregated returns. That is, both hedge funds and mutual funds decrease the momentum loading following high prior momentum volatility. Mutual funds trade in the wrong direction in January, that is, they engage in more momentum trading in January. Hedge funds, in contrast, decrease their level of momentum trading in January. Neither hedge funds nor mutual funds significantly changed their momentum loadings during periods of high investor sentiment. Figure 4 plots the distribution of the fund-level timing skill coefficients with the conditioning variables. In each panel, we again compare the actual distribution of the

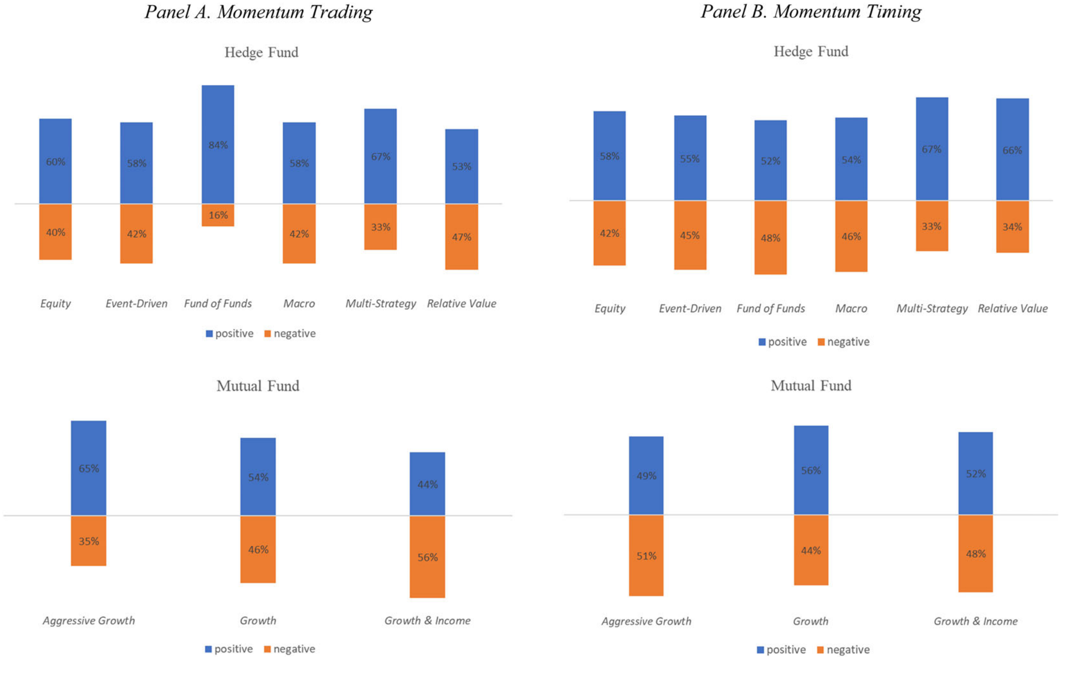

FIGURE 3 Momentum trading and timing skills by investment styles. This figure plots the percentage of funds with positive (negative) trading or timing coefficients within each investment style. We classify hedge funds into six groups based on their investment styles: *Equity*, *Event-Driven*, *Fund of Funds*, *Macro*, *Multistrategy*, and *Relative Value*. We classify mutual funds into three groups based on their investment styles: *Aggressive Growth*, *Growth*, and *Growth and Income*. For momentum trading, we estimate the regression equation: $r_t = \alpha + \beta_1 MOM_t + \boldsymbol{\gamma}'\mathbf{X_t} + e_t$. For momentum timing, we estimate the regression equation: $r_t = \alpha + \beta_1 MOM_t + \beta_2 \max(MOM_t, 0) + \boldsymbol{\gamma}'\mathbf{X_t} + e_t$. The sample period is 1994–2020 for hedge funds and 1984–2020 for mutual funds. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 7 Momentum timing skill with conditioning variables: Distribution of *t*-statistics at the fund level

This table reports the distribution of fund managers' momentum timing skills with conditioning variables. To measure managers' timing skill, we add a conditioning variable and the interaction between the conditioning variable and the momentum return to the regression model. UP is a dummy variable which is equal to 1 if past 36-month cumulative market return is positive. We obtain the sentiment data from Jeffery Wurgler's website. HighSent is a dummy variable that equals one if the investor sentiment is above the median during the sample period. January is a dummy variable for the month of January. Momentum volatility is the volatility of momentum daily returns over the past 6 months. We require that funds have at least 24 months' observations. We present the distribution of the *t*-statistics of the estimated coefficients for the interaction term. The sample period is 1994–2020 for hedge funds and 1984–2020 for mutual funds.

Panel A. Momentum timing—Market state							
	P1	**P5**	**P10**	**P50**	**P90**	**P95**	**P99**
Hedge fund							
All funds	−2.91	−1.72	−1.22	0.46	2.25	2.83	4.11
Equity	−3.20	−1.95	−1.38	0.45	2.52	3.16	4.59
Event Driven	−3.49	−2.00	−1.67	−0.04	1.69	2.07	2.99
Fund of Funds	−2.00	−1.35	−0.89	0.70	2.30	2.78	3.80
Macro	−2.57	−1.54	−1.02	0.51	2.17	2.47	3.72
Multistrategy	−2.12	−1.54	−1.10	0.66	2.31	2.90	4.05
Relative Value	−3.37	−1.89	−1.37	0.11	1.67	2.28	3.90
Mutual fund							
All funds	−4.11	−2.77	−2.11	0.44	3.09	3.89	5.24
Aggressive Growth	−3.67	−2.72	−2.02	0.80	3.45	4.34	5.28
Growth	−3.73	−2.62	−2.00	0.36	3.08	3.71	5.49
Growth and Income	−4.62	−3.23	−2.37	0.24	2.84	3.58	4.95
Panel B. Momentum timing—Sentiment							
	P1	**P5**	**P10**	**P50**	**P90**	**P95**	**P99**
Hedge fund							
All funds	−3.27	−1.95	−1.43	0.14	1.69	2.19	3.20
Equity	−3.75	−2.37	−1.70	0.14	1.81	2.30	3.46
Event-Driven	−2.90	−1.93	−1.55	−0.09	1.37	1.73	2.75
Fund of Funds	−2.65	−1.72	−1.20	0.22	1.79	2.26	3.07
Macro	−2.37	−1.62	−1.25	0.31	1.74	2.28	3.18
Multistrategy	−3.56	−1.82	−1.33	0.16	1.58	2.03	3.24
Relative Value	−2.82	−1.72	−1.25	−0.04	1.24	1.72	2.69
Mutual fund							
All funds	−4.33	−2.97	−2.26	0.03	2.10	2.72	3.78
Aggressive Growth	−3.86	−2.53	−1.99	0.02	2.14	2.67	3.68

(Continues)

TABLE 7 (Continued)

Panel B. Momentum timing—Sentiment							
	P1	P5	P10	P50	P90	P95	P99
Growth	−4.88	−3.38	−2.67	−0.14	2.00	2.68	4.04
Growth and Income	−3.81	−2.46	−1.94	0.27	2.23	2.74	3.62
Panel C. Momentum timing—January							
	P1	**P5**	**P10**	**P50**	**P90**	**P95**	**P99**
Hedge fund							
All funds	−2.89	−2.06	−1.58	−0.19	1.16	1.63	2.62
Equity	−3.00	−2.03	−1.58	−0.10	1.33	1.85	2.90
Event-Driven	−3.05	−1.88	−1.38	−0.10	1.34	1.81	2.64
Fund of Funds	−2.89	−2.15	−1.61	−0.36	0.96	1.31	2.18
Macro	−2.86	−1.99	−1.55	−0.20	1.22	1.70	2.92
Multi-Strategy	−2.65	−1.91	−1.57	−0.20	0.96	1.37	2.14
Relative Value	−2.86	−2.14	−1.63	−0.18	0.98	1.38	2.26
Mutual fund							
All funds	−2.79	−1.82	−1.38	0.20	1.95	2.47	3.52
Aggressive Growth	−2.47	−1.79	−1.26	0.31	2.04	2.54	3.88
Growth	−2.92	−1.82	−1.39	0.20	2.00	2.53	3.43
Growth and Income	−2.79	−1.89	−1.43	0.07	1.78	2.35	3.45
Panel D. Momentum timing—Momentum volatility							
	P1	**P5**	**P10**	**P50**	**P90**	**P95**	**P99**
Hedge fund							
All funds	−3.56	−2.52	−1.99	−0.34	1.23	1.75	2.84
Equity	−4.14	−2.76	−2.16	−0.37	1.29	1.80	2.87
Event-Driven	−3.63	−2.52	−1.87	−0.02	1.51	2.21	3.24
Fund of Funds	−3.05	−2.40	−1.94	−0.52	1.05	1.61	2.93
Macro	−3.14	−2.13	−1.73	−0.16	1.29	1.70	2.54
Multistrategy	−3.61	−2.54	−2.15	−0.45	1.03	1.57	2.90
Relative Value	−3.42	−2.46	−1.89	−0.29	1.18	1.62	2.50
Mutual fund							
All funds	−5.07	−3.80	−3.13	−0.75	1.37	1.99	3.24
Aggressive Growth	−5.07	−3.88	−2.98	−0.72	1.32	1.88	2.93
Growth	−5.11	−3.95	−3.36	−0.90	1.28	1.96	3.15
Growth and Income	−4.90	−3.37	−2.84	−0.51	1.64	2.14	3.48

timing skill coefficients with a particular conditioning variable across funds with normal distribution.

3.3.2 | Fund performance

Momentum strategies are high-turnover strategies, and the literature is ambiguous about whether momentum profits survive trading costs (e.g., Asness et al., 2014; Korajczyk & Sadka, 2004; Lesmond et al., 2004; Patton & Weller, 2020). Momentum timing, given its dynamic nature, may incur even higher trading costs. Therefore, it is not clear whether hedge funds and mutual funds that follow or time momentum strategies can deliver superior performance after cost.

To investigate this issue, we sort all hedge funds or mutual funds into decile portfolios based on the *t*-statistics of their momentum trading or momentum timing coefficient estimates.[10] We then calculate both raw returns and risk-adjusted returns for each fund portfolio. For risk-adjusted returns, we continue to use the Fung and Hsieh seven-factor model for hedge funds and the Fama and French three-factor model for mutual funds. We also augment the above models by including the momentum factor following Grinblatt et al. (2020). In addition to the performance for each fund decile, we also report the difference between the two extreme deciles.

Panel A of Table 8 presents the results for momentum trading. The first three columns present the results for hedge funds. We find funds that trade most aggressively on momentum (D10) do not outperform those that trade least aggressively on momentum (D1). The point estimates actually indicate that D10 underperforms D1, and the difference is not statistically significant for raw returns and seven-factor alphas but significant for 8-factor alphas once we control for the momentum factor.

The next three columns report the results for mutual funds. We find that mutual funds that trade most aggressively on momentum outperform their peers in raw returns and three-factor alphas, albeit the difference is not statistically significant. Specifically, D10 outperforms D1 by 14 basis points per month using raw returns, but this outperformance is statistically insignificant with a *t*-statistic of 0.99. When we include the momentum factor in the performance evaluation model, the outperformance of momentum trading mutual funds disappears. In fact, D10 underperforms D1 by eight basis points (*t*-statistic = 1.16) per month using four-factor alphas. Overall, we find little reliable evidence that momentum trading hedge funds or mutual funds deliver superior returns to fund investors.

Panel B presents the results for momentum timing. We sort all hedge funds or mutual funds into decile portfolios based on their momentum timing abilities, that is, *t*-statistics of β_2 from regression Equation (1). We then evaluate the raw and risk-adjusted performance of each quintile portfolio of funds. We find significant evidence that funds with the highest momentum timing ability outperform funds with the lowest momentum timing ability. For example, the raw return is 53 basis points per month for hedge funds in D1 (i.e., the lowest momentum

[10] We estimate momentum trading and timing coefficients using full sample of fund returns. Our objective is to study whether momentum trading and momentum timing abilities are associated with superior fund performance, rather than devising a trading strategy for real time investors. A real-time strategy based on, for example, rolling regressions, would have low power because most funds and particularly hedge funds have short histories.

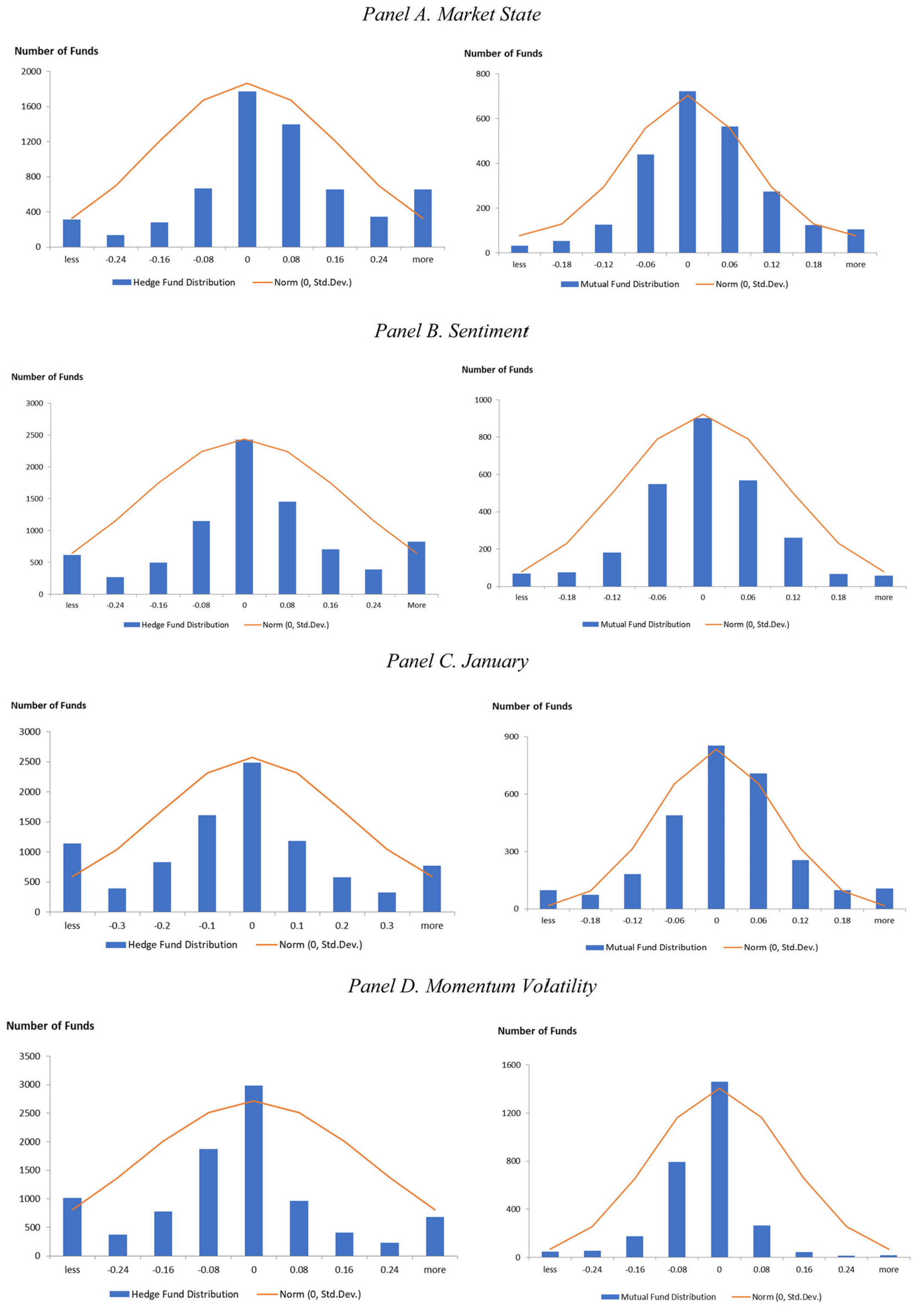

FIGURE 4 (See caption on next page)

timing ability), and 77 basis points per month for D10 (i.e., the highest momentum timing ability). The difference of 24 basis points is economically meaningful and statistically significant (t-statistic = 2.86). The difference remains large and statistically significant when examining seven- or eight-factor alphas.

The results for mutual funds are weaker but qualitatively similar. For example, the three-factor alpha is −13 basis points per month for D1 and −3 basis points per month for D10. The difference is economically and statistically significant (t-statistic = 2.16). The difference remains positive at eight basis point when we examine four-factor alphas, but statistical significance becomes marginal. Overall, we find that momentum trading per se has little impact on fund performance; however, momentum timing abilities significantly enhance fund performance.

3.4 | Additional analyses on momentum timing skills

In this section, we conduct additional analyses to provide more insights into the value of momentum timing in improving fund performance, and the relation between fund characteristics and fund managers' momentum timing skills.

3.4.1 | Time-varying momemtum loadings

Despite the strong positive average returns, the momentum strategy is much riskier compared to other well-known factors. Daniel and Moskowitz (2016) find that 'the optimal dynamic strategy significantly outperformed the standard static momentum strategy'. Therefore, we conjecture that funds which follow dynamic momentum strategies should outperform funds which follow static momentum strategies.

In this analysis, we use a rolling window of 60 months to measure the return loadings on the long-short returns of the momentum strategy over time for each fund. We then use the standard deviation of the loadings to measure how frequently a fund manager adjusts the momentum loadings. For funds which follow a static momentum trading strategy, the loading variation over time should be small. Panel A of Table 9 presents the distribution of the standard deviations of momentum loadings across sample funds.

Based on the standard deviation of the loadings, we sort hedge funds or mutual funds into decile portfolios. We then calculate both raw returns and risk-adjusted returns for each fund portfolio. In addition to the performance for each fund decile, we also calculate the difference between the two extreme deciles. Panel B of Table 9 reports the detailed

FIGURE 4 Distribution of fund-level timing with conditioning variables. This figure plots the distribution of the timing skill coefficients with conditioning variables across sample funds. To measure the manager's timing skill, we add a conditioning variable and the interaction between the conditioning variable and the momentum return to the regression model. The interaction term is the measure for timing skill with conditioning variables. UP is a dummy variable which is equal to 1 if past 36-month cumulative market return is positive. We obtain the sentiment data from Jeffery Wurgler's website. HighSent is a dummy variable that equals one if the investor sentiment is above the median. January is a dummy variable for the month of January. Momentum volatility is the volatility of momentum daily returns over the past 6 months. The sample period is 1994–2020 for hedge funds and 1984–2020 for mutual funds. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 8 Momentum trading, momentum timing, and fund performance—portfolio sort

This table reports the relation between fund managers' momentum trading or timing skills and fund performance. For each fund, we regress fund returns on the time series of momentum returns while accounting for a set of control variables. For momentum trading, we estimate the regression model: $r_t = \alpha + \beta_1 MOM_t + \boldsymbol{\gamma}'\mathbf{X_t} + e_t$. For momentum timing, we estimate the regression model $r_t = \alpha + \beta_1 MOM_t + \beta_2 \max(MOM_t, 0) + \boldsymbol{\gamma}'\mathbf{X_t} + e_t$. We require that funds have at least 24 months' observations. In Panel A, we sort all sample funds into 10 decile portfolios based on the t-statistics of the momentum loadings (with D10 the highest and D1 the lowest). In Panel B, we sort all sample funds into 10 decile portfolios based on momentum timing skill (with D10 the highest skill and D1 the lowest skill). We require that funds have at least 24 months' observations for regressions. We report the raw returns and alphas of each portfolio. The sample period is 1994–2020 for hedge funds and 1984–2020 for mutual funds. Number in parentheses are t-statistics.

Panel A: Momentum trading

	Hedge funds			Mutual funds		
	Raw return	7-factor alpha	8-factor alpha	Raw return	3-factor alpha	4-factor alpha
D1 (lowest)	0.69	0.21	0.30	0.90	−0.14	−0.04
D2	0.59	0.20	0.23	0.86	−0.16	−0.09
D3	0.56	0.18	0.19	0.88	−0.13	−0.09
D4	0.55	0.16	0.15	0.89	−0.11	−0.08
D5	0.57	0.19	0.17	0.90	−0.12	−0.11
D6	0.52	0.12	0.08	0.91	−0.11	−0.12
D7	0.52	0.14	0.09	0.94	−0.08	−0.12
D8	0.64	0.22	0.15	0.99	−0.03	−0.09
D9	0.62	0.17	0.07	1.03	0.00	−0.10
D10 (highest)	0.65	0.17	0.06	1.04	0.02	−0.12
D10–D1	−0.04 (−0.27)	−0.04 (−0.24)	−0.24 (−2.39)	0.14 (0.99)	0.16 (1.64)	−0.08 (−1.16)

Panel B: Momentum timing

	Hedge funds			Mutual funds		
	Raw return	7-factor alpha	8-factor alpha	Raw Rreturn	3-factor alpha	4-factor alpha
D1 (lowest)	0.53	0.17	0.14	0.88	−0.13	−0.13
D2	0.53	0.12	0.09	0.90	−0.11	−0.11
D3	0.56	0.17	0.14	0.88	−0.13	−0.13
D4	0.57	0.18	0.16	0.93	−0.09	−0.10
D5	0.57	0.18	0.15	0.92	−0.10	−0.10
D6	0.53	0.12	0.09	0.94	−0.08	−0.09
D7	0.61	0.17	0.15	0.96	−0.06	−0.07
D8	0.60	0.18	0.15	0.95	−0.07	−0.08

TABLE 8 (Continued)

Panel B: Momentum timing						
	Hedge funds			**Mutual funds**		
	Raw return	**7-factor alpha**	**8-factor alpha**	**Raw Rreturn**	**3-factor alpha**	**4-factor alpha**
D9	0.65	0.18	0.15	0.97	−0.06	−0.08
D10 (highest)	0.77	0.31	0.29	1.02	−0.03	−0.05
D10–D1	0.24 (2.86)	0.14 (1.80)	0.15 (1.87)	0.14 (1.93)	0.11 (2.16)	0.08 (1.54)

results. We find that the portfolio returns increase with the momentum loading variations. Specifically, hedge funds with the smallest momentum loading variations (D1) significantly underperform those with the largest momentum loading variations (D10). The raw return difference is 47 basis points per month and the risk-adjusted return difference is around 13 basis points per month. For mutual funds, we find a similar pattern. That is, funds which vary the intensity of momentum trading more actively over time tend to have better performance. This finding supports our conjecture on the value of the dynamic momentum strategy.

3.4.2 | Trading during momentum crashes

Momentum profits vary substantially with market conditions and occasionally exhibit crashes (Daniel & Moskowitz, 2016). During our sample period 1984–2020, the maximum drawdown to the momentum strategy is almost 70%, and the longest duration of drawdowns is more than 12 years. In this section, we investigate whether fund managers are able to time momentum crashes, and whether such timing skill enhances fund performance.

We define CRASH as an indicator variable, which takes the value of 1 if the momentum return during a given month is less than −5%, and then we use a modified timing model to see whether funds' momentum loadings are substantially decreased in the event of momentum crashes. Specifically, we add an interaction term between CRASH and momentum return to the regression model of fund returns. If hedge funds or mutual funds are able to time momentum crashes, the coefficient for the interaction term should be significantly *negative*. In Panel A of Table 10, we present the distribution of the t-statistics for the interaction term, which is the measure for timing skill on momentum crashes.

In Panel B of Table 10, we sort sample funds into decile portfolios based on the t-statistics of the interaction term. Using the same portfolio approach, we find evidence that funds with the highest ability to time momentum crashes (D1) outperform funds with the lowest timing ability for crashes (D10). For hedge funds, D1 outperform D10 by 25 basis points per month in raw returns and 10 basis points per month in risk-adjusted returns. For mutual funds, the return patterns are similar. The results of this analysis confirm that managing the risk of the momentum strategy leads to substantial economic gains (Barroso & Santa-Clara, 2015).

TABLE 9 Time-varying momentum loadings and fund performance

This table reports the relation between momentum loading variation over time and fund performance. For each fund, we use a rolling window of 60 months to estimate the time-series of fund loading on momentum returns and calculate the standard deviation of the loadings to measure the loading variation over time. Panel A reports the distribution of the standard deviation of momentum loadings. In Panel B, we sort all sample funds into 10 decile portfolios based on loading variation (with D10 the highest and D1 the lowest), and report the raw returns and alphas of each portfolio. The sample period is 1994–2020 for hedge funds and 1984–2020 for mutual funds. Numbers in parentheses are *t*-statistics.

Panel A. Distribution of momentum loading variation

	P1	P5	P10	P50	P90	P95	P99
Hedge fund	0.003	0.007	0.010	0.033	0.101	0.136	0.246
Mutual fund	0.003	0.009	0.013	0.037	0.077	0.091	0.128

Panel B. Fund performance sorted by momentum loading variation

	Hedge funds			Mutual funds		
	Raw return	7-factor alpha	8-factor alpha	Raw return	3-factor alpha	4-factor alpha
D1 (lowest)	0.53	0.22	0.21	0.87	−0.13	−0.12
D2	0.56	0.24	0.22	0.87	−0.12	−0.11
D3	0.59	0.25	0.23	0.94	−0.07	−0.07
D4	0.58	0.22	0.20	0.94	−0.06	−0.06
D5	0.61	0.20	0.17	0.92	−0.10	−0.10
D6	0.67	0.29	0.27	0.97	−0.06	−0.07
D7	0.69	0.25	0.22	0.96	−0.07	−0.09
D8	0.74	0.26	0.24	0.97	−0.05	−0.07
D9	0.77	0.24	0.20	1.01	−0.03	−0.06
D10 (highest)	1.00	0.36	0.32	1.01	−0.05	−0.10
D10–D1	0.47 (2.95)	0.13 (1.26)	0.12 (1.11)	0.14 (1.63)	0.08 (1.74)	0.02 (0.55)

3.4.3 | Momentum timing skills and fund characteristics

We have found evidence that the average hedge fund has some momentum timing skills and the average mutual fund possesses no such skills. However, we have also observed a large variation in momentum timing skills across different funds. In this section, we examine whether the momentum timing skill is associated with certain fund characteristics. This analysis may help investors pick funds with better skills and better future performance.

We first estimate fund momentum timing skills based on the modified Henriksson and Merton (1981) model (i.e., Equation 1). We then perform the cross-sectional regression analysis of fund's momentum timing skills on various fund characteristics. For hedge funds, the fund characteristics include fund size, fund age, management fee, incentive fee,

TABLE 10 Timing skills on momentum crashes and fund performance

This table reports fund managers' momentum timing skills to avoid momentum crashes. To examine whether managers can time momentum crashes, we estimate regression model $r_t = \alpha + \beta_1 MOM_t + \beta_2 MOM_t \times Crash_t + \beta_3 Crash_t + \boldsymbol{\gamma}'\mathbf{X}_t + e_t$, where $Crash_t$ is an indicator variable that takes the value of 1 if the momentum return in a given month is lower than −5%. In Panel A, we present the distribution of the t-statistics for the interaction term, which is the measure for timing skill on momentum crashes. In Panel B, we sort all sample funds into 10 decile portfolios based on the t-statistics of the interaction term (with D1 the highest skill and D10 the lowest skill). We report raw returns and alphas for each portfolio. The sample period is 1994–2020 for hedge funds and 1984–2020 for mutual funds. Numbers in parentheses are t-statistics.

Panel A. Distribution of timing skills on momentum crashes

	P1	P5	P10	P50	P90	P95	P99
Hedge fund	−3.43	−2.19	−1.70	−0.20	1.28	1.77	2.98
Mutual fund	−4.41	−2.77	−2.26	−0.33	1.51	2.10	3.32

Panel B. Fund performance sorted by timing skills on momentum crashes

	Hedge funds			Mutual funds		
	Raw return	7-factor alpha	8-factor alpha	Raw return	3-factor alpha	4-factor alpha
D1 (highest)	0.73	0.24	0.22	1.00	−0.04	−0.03
D2	0.62	0.17	0.14	0.98	−0.04	−0.05
D3	0.58	0.14	0.11	0.95	−0.07	−0.09
D4	0.64	0.21	0.17	0.95	−0.07	−0.08
D5	0.58	0.17	0.14	0.95	−0.08	−0.10
D6	0.58	0.19	0.16	0.93	−0.09	−0.10
D7	0.59	0.19	0.17	0.91	−0.11	−0.11
D8	0.61	0.21	0.19	0.90	−0.12	−0.14
D9	0.54	0.14	0.12	0.90	−0.11	−0.12
D10 (lowest)	0.48	0.14	0.11	0.87	−0.12	−0.12
D1–D10	0.25 (2.65)	0.10 (1.24)	0.11 (1.37)	0.13 (2.41)	0.09 (2.09)	0.09 (2.19)

the use of high-water-mark provision, minimum investment, redemption notice period and lockup period. For mutual funds, the fund characteristics include fund size, fund age, expense ratio, turnover ratio and total load. In Table 11, we report the regression results for all funds, and for funds within each investment style. For hedge funds, we find that larger funds, older funds, and funds with higher incentive fees and longer redemption notice periods are more likely to have momentum timing skills. For mutual funds, momentum timers tend to have longer histories, smaller size, and higher expense ratios. When we examine the funds within each investment style, the results are generally consistent with the results for all funds.

TABLE 11 Fund characteristics and momentum timing skills

This table reports the relation between fund characteristics and fund managers' momentum timing skills. We estimate the model $r_t = \alpha + \beta_1 MOM_t + \beta_2 \max(MOM_t, 0) + \boldsymbol{\gamma}'\mathbf{X}_t + e_t$ and use the t-statistics of the timing coefficient to measure fund timing skills. We require that funds have at least 24 months' observations for regressions. Size is the log of AUM. Age is the log of fund age. Flow is monthly fund flows. HighWaterMark is a dummy variable for the high-water-mark provision. MinimumInvest is log(1 + minimum investment). RedemptionNotice is log (1 + redemption-notice-period). Lockupperiod is log (1 + lock-up period). Numbers in parentheses are t-statistics, which are computed based on White heteroscedasticity consistent standard errors. ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively.

Panel A. Hedge fund							
	All funds	*Equity*	*Event-Driven*	*Fund of Funds*	*Macro*	*Multistrategy*	*Relative Value*
Intercept	−0.747***	−0.686***	−1.186***	−0.508**	−0.924***	−0.263	−0.357
	(−6.98)	(−3.62)	(−2.74)	(−2.58)	(−3.39)	(−0.34)	(−1.13)
Size	0.028***	0.021	0.024	0.003	0.031	0.023	0.062**
	(3.07)	(1.23)	(0.64)	(0.17)	(1.46)	(0.43)	(2.53)
Age	0.137***	0.181***	0.052	0.096***	0.185***	−0.032	0.175***
	(6.76)	(5.13)	(0.75)	(2.72)	(3.59)	(−0.22)	(2.74)
ManagementFee	−0.034	−0.062	−0.039	0.035	−0.006	0.069	−0.142*
	(−1.44)	(−1.24)	(−0.40)	(0.74)	(−0.14)	(0.58)	(−1.84)
IncentiveFee	0.010***	0.007	0.030***	−0.002	−0.015**	0.005	−0.008
	(5.29)	(1.48)	(2.63)	(−0.63)	(−2.27)	(0.40)	(−1.22)
HighWaterMark	−0.006	−0.162**	0.113	0.069	0.179	0.358*	0.144
	(−0.18)	(−2.50)	(0.89)	(1.31)	(1.59)	(1.73)	(1.23)
MinimumInvest	−0.062***	−0.101**	−0.054	−0.092**	−0.090**	−0.183	0.015
	(−2.62)	(−2.07)	(−0.61)	(−2.10)	(−1.98)	(−1.32)	(0.21)

TABLE 11 (Continued)

Panel A. Hedge fund							
	All funds	***Equity***	***Event-Driven***	***Fund of Funds***	***Macro***	***Multistrategy***	***Relative Value***
RedemptionNotice	0.053***	0.071**	0.117**	0.032	0.117***	0.083	0.015
	(4.75)	(3.22)	(2.04)	(1.53)	(4.32)	(1.51)	(0.43)
Lockupperiod	0.001	0.010	−0.013	−0.031	−0.060	0.069	−0.013
	(0.11)	(0.55)	(−0.39)	(−1.44)	(−1.16)	(1.08)	(−0.38)
Adj R^2	1.26%	1.33%	1.80%	0.53%	3.08%	2.91%	1.45%

Panel B. Mutual fund				
	All funds	***Aggressive Growth***	***Growth***	***Growth and Income***
Intercept	0.001	−0.669*	0.034	0.450
	(0.01)	(−1.75)	(0.12)	(1.17)
Size	0.071***	0.095**	0.065**	0.083**
	(3.45)	(2.00)	(2.30)	(2.18)
Age	−0.113**	−0.042	−0.085	−0.258***
	(−2.49)	(−0.46)	(−1.32)	(−2.79)
Expense ratio	0.191***	0.248**	0.228**	0.148
	(3.13)	(2.13)	(2.36)	(1.31)
Turnover ratio	−0.000	0.001	−0.001**	0.001
	(−1.34)	(1.12)	(−2.32)	(0.68)
Total Load	−0.004	−0.030	0.018	−0.024
	(−0.26)	(−0.98)	(0.86)	(−0.88)
Adj R^2	0.51%	0.39%	0.95%	0.86%

4 | CONCLUSIONS

Using fund returns we examine whether mutual fund and hedge fund managers trade and time the momentum anomaly, and whether momentum trading and timing enhance fund performance. We find that both mutual funds and hedge funds trade on momentum and the evidence is stronger for hedge funds. More importantly, we find that the average hedge fund possesses modest momentum timing ability, while the average mutual fund exhibits no such ability. We also find evidence that fund managers exploit the predictability of momentum returns conditioning on market state and prior momentum volatility. The momentum trading and timing skills vary considerably with fund investment styles. There is little evidence that funds who trade on momentum earn abnormal returns. In contrast, there is significant evidence that funds that time momentum well tend to perform better. This evidence indicates that it is not momentum trading per se, but momentum timing that enhances fund performance.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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APPENDIX

See Table A1

TABLE A1 Fund characteristics by investment style

This table reports summary statistics of sample funds for different investment styles. Hedge fund data are from the consolidated database of Lipper TASS and Hedge Fund Research (HFR). Mutual fund data are from CRSP mutual fund database. We classify hedge funds into six groups based on their investment styles: *Equity*, *Event-Driven*, *Fund of Funds*, *Macro*, *Multistrategy*, and *Relative Value*. We classify mutual funds into three groups based on their investment styles: *Aggressive Growth*, *Growth*, and *Growth and Income*. Our final sample includes 11,365 hedge funds and 2940 mutual funds. We report the average statistics across sample funds in each investment style. *N* is the number of sample funds for each investment style. The sample period is 1994–2020 for hedge funds and 1984–2020 for mutual funds.

Panel A. Hedge fund						
	Equity	***Event Driven***	***Fund of Funds***	***Macro***	***Multistrategy***	***Relative Value***
N	4270	954	2830	1495	396	1420
Fund_AUM ($ million)	135.45	208.35	161.71	255.37	224.46	251.00
Fund_Age (month)	69.24	70.17	75.65	73.28	66.68	64.57
Management fee (%)	1.40	1.49	1.29	1.69	1.48	1.43
Incentive fee (%)	18.32	18.73	7.64	18.50	15.35	17.87
Minimum investment ($ million)	1.03	1.70	0.94	1.87	1.47	1.48
Lock-up	0.33	0.45	0.22	0.09	0.27	0.33
Lock-up period (month)	4.32	6.20	2.76	1.05	3.24	4.34
Redemption notice period (days)	37.57	59.03	49.47	20.70	38.19	50.56
High water mark	0.83	0.84	0.60	0.85	0.60	0.83

Panel B. Mutual fund			
	Aggressive Growth	***Growth***	***Growth and Income***
N	806	1,249	885
Fund_AUM ($ million)	545.56	791.27	614.57

TABLE A1 (Continued)

Panel B. Mutual fund			
	Aggressive Growth	*Growth*	*Growth and Income*
Fund_Age (month)	113.88	106.67	101.51
Turn_ratio (%)	99.58	87.74	75.64
Exp_ratio (%)	1.34	1.19	1.17
Load (%)	1.19	1.10	0.98