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Relative strength over investment horizons and stock returns

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ABSTRACT: *In this article, the authors propose a simple and novel measure of relative strength over investment horizons that synthesizes short- and intermediate-term price information. The relative-strength measure compares the short-term price trend with the intermediate-term price trend. The relative strength strategy generates substantial profits, which are greater than a simple sum of traditional short-term reversal and momentum profits. The superior performance of the relative strength strategy is evident after risk adjustments for various factor models and is robust across subperiods and different market conditions. These findings seem consistent with investor conservatism and the idea that investors are slow to adjust to new information.*

TOPICS: ***Analysis of individual factors/risk premia, factor-based models, style investing****

KEY FINDINGS

- A novel relative-strength measure over investment horizons that synthesizes short- and intermediate-term price information can significantly predict subsequent short-term returns.
- The relative-strength strategy generates substantial profits, which are greater than a simple sum of traditional short-term reversal and momentum profits.
- The superior performance of the relative-strength strategy is evident after risk adjustments for various factor models and is robust across subperiods and different market conditions.

Jegadeesh (1990) and Jegadeesh and or losers, Han, Zhou, and Zhu (2016) conTitman (1993) documented that past short- and intermediate-term returns short-, intermediate-, and long-term price can significantly predict future returns. information from cross-sectional regressions. Since then, considerable time and effort have been spent on exploring these two anomalies. However, until recently, most studies have ignored the possibility that the two phenomena might be interconnected, instead treating them as separate and independent anomalies. In this article, we ask the following simple question: Can investors benefit from jointly using short- and intermediate term price information?

Several recent studies have examined the interaction between momentum and short-term reversal and found that shortterm reversals are more pronounced among momentum losers (Zhu and Yung 2016; Cheng et al. 2017). Unlike these studies that double sort on extreme past short- and intermediate-term returns to identify extreme momentum and reversal winners or losers, Han, Zhou, and Zhu (2016) constructed a trend factor that combines the short-, intermediate, and long-term price information from cross-sectional regressions. They showed that the trend factor generates substantial economic gains.

In this article, we propose an alternative and simple measure that synthesizes short- and intermediate-term price information. Unlike Han, Zhou, and Zhu (2016), Zhu and Yung (2016), or Cheng et al. (2017), whose methods rely on sophisticated econometric/statistical analysis, we develop a straightforward relative-strength measure by comparing short- and intermediate-term returns. Relative strength over investment horizons is based on the difference between past short- and intermediate-term returns. Specifically, a stock's relative strength over short and intermediate horizons is defined as the difference between past 1-month return and the lagged past 11-month cumulative return (DSI). The proposed relative strength strategy takes a long position in stocks with the lowest DSI and shorts those with the highest DSI.

Our DSI measure is directly inspired by the behavioral finance literature. It is well known that investors exhibit conservatism bias, which suggests that investors tend to adhere to prior dominant beliefs even in the face of new disconfirming or contradictory information (e.g., Edwards 1968; Lord, Ross, and Lepper 1979; Daniel, Hirshleifer, and Subrahmanyam 1998). We conjecture that some stocks with new disconfirming or contradictory information experience temporary price pressure, possibly because of short squeeze or other shocks, but investors with conservatism bias subsequently force prices in line with the long-run trend. Therefore, it is reasonable to conjecture that investors with conservatism bias would buy stocks with the most negative DSI and short stocks with the most positive DSI. Empirically, several recent studies (Han, Zhou, and Zhu 2016; Zhu and Yung 2016; Cheng et al. 2017) also have showed that combining short- and intermediate-term price information is a promising approach and can help investors improve their portfolio performance. From a practical perspective, our easily constructed and implemented DSI measure is more attractive than these alternative approaches that rely heavily on complicated statistical techniques. In spite of its simplicity, we find that DSI has predictive power comparable to that of the trend factor approach proposed by Han, Zhou, and Zhu (2016). Moreover, DSI does not rely on the selection of some extreme momentum and short-term winners or losers, as in work by Zhu and Yung (2016) and Cheng et al. (2017).

We provide intriguing evidence that relative strength over short and intermediate horizons can significantly predict future returns. In our sample period from January 1967 to December 2017, the DSI strategy earns an average monthly raw return of 2.34% (*t*-value = 11.23), which significantly exceeds the average returns of 1.06% (*t*-value = 5.92) and 1.10% (*t*-value = 4.51) achieved by short-term reversal and momentum, respectively. The profitability of DSI is greater than the sum of short-term reversal and momentum, suggesting that DSI contains substantial information beyond a simple sum of past 1-month and 11-month returns. Moreover, Chordia, Subrahmanyam, and Tong (2014) showed that most capital market anomalies are attenuated by increasing liquidity and trading activities after 2000. However, we report that the DSI strategy survives this test and generates an average monthly raw return of 1.19% (*t*-value = 3.02) during the post2000 subperiod from 2001 to 2017, which dwarfs the average returns of 0.51% (*t*-value = 2.20) and 0.55% (*t*-value = 1.16) earned by traditional short-term reversal and momentum, respectively. Taken together, the results documented in this article provide strong evidence that synthesizing short- and intermediate-term price information generates substantial economic gains.

The superior performance of relative strength over short and intermediate horizons is robust to various factor models and control variables. The alphas of the Fama–French three-factor (FF3: market, size, book-tomarket ratio), four-factor (FF3 plus a liquidity factor), and five-factor (FF3 plus momentum and short-term reversal factors) models and the trend factor model are 2.52%, 2.43%, 1.53%, and 2.33%, respectively. Our findings are robust to the use of value-weighted returns. Moreover, bivariate portfolio analysis shows that our results are robust after controlling for various variables such as firm size, short-term reversal, momentum, moving average, idiosyncratic volatility, illiquidity, and fundamentals.

To summarize, our contributions to the literature are as follows. First, we provide novel evidence that synthesizing short- and intermediate-term price information can generate considerable economic gains that are greater than the simple sum of short-term reversal and momentum. Second, we propose a new measure of combined short- and intermediate-term price information that is straightforward and much easier to construct and implement than its peers. Third, our DSI strategy has significant practical implications because the performance of relative strength over investment horizons is quite robust after controlling for various explanatory variables and market conditions. In addition, because the DSI measure contains only historical price information, our findings cast doubt on weak-form market efficiency. Last, but not least, the success of the DSI strategy is supportive of the notion that at least some investors tend to overweight prior information or experience and underweight more recent information. In other words, investors are slow to digest new information.

DATA AND METHODOLOGY

Our sample consists of all common stocks (share code 10 or 11) listed in the NYSE, AMEX, and NASDAQ. Stock information such as returns, prices, trading volumes, shares outstanding, and industry codes are from the Center for Research in Security Prices (CRSP). Financial statement data are obtained from Compustat. The sample period is from January 1967 to December 2017. To alleviate concerns about market microstructure–induced biases, we exclude stocks with prices less than $5 at the end of the portfolio formation period. The Baker and Wurgler (2006) investor sentiment data are from Jeffrey Wurgler's website. Following Shumway (1997), we set delisting returns of -30% to NYSE/AMEX delisted stocks and -50% to NASDAQ delisted stocks if their delisting returns are missing or zero and delisting was done for performance reasons.

In our main empirical analysis, we adopt a two-step procedure to construct our relative-strength measure over short and intermediate horizons. First, we calculate a relative-strength return that is the difference between past 1-month return and lagged past 11-month (from month t - 12 to t - 2) cumulative returns (DSI), where $DSI_{t-1} = Ret_{t-1} - Ret_{t-2,t-12}$. We divide all sample stocks into two groups based on whether DSI is positive or negative. Second, within each group, we further equally sort stocks into quintile portfolios based on the magnitude of DSI. Thus, we obtain a total of 10 portfolios.

It should be noted that our results are robust to different methods of portfolio formation. For example, following traditional portfolio analysis, we simply assign stocks into deciles based on DSI directly without first dividing stocks into two groups. In addition, we examine the performance of two groups of stocks based on whether DSI is positive or negative. In both cases, we obtain similar results.

MAIN EMPIRICAL RESULTS

Univariate Portfolio Analysis

Exhibit 1 reports the average monthly equal-weighted (Panel A) and value-weighted (Panel B) returns for portfolios of stocks sorted on relative strength over short and intermediate horizons. There are three main findings. First, the lowest DSI portfolio has the highest raw return of 1.79% (t-value = 5.74) per month, and the highest DSI portfolio has the lowest raw return of -0.55% (t-value = -1.79) per month. The low–high DSI hedge portfolio has an average monthly raw return of 2.34% (t-value = 11.23). These results suggest that relative strength over short and intermediate horizons can significantly predict future returns. These findings also suggest that investors adhere to prior dominant beliefs even when new information is contradictory.

Second, the portfolio returns negatively and monotonically vary with DSI, suggesting a linear relation between DSI and future returns. Third, the significant return predictability is robust to various factor models. The lowest (highest) DSI portfolio generates economically and statistically significant positive (negative) alphas for various factor models. For example, for the lowest DSI portfolio, the alphas of capital asset pricing model (CAPM), FF3, four-factor, five-factor, Fama–French five-factor, and trend factor models are 0.70%, 0.72%, 0.71%, 0.24%, 0.83%, and 0.63%, respectively. For the highest DSI portfolio, the alphas of CAPM, FF3, four-factor, five-factor, Fama– French five-factor, and trend factor models are -1.63%, -1.80%, -1.72%, -1.29%, -1.62%, and -1.70%, respectively. For the long–short hedge portfolio, the alphas of CAPM, FF3, four-factor, five-factor, Fama–French five-factor, and trend factor models are 2.34%, 2.52%, 2.43%, 1.53%, 2.45%, and 2.33%, respectively. All these alphas are significant. These results suggest that the momentum and short-term reversal factors and the trend factor could not explain the predictability of relative strength over investment horizons.

Panel B in Exhibit 1 reports the value-weighted returns. We find very similar results. For example, the value-weighted long–short DSI portfolio generates an average monthly raw return of 1.90% with a highly significant t-statistic of 7.16. In addition, all factor model adjusted average returns are positive and highly significant. Overall, these findings are consistent with the psychological evidence that investors suffer from anchoring bias and suggest that investors can reap significant economic gains by jointly extracting short- and intermediate-term price information. Importantly, existing well-known pricing factors such as momentum, short-term reversal, and the trend factor fail to explain the predictive power of the DSI strategy.

Descriptive Statistics

To provide a clearer picture of the characteristics of DSI portfolios, Exhibit 2 presents the summary statistics for stocks in the DSI portfolios. Specifically, this exhibit presents the average monthly mean values of stock characteristics for portfolios sorted by DSI.

The DSI portfolios exhibit some interesting patterns. From the lowest to the highest DSI portfolio, the DSI increases from -117.16% to 52.45%, the past 1-month return increases from -1.11% to 14.35%, and the lagged past 11-month cumulative returns decrease from 116.05% to -38.11%. The relation between DSI and these variables is monotonic. For comparison, the last two columns show the past 1-month and past 11-month returns for traditional short-term reversal and momentum strategies. A simple comparison suggests that the stocks with the lowest DSI are momentum winners and those with the highest DSI are momentum losers and short-term winners. Such a comparison could explain why stocks with the highest (lowest) DSI experience significantly negative (positive) returns in the subsequent one month. However, not all stocks in extreme DSI portfolios are traditional short-term reversal winners or losers based on their past one-month returns.

Stocks in the highest DSI portfolio are the smallest stocks and have the lowest stock prices and book-to-market ratios but the highest idiosyncratic volatility, illiquidity, turnover, and average of five-day maximum daily returns with past one-month returns. By contrast, stocks in the lowest DSI portfolio are also small in size and have modest stock prices, idiosyncratic volatility, and MAX returns, but they have the highest book-to-market ratios and turnover and the lowest illiquidity. Overall, stocks in the two extreme DSI portfolios have relatively extreme characteristics.

E x h i b i t 1: Returns on Portfolios of Stocks Sorted by DSI

Panel A: Equal-Weighted Portfolios

DSI	Raw	CAPM	FF3	FF3MR	FF4	FF5	Trend
Low	1.79	0.70	0.72	0.24	0.71	0.83	0.63
	(5.74)	(3.99)	(5.53)	(2.56)	(5.49)	(5.99)	(4.65)
2	1.51	0.55	0.45	0.18	0.46	0.43	0.42
	(6.27)	(4.32)	(6.35)	(3.45)	(6.23)	(5.81)	(5.81)
3	1.34	0.44	0.29	0.12	0.35	0.22	0.30
	(6.14)	(3.89)	(4.64)	(1.94)	(5.44)	(3.71)	(4.58)
4	1.25	0.38	0.22	0.13	0.31	0.14	0.23
	(6.06)	(3.51)	(3.54)	(1.83)	(5.26)	(2.32)	(3.96)
5	1.16	0.31	0.14	0.13	0.19	0.07	0.17
	(5.80)	(2.89)	(2.33)	(1.69)	(3.03)	(1.24)	(2.68)
6	0.93	0.05	–0.13	–0.09	–0.06	–0.20	–0.11
	(4.41)	(0.47)	(–1.76)	(–1.03)	(–0.80)	(–2.49)	(–1.36)
7	0.87	–0.04	–0.23	–0.12	–0.15	–0.28	–0.19
	(3.83)	(–0.28)	(–2.92)	(–1.39)	(–1.93)	(–3.24)	(–2.17)
8	0.66	–0.28	–0.49	–0.30	–0.40	–0.50	–0.40
	(2.71)	(–2.16)	(–5.65)	(–3.56)	(–4.57)	(–4.97)	(–3.94)
9	0.42	–0.58	–0.77	–0.45	–0.71	–0.72	–0.72
	(1.57)	(–4.22)	(–8.40)	(–5.48)	(–7.43)	(–6.38)	(–6.36)
High	–0.55	–1.63	–1.80	–1.29	–1.72	–1.62	–1.70
	(–1.79)	(–9.76)	(–16.60)	(–12.68)	(–14.24)	(–13.10)	(–10.00)
Low–High	2.34	2.34	2.52	1.53	2.43	2.45	2.33
	(11.23)	(11.6)	(12.57)	(11.16)	(11.81)	(10.19)	(8.45)

Panel B: Value-Weighted Portfolios

DSI	Raw	CAPM	FF3	FF3MR	FF4	FF5	Trend
Low	1.53	0.48	0.64	0.08	0.62	0.73	0.53
	(5.32)	(3.19)	(4.40)	(0.72)	(4.49)	(4.25)	(3.25)
2	1.20	0.27	0.30	–0.05	0.28	0.25	0.31
	(5.61)	(2.86)	(3.37)	(–0.71)	(3.19)	(2.42)	(3.01)
3	1.06	0.18	0.19	–0.02	0.21	0.08	0.24
	(5.72)	(3.08)	(3.07)	(–0.32)	(3.01)	(1.29)	(2.57)
4	0.91	0.06	0.05	–0.04	0.10	–0.05	0.05
	(5.10)	(1.07)	(0.81)	(–0.56)	(1.95)	(–0.95)	(0.87)
5	0.82	–0.02	–0.07	–0.05	–0.03	–0.15	–0.07
	(4.58)	(–0.23)	(–0.92)	(–0.60)	(–0.46)	(–2.04)	(–0.96)
6	0.66	–0.20	–0.25	–0.17	–0.20	–0.28	–0.29
	(3.43)	(–2.07)	(–2.63)	(–1.47)	(–2.11)	(–2.79)	(–2.66)
7	0.65	–0.22	–0.28	–0.08	–0.32	–0.33	–0.23
	(3.36)	(–2.35)	(–2.82)	(–0.72)	(–2.97)	(–3.10)	(–2.11)
8	0.48	–0.45	–0.54	–0.26	–0.53	–0.52	–0.41
	(2.20)	(–3.70)	(–4.52)	(–2.09)	(–4.14)	(–3.59)	(–2.98)
9	0.36	–0.65	–0.74	–0.27	–0.76	–0.73	–0.73
	(1.41)	(–4.70)	(–5.46)	(–2.23)	(–5.20)	(–4.76)	(–4.83)
High	–0.38	–1.46	–1.56	–0.95	–1.59	–1.40	–1.48
	(–1.26)	(–9.07)	(–9.99)	(–7.14)	(–9.13)	(–8.29)	(–7.16)
Low–High	1.90	1.95	2.19	1.04	2.21	2.13	2.01
	(7.16)	(7.50)	(8.62)	(6.02)	(8.29)	(7.06)	(6.39)

Notes: This exhibit reports the equal-weighted (Panel A) and value-weighted (Panel B) average monthly raw and factor-adjusted returns (in percentage) on portfolios of stocks sorted by the difference between past 1-month returns (month t - 1) and past 11-month cumulative returns (month t - 12 to t - 2) (DSI). Each month, stocks are first assigned into two groups based on whether DSI is greater or less than 0. Then, within each group, stocks are further sorted into quintile portfolios based on the magnitude of DSI, where Low (High) denotes the portfolio of stocks with the lowest (highest) DSI. Low–High denotes the returns to the long–short portfolios that are long low portfolios and short high portfolios. CAPM denotes the market-adjusted returns; FF3 denotes the alphas with respect to the Fama–French (1993) three-factor model; FF4 denotes the alphas with respect to the four-factor model with the FF three factors and the Pastor and Stambaugh (2003) liquidity factor; FF3MR denotes the alphas with respect to the five-factor model with the FF three factors, the short-term reversal factor, and the Carhart (1997) factor; FF5 denotes the alphas with respect to the Fama–French (2015) five-factor model; Trend denotes the alphas with respect to the FF three factors and Han, Zhou, and Zhu (2016) trend factor. The holding period of decile portfolios is one month. Portfolios are formed with common stocks listed in NYSE, AMEX, and NASDAQ. Stocks with a price of less than $5 at the end of formation month t - 1 are excluded. The sample period is from January 1967 to December 2017. Newey and West (1987) heteroskedasticity and autocorrelation consistent t-*statistics are reported in parentheses.*

Bivariate Portfolio Analysis

In this section, we examine whether firm characteristics can significantly explain the return predictability of the DSI anomaly. We use two-way dependent sorts on various characteristics and the relative-strength measure. Specifically, we first sort all sample stocks into deciles based on the characteristic variable of interest in month t - 1. Then, within each characteristic decile, we sort all stocks into 10 portfolios based on DSI. We report the average returns across 10 characteristic deciles to produce decile portfolios with variations in DSI but similar levels of the characteristic variable. To conserve space, we only report returns for 10 characteristic adjusted DSI portfolios. Each characteristic-adjusted DSI portfolio contains stocks with the same level of DSI but different firm characteristics.

E x h i b i t 2: Characteristics of Portfolios of Stocks Sorted by DSI

Portfolio	DSI	Size	BM	Ret ($t-1$)	Ret ($t-12, t-2$)	Ret ($t-7, t-2$)	Price	IVOL	ILLIQ	TO	MAX5	N	REV	MOM11
1	−117.16	1,448	0.91	−1.11	116.05	57.00	28.75	2.41	0.27	13.85	3.66	405	−15.78	130.51
2	−46.12	2,552	0.86	−0.85	45.27	25.02	40.82	1.91	0.31	8.62	2.90	407	−7.81	54.54
3	−27.73	2,993	0.85	−0.42	27.31	15.83	55.95	1.74	0.33	7.28	2.66	408	−4.55	35.62
4	−15.74	3,019	0.84	0.02	15.77	9.86	61.40	1.67	0.34	6.67	2.58	409	−2.19	24.05
5	−5.43	2,844	0.84	0.61	6.04	4.87	55.80	1.70	0.37	6.48	2.64	408	−0.15	15.22
6	3.34	2,538	0.83	1.38	−1.96	0.77	42.18	1.81	0.39	6.93	2.84	244	1.86	7.56
7	10.01	2,222	0.81	2.00	−8.01	−2.46	49.68	1.92	0.41	7.28	3.06	245	4.09	0.16
8	17.74	1,761	0.80	3.01	−14.73	−6.10	23.99	2.10	0.44	8.05	3.40	245	6.86	−7.87
9	28.25	1,262	0.78	4.85	−23.40	−11.26	18.72	2.38	0.46	9.37	3.92	245	11.07	−18.09
10	52.45	690	0.73	14.35	−38.11	−20.39	14.56	3.28	0.47	14.82	5.68	244	24.87	−37.67

Notes: This exhibit presents the average monthly mean values of characteristics for portfolios of stocks sorted by DSI. Portfolio 1 (10) is the portfolio of stocks with the lowest (highest) difference between past 1-month returns and past 11-month returns. DSI (in percentage) is the difference between past 1-month returns (month $t-1$) and past 11-month returns (month $t-12$ to $t-2$). Size is the market capitalization (in millions of dollars) at the end of month $t-1$. BM is the book-to-market ratio. Ret ($t-1$), Ret ($t-12$, $t-2$), and Ret ($t-7$, $t-2$) measures returns (in percentage) in month $t-1$, month $t-2$ to $t-12$, and month $t-2$ to $t-7$, respectively. IVOL is the idiosyncratic volatility in month $t-1$. ILLIQ is the Amihud (2002) stock illiquidity measure. TO (in percentage) is the ratio of trading volume to total shares outstanding in month $t-1$. MAX5 is the average of five highest daily returns in month $t-1$. N is the average number of stocks in each portfolio each month. REV (in percentage) is the returns in the formation month $t-1$ for the simple short-term reversal strategy documented by Jegadeesh (1990). MOM11 (in percentage) is the returns during month $t-2$ to $t-12$ for the simple momentum strategy of Jegadeesh and Titman (1993). REV and MOM11 are based on decile ranking.

Exhibit 3 reports the results. After controlling for firm size, the lowest DSI portfolio has a monthly return of 1.74% and the highest DSI portfolio has a monthly return of -0.53%. The long–short DSI portfolio has an average monthly raw return of 2.28% with a *t*-value of 11.13. The alphas of the hedge portfolio in various factors models are economically and statistically significant. These findings suggest that firm size cannot explain the significant return predictability of relative strength over short and intermediate horizons.

We control for other variables in the same way. In particular, we are interested in knowing whether DSI portfolios adjusted by past 1-month or lagged 11-month returns lose any statistical or economic significance. Because our relative-strength measure is constructed by the past 1-month and the lagged 11-month return, we view this approach as a very stringent test of the DSI anomaly, and naturally we would expect them to explain approximately half of the predictability by the DSI measure. However, after controlling for past 1-month return or the lagged 11-month return separately, the long–short DSI portfolio still has a monthly raw return of 1.96% and 1.95%, respectively. Though the returns of conditional hedge portfolio are somewhat smaller than the unconditional return of 2.34%, the returns are economically and statistically significant.

We find similar results when controlling for fundamental variables such as book-to-market ratio; technical trading rules such as the moving average; and short-term return predictors such as idiosyncratic volatility, the Amihud (2002) illiquidity measure, and the MAX effect (Bali, Cakici, and Whitelaw 2011). To summarize, these results indicate that well-known cross-sectional return determinants such as size, book-to-market, short-term reversal, momentum, illiquidity, and idiosyncratic volatility cannot explain the significant return predictability of the relative-strength measure proposed in this article.

Market Conditions

In this section, we explore the performance of the relative-strength strategy under various market conditions. Existing studies document that investor sentiment, market states, and market volatility have a significant impact on short-term reversal and momentum. Momentum is more pronounced following periods of high investor sentiment, up markets, and highly volatile markets (e.g., Antoniou, Doukas, and Subrahmanyam 2013; Cooper, Gutierrez, and Hameed 2004; Wang and Xu 2015). Short-term reversal is stronger following down markets and highly volatile markets (e.g., Hameed, Kang, and Viswanathan 2010; Da, Liu, and Schaumburg 2014). Moreover, Da, Liu, and Schaumburg (2014) showed that investor sentiment significantly explains the reversal of short-term winners. Because the relative-strength measure combines both short- and intermediate-term price information, it is interesting to understand how market conditions affect the performance of the relative-strength strategy.

E x h i b i t 3: Portfolio Returns Sorted by DSI Conditional on Characteristics

DSI	Size	BM	REV	MOM11	IVOL	ILLIQ	MAX	MA
Low	1.74	1.81	1.74	1.57	1.79	1.78	1.83	1.91
2	1.52	1.58	1.49	1.54	1.50	1.50	1.49	1.51
3	1.33	1.37	1.37	1.39	1.34	1.34	1.35	1.30
4	1.29	1.25	1.27	1.32	1.25	1.25	1.22	1.21
5	1.17	1.21	1.19	1.22	1.17	1.18	1.16	1.12
6	0.95	0.88	0.88	1.03	0.89	0.96	0.84	0.94
7	0.79	0.85	0.76	0.88	0.75	0.81	0.72	0.89
8	0.73	0.74	0.56	0.54	0.62	0.70	0.57	0.62
9	0.38	0.49	0.35	0.27	0.38	0.37	0.36	0.39
High	–0.53	–0.35	–0.22	–0.39	–0.31	–0.51	–0.15	–0.52
Low–High	2.28	2.16	1.96	1.95	2.10	2.30	1.98	2.43
	(11.13)	(10.56)	(8.85)	(13.39)	(10.83)	(11.02)	(10.59)	(12.44)
FF3	2.45	2.35	2.19	1.94	2.28	2.47	2.15	2.55
	(12.35)	(12.20)	(10.51)	(12.71)	(12.46)	(12.19)	(12.10)	(13.66)
FF3MR	1.48	1.42	1.22	1.35	1.39	1.51	1.34	1.65
	(10.99)	(10.74)	(9.72)	(12.27)	(11.91)	(11.20)	(11.29)	(12.40)
FF4	2.35	2.27	2.18	1.71	2.19	2.38	2.05	2.45
	(11.29)	(11.57)	(10.85)	(11.69)	(11.76)	(11.58)	(11.52)	(12.70)
FF5	2.38	2.29	2.09	1.94	2.19	2.38	2.09	2.48
	(10.08)	(10.01)	(8.05)	(12.62)	(10.05)	(10.20)	(9.93)	(11.72)
Trend	2.26	2.21	1.98	1.76	2.13	2.31	2.03	2.43
	(8.50)	(8.71)	(7.69)	(8.18)	(8.72)	(8.76)	(9.11)	(9.33)

Notes: This exhibit presents the equal-weighted returns to portfolios of stocks sorted by DSI after controlling for various firm characteristics. In each case, all sample stocks are assigned into control deciles based on the control variable. Within each control decile, stocks then are further assigned into 10 groups based on DSI in the formation month. This exhibit presents average returns across 10 control deciles to produce decile portfolios with variation in DSI but similar levels of the control variable. The sample period is from 1967 to 2017. Newey and West (1987) adjusted t*-statistics are in parentheses.*

We examine three market conditions: (1) down market, which takes a value of 1 if the past three-month CRSP value-weighted market index is negative and 0 otherwise (e.g., Hameed, Kang, and Viswanathan 2010); (2) the realized market return volatility in the formation month (e.g., Da, Liu, and Schaumburg 2014); and (3) Baker and Wurgler's (2006) composite investor sentiment index. Following Stambaugh, Yu, and Yuan (2012) and Da, Liu, and Schaumburg (2014), we conduct predictive regressions to examine whether the lagged proxies for market conditions significantly affect the performance of the relative-strength strategy.

Exhibit 4 reports the results of regression analysis. First, we regress the one-month returns of the relative-strength strategy on the one-month lagged sentiment index, a down market dummy, and market volatility, separately. We find that the coefficients of these market condition proxies are insignificant. We then run the regression with all three market condition variables. We find that these coefficients of market condition proxies remain the same. These results indicate that the performance of the relative-strength strategy is quite robust to different market conditions.

E x h i b i t 4: Performance of Relative-Strength Strategy and Market Conditions

	1	2	3	4
Intercept	0.0263	0.0266	0.0351	0.0351
	(12.92)	(12.62)	(5.98)	(6.06)
Sentiment	0.0003			0.0001
	(0.18)			(0.06)
DOWN		–0.0009		0.0041
		(–0.16)		–0.79
MKTVOL			–1.0115	–1.1562
			(–1.44)	(–1.56)
MKT	–0.0601	–0.0602	–0.0719	–0.0739
	(–0.90)	(–0.90)	(–1.06)	(–1.10)
SMB	–0.0699	–0.0720	–0.0639	–0.0572
	(–0.51)	(–0.52)	(–0.47)	(–0.41)
HML	–0.3950	–0.3951	–0.4172	–0.4185
	(–2.13)	(–2.14)	(–2.22)	(–2.22)

Notes: This exhibit presents average coefficients for the predictive regressions:

$$R_{it} = a + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 X_{t-1} + \varepsilon_t$$

The dependent variable is the returns to the long–short portfolio based on DSI. The independent variables include Fama–French three factors (market, size, and book-to-market ratio) and lagged proxies for market conditions (X). Variable X refers to the down market dummy, realized market volatility, and Baker and Wurgler (2006) aggregate sentiment index (sentiment), respectively. The down market dummy takes a value of 1 if the past three-month CRSP value-weighted market index is negative and 0 otherwise. The realized market volatility is calculated as the standard deviation of the realized market index in the formation month. The aggregate sentiment index is from Baker and Wurgler (2006). The sample period is from 1967 to September 2015. Newey and West (1987) adjusted t-statistics are reported in parentheses.

ROBUSTNESS TESTS

In this section, we provide a battery of robustness tests of the performance of relative strength over short and intermediate horizons. Exhibit 5 reports the results.

Subperiods

Capital market anomalies are attenuated after 2000 by increasing liquidity and arbitrage and trading activities (e.g., Chordia, Subrahmanyam, and Tong 2014; McLean and Pontiff 2016). Specifically, traditional price momentum suffers from large crashes, and traditional short-term reversal strategies do not generate significant profits after 2000 (e.g., Daniel and Moskowitz 2016; Novy-Marx and Velikov 2016).

Panel A in Exhibit 5 reports the results. We find that the relative-strength strategy generates economically and statistically significant profits in three subperiods. The profitability is expected to become smaller after 2000. However, the monthly return of 1.19% is still economically and statistically significant and much higher than that of other well-known capital market anomalies.

January Seasonality

Short-term reversal performs best in January, but price momentum performs worst (Jegadeesh 1990; Jegadeesh and Titman 1993). Panel B of Exhibit 5 reports the performance of the relative-strength strategy in January and other non-January months. These results show that the strategy performs much better in non-January months in terms of raw return. However, there is no January effect after controlling for risk factors.

Earnings Announcements

Our relative-strength strategy is based on only past price information over different horizons. We are interested in knowing how public fundamental information affects the performance of the strategy. Existing studies document that short-term reversals are weakened by the arrival of public fundamental information (Nagel 2012; Hameed and Mian 2015) and that price momentum can be explained by fundamentals (e.g., Chordia and Shivakumar 2006; Novy-Marx 2015).

We divide our sample into two groups: report date of quarterly earnings (RDQ) versus non-RDQ. We use the RDQ to identify the real-time fundamental information available to investors to better match trading data and available fundamental information. If the earnings announcements occur in the formation month, then the observation for a stock belongs to the RDQ subsample.

Panel C in Exhibit 5 reports the results. In the RDQ subsample, the relative-strength strategy experiences a monthly raw return of 1.54% (t-value = 5.98). In contrast, the return is 2.61% (t-value = 12.29) in the non-RDQ subsample. These results indicate that the arrival of public fundamental information appears to have weakening effect on the DSI strategy, and investors can harvest higher profits when there is no scheduled release of public financial information.

Alternative Measures of Past Intermediate-Term Returns

In the main analysis, we rely on the past 11-month cumulative returns to measure the intermediate-term price information. Here we examine whether similar results are obtained when different intermediate-term returns are used. For example, Cheng et al. (2017) found that short-term reversals are stronger among past three-month losers. Novy-Marx (2012) showed that intermediate-term past performance (t - 7 to t - 12) contains more predictive information than recent past performance (t - 2 to t - 6). We construct our alternative relative-strength measure by deducting these alternative intermediate-term returns from past one-month return.

Panel D in Exhibit 5 reports the results. The average monthly raw return of the long–short DSI portfolio is 1.49%, 2.14%, and 1.70% for lagged three-month returns (t - 2, t - 4), recent past performance (t - 2 to t - 6), and intermediate-term past performance (t - 7 to t - 12), respectively. Overall, the relative strength strategy generates consistent profits based on alternative intermediate-term returns, though the lagged past 11-month returns seem best. One potential explanation is that the past 11-month returns contain more information.

E x h i b i t 5: Robustness Tests

Panel A: Subperiods

	1967–1989			1990–2000			2001–2017		
DSI	**Raw**	**FF4**	**FF3MR**	**Raw**	**FF4**	**FF3MR**	**Raw**	**FF4**	**FF3MR**
Low	2.05	0.90	0.35	2.50	1.17	0.57	1.03	0.24	–0.09
2	1.73	0.69	0.24	1.87	0.56	0.26	1.04	0.27	0.13
3	1.53	0.48	0.12	1.47	0.21	0.16	1.05	0.33	0.21
4	1.45	0.45	0.18	1.30	0.05	0.14	0.99	0.36	0.22
5	1.56	0.51	0.43	1.18	–0.03	0.23	0.98	0.32	0.23
6	1.04	–0.09	–0.07	0.85	–0.40	–0.02	0.83	0.14	0.07
7	0.92	–0.28	–0.16	0.81	–0.42	0.01	0.81	0.11	0.05
8	0.68	–0.57	–0.32	0.58	–0.71	–0.18	0.68	–0.11	–0.12
9	0.39	–0.98	–0.50	0.30	–0.98	–0.32	0.50	–0.37	–0.31
High	–0.87	–2.30	–1.63	–0.61	–1.76	–1.10	–0.15	–1.16	–0.98
Low–High	2.92	3.20	1.97	3.11	2.93	1.67	1.19	1.39	0.89
	(14.32)	(11.77)	(13.46)	(6.71)	(7.86)	(6.16)	(3.02)	(4.46)	(4.06)

Panel B: January vs. Non-January

	January			February–December		
DSI	**Raw**	**FF4**	**FF3MR**	**Raw**	**FF4**	**FF3MR**
Low	3.01	1.19	1.31	1.68	0.66	0.18
2	2.56	0.54	0.62	1.42	0.46	0.16
3	2.35	0.26	0.30	1.25	0.36	0.12
4	2.19	0.11	0.16	1.16	0.33	0.14
5	2.30	0.11	0.22	1.06	0.18	0.13
6	2.32	0.18	0.19	0.81	–0.09	–0.09
7	2.59	0.28	0.34	0.71	–0.20	–0.15
8	2.44	–0.04	–0.06	0.51	–0.45	–0.31
9	2.66	0.03	0.04	0.22	–0.79	–0.46
High	1.93	–0.82	–0.81	–0.77	–1.82	–1.33
Low–High	1.08	2.01	2.12	2.45	2.48	1.51
	(1.47)	(3.38)	(2.45)	(11.24)	(11.66)	(10.58)

Panel C: RDQ vs. Non-RDQ

	RDQ			Non-RDQ		
DSI	**Raw**	**FF4**	**FF3MR**	**Raw**	**FF4**	**FF3MR**
Low	1.47	0.40	0.08	1.84	0.75	0.26
2	1.29	0.25	–0.01	1.52	0.47	0.19
3	1.30	0.33	0.16	1.36	0.35	0.12
4	1.09	0.20	0.01	1.26	0.33	0.14
5	1.39	0.32	0.32	1.11	0.13	0.09
6	1.00	–0.01	–0.03	0.87	–0.12	–0.15
7	0.98	0.01	0.00	0.76	–0.28	–0.23
8	0.89	–0.02	–0.08	0.53	–0.57	–0.45
9	0.70	–0.44	–0.12	0.28	–0.86	–0.61
High	–0.08	–1.17	–0.84	–0.78	–1.93	–1.51
Low–High	1.54	1.57	0.92	2.61	2.68	1.77
	(5.98)	(6.26)	(4.42)	(12.29)	(12.13)	(11.87)

Panel D: Alternative Measures of Past Intermediate-Term Returns

	MOM ($t-4$, $t-2$)			MOM ($t-7$, $t-2$)			MOM ($t-12$, $t-7$)		
DSI	**Raw**	**FF4**	**FF3MR**	**Raw**	**FF4**	**FF3MR**	**Raw**	**FF4**	**FF3MR**
Low	1.36	0.24	–0.03	1.71	0.65	0.23	1.63	0.38	0.20
2	1.25	0.20	–0.04	1.34	0.31	0.02	1.48	0.37	0.22
3	1.20	0.18	0.02	1.26	0.28	0.03	1.37	0.31	0.19
4	1.20	0.19	0.10	1.21	0.26	0.08	1.31	0.30	0.23
5	1.16	0.19	0.09	1.14	0.21	0.08	1.14	0.19	0.13
6	1.14	0.15	0.08	1.10	0.13	0.07	0.96	–0.02	–0.04
7	1.12	0.12	0.10	0.94	–0.07	–0.07	0.87	–0.11	–0.09
8	0.99	–0.05	–0.03	0.92	–0.12	–0.06	0.73	–0.25	–0.20
9	0.77	–0.35	–0.19	0.60	–0.57	–0.33	0.51	–0.48	–0.40
High	–0.13	–1.24	–0.98	–0.43	–1.58	–1.23	–0.07	–1.07	–0.86
Low–High	1.49	1.47	0.95	2.14	2.23	1.46	1.70	1.45	1.06
	(10.56)	(9.38)	(6.69)	(11.74)	(12.36)	(9.78)	(9.36)	(8.63)	(7.2)

Notes: Panel A reports the average monthly raw and factor-adjusted returns to the long–short portfolio based on the relative strength over short and intermediate horizons (DSI) in three subperiods. Panel B reports the returns in January and non-January subsamples. Panel C reports the returns in RDQ and non-RDQ subsamples. If the earnings announcements occur in the formation month, then the observation for a stock belongs to the RDQ subsample. Panel D reports the returns when intermediate-term returns are measured in different lengths. The sample period is from 1967 to 2017. Newey and West (1987) adjusted t-statistics are reported in parentheses.

LONG-TERM PERFORMANCE

In this section, we track the average portfolio returns in each of the 12 months following the formation month. This event-time analysis provides insights about the persistence of the relative-strength strategy.

Exhibit 6 reports the average monthly raw returns for long, short, and long–short portfolios. First, the lowest DSI portfolio generates large and positive returns in the subsequent one year. Moreover, the positive returns decrease over time. Second, the highest DSI portfolio generates significantly lower returns than the lowest DSI portfolio in the first half year. Moreover, the returns of the highest DSI portfolio increase over time. Last, the DSI strategy performs well in the first half year after the formation period. Overall, the superior performance of the DSI strategy is quite persistent in the first half year, suggesting that the momentum component in the DSI dominates the short-term reversal component.

E x h i b i t 6: Relative Strength vs. Short-Term Reversal vs. Momentum in Event Time

	DSI				Short-Term Reversal				Momentum			
Month	Long	Short	Long–Short	*t*-Stat	Long	Short	Long–Short	*t*-Stat	Long	Short	Long–Short	*t*-Stat
1	1.79	–0.55	2.34	(11.23)	1.55	0.50	1.06	(5.92)	1.65	0.54	1.10	(4.51)
2	1.53	0.06	1.47	(8.14)	0.76	1.05	–0.28	(–1.80)	1.73	0.22	1.50	(6.34)
3	1.34	0.42	0.92	(4.80)	0.59	1.23	–0.63	(–4.48)	1.59	0.23	1.36	(5.92)
4	1.30	0.41	0.89	(4.34)	0.66	1.10	–0.44	(–3.54)	1.41	0.38	1.03	(4.52)
5	1.21	0.53	0.68	(3.55)	0.69	1.13	–0.44	(–3.31)	1.34	0.43	0.92	(4.05)
6	1.10	0.72	0.39	(2.20)	0.61	1.24	–0.63	(–3.72)	1.24	0.52	0.72	(3.28)
7	1.02	0.77	0.26	(1.27)	0.71	1.15	–0.44	(–3.19)	1.10	0.61	0.48	(2.33)
8	0.97	0.80	0.17	(0.99)	0.76	1.13	–0.37	(–2.61)	1.07	0.69	0.38	(1.82)
9	0.93	0.94	0.00	(–0.01)	0.73	1.19	–0.46	(–2.78)	0.94	0.74	0.20	(1.03)
10	0.92	0.88	0.04	(0.26)	0.83	1.12	–0.28	(–1.90)	0.93	0.90	0.02	(0.12)
11	0.81	1.14	–0.33	(–2.11)	0.62	1.22	–0.59	(–4.42)	0.84	0.92	–0.08	(–0.47)
12	0.69	1.17	–0.48	(–2.94)	0.55	1.26	–0.71	(–4.54)	0.77	1.04	–0.26	(–1.57)

Notes: This exhibit presents the average monthly raw returns to relative strength over short and intermediate horizons (DSI), simple short-term reversal, and simple price momentum strategies in each month following the formation month. The simple short-term reversal strategy buys recent losers in the bottom decile and sells recent winners in the top decile based on the past one-month returns. The simple price momentum strategy buys winners in the top decile and sells losers in the bottom decile based on their past 11-month cumulative returns. The sample period is from January 1967 to December 2017. Newey and West (1987) adjusted t-statistics are reported in parentheses.

RELATIVE STRENGTH VERSUS SHORT-TERM REVERSAL VERSUS MOMENTUM

In this section, we explicitly compare relative strength over short and intermediate horizons with its two components (short-term reversal and momentum). We track the average portfolio returns in each of the 12 months following the formation month for these three return-based strategies. This event-time analysis provides insights about their differences.

Exhibit 6 reports the results. The simple short-term reversal and momentum strategies exhibit expected return patterns, consistent with previous studies. The relative-strength strategy, however, outperforms a simple sum of traditional short-term reversal and momentum strategies after the formation period. For example, the relative strength strategy has a monthly raw return of 2.34%, compared with 1.06% and 1.10% for short-term reversal and momentum, respectively. The combination of simple short-term reversal and momentum cannot explain relative strength over investment horizons. This finding suggests the superiority of the relative strength strategy over simple short-term reversal and momentum strategies.

PERFORMANCE EVALUATION OF RELATIVE STRENGTH STRATEGY

In this section, we evaluate the relative-strength strategy based on some risk measures. In Panel A in Exhibit 7, we compare the simple relative strategy, the DSI strategy with a holding period of two months, and the simple momentum strategy. The results show that the relative strategies have higher mean returns, lower volatility, and higher Sharpe ratios than the simple momentum strategy.

Panel B shows the performance of the three strategies in the 20 worst months. There are two main findings. First, to some extent, the relative-strength strategy (DSI) is similar to the simple price momentum strategy, so the DSI strategy also experiences dramatic losses in some months. Second, because the DSI strategy considers the information in short-term returns, its losses in crash periods are smaller than the losses of the simple momentum strategy. This finding suggests that short-term reversal is a good hedge to the price momentum strategy.

E x h i b i t 7: Performance Evaluation of Relative Strength Strategy

Panel A: Performance Statistics

	Mean Return	Standard Deviation	Skewness	Kurtosis	Sharpe Ratio
DSI (1)	2.34	4.86	–0.26	7.58	0.48
DSI (2)	1.91	4.52	0.00	7.82	0.42
Momentum	1.50	5.79	–0.60	7.46	0.30

Panel B: 20 Worst Performances

	DSI (1)				DSI (2)				Momentum		
Date	Long	Short	L–S	Date	Long	Short	L–S	Date	Long	Short	L–S
April 2009	–1.75	27.47	–29.22	April 2009	1.81	25.82	–24.01	April 2009	4.55	39.35	–34.81
April 2000	–22.98	–5.03	–17.96	November 2000	–24.73	–7.86	–16.87	January 2001	1.09	34.40	–33.31
January 2001	3.39	20.59	–17.19	May 2000	–17.46	–1.04	–16.43	April 2000	–23.07	–4.64	–18.43
May 2000	–16.62	–0.70	–15.92	November 2002	5.09	19.97	–14.89	November 2002	4.04	21.28	–17.24
November 2002	4.27	20.14	–15.87	January 2001	6.30	20.65	–14.35	January 1975	15.11	32.13	–17.02
November 2000	–23.65	–7.81	–15.85	September 2008	–19.63	–7.34	–12.29	September 1970	7.65	24.13	–16.47
September 2008	–17.98	–7.56	–10.42	April 2000	–21.82	–9.64	–12.18	January 2008	–13.00	1.83	–14.82
January 2008	–12.16	2.21	–9.96	January 2008	–12.27	–1.15	–11.12	July 1973	7.14	21.36	–14.23
January 1975	14.97	24.92	–9.95	January 1975	15.36	25.96	–10.60	January 1974	1.78	15.98	–14.20
January 1971	5.96	15.76	–9.80	October 2001	6.19	15.42	–9.23	March 2000	–10.26	3.75	–14.01
November 2001	5.28	15.04	–9.76	July 2000	–10.60	–1.70	–8.90	May 2000	–16.95	–2.95	–13.99
August 2009	–0.39	7.95	–8.34	January 1971	6.88	15.65	–8.77	October 2001	7.46	21.34	–13.88
August 2008	–2.56	5.76	–8.32	January 1974	2.57	11.24	–8.68	November 2001	4.51	18.30	–13.79
July 1973	9.29	17.03	–7.74	May 2005	6.85	14.82	–7.97	May 2009	0.88	13.91	–13.03
April 2015	–3.52	4.05	–7.57	July 1973	10.02	17.73	–7.72	October 1978	–28.19	–15.30	–12.90
May 2005	7.31	14.86	–7.55	August 2008	–2.02	5.52	–7.54	January 1971	6.93	18.54	–11.61
September 1970	10.24	17.06	–6.82	November 2001	6.81	14.04	–7.23	August 2009	–1.07	9.89	–10.96
May 2009	0.72	7.42	–6.70	April 2015	–3.57	3.49	–7.06	October 1969	6.83	17.67	–10.84
April 2016	0.58	7.17	–6.59	August 2009	–0.60	6.40	–6.99	July 2000	–10.61	0.12	–10.74
July 2000	–10.82	–4.24	–6.58	May 2009	0.31	7.28	–6.98	November 2000	–24.49	–13.99	–10.50

Notes: Panel A reports the average monthly returns, monthly standard deviation, skewness, kurtosis, and monthly Sharpe ratios for the relative-strength strategies (DSI) and simple momentum strategy. DSI (1) is the relative strength strategy with a one-month holding period; DSI (2) is the relative strength strategy with a two-month holding period. The portfolio in DSI (2) is rebalanced monthly. The sample period is from 1967 to 2017. Panel B reports the worst 20 performances of the long leg, the short leg, and the long–short portfolio of the relative strength strategies and simple price momentum strategy during 1967 to 2017. Returns are in percentage.

An unreported table shows that the relative strategy experiences a loss greater than 20% (i.e., -29% in April 2009) only in 1 month among 611 from 1967 to 2017, a loss between 10% and 20% in 6 months, a loss between 6% and 10% in 15 months, and a loss between 4% to 6% in 16 months. Overall, the relative-strength strategy performs much better than the traditional momentum strategy in terms of crash risk. The main drawdowns for the DSI strategy happen during the financial crisis in 2009: The drawdown reaches up to 50% in the financial crisis period of August 2009 to January 2010, though in reality investors could adopt a risk-managed relative strength strategy to avoid the large drawdown.

CONCLUSION

In this article, we propose a simple and novel measure of relative strength over investment horizons that incorporates short- and intermediate-horizon price information. This measure compares the short-term and intermediate-term price trends. Our relative-strength strategy can generate an average unadjusted monthly return of 2.34%. Moreover, the relative-strength strategy performs better than the combination of simple short-term reversal and momentum strategies, suggesting that synthesizing the short- and intermediate-horizon price information yields more incremental information.

The superior performance of the relative-strength strategy is robust to various factor models, wellknown return determinants, and market conditions. The strategy generates economically and statistically significant profits even in the recent decade, outperforming other well-known capital market anomalies. We view the success of the DSI strategy as a manifestation of investor conservatism. We show that investors benefit from trading in the direction of longer-term price trend but against the direction of the near-term price trend, which is consistent with the notion that investors tend to underweight recent information. Moreover, the performance of the DSI strategy is quite persistent in the short horizon. Our future research will be directed toward discovering additional evidence regarding the relation between the DSI anomaly and investor behavior, such as by using data from various international markets.

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Additional Reading

The Interaction of Short-Term Reversal and Momentum Strategies. Zhaobo Zhu and Kenneth Yung

The Journal of Portfolio Management https://jpm.pm-research.com/content/42/4/96

ABSTRACT: *This article investigates the interaction between short-term reversal and momentum strategies. The authors find that the magnitude of price reversals of short-term winners and losers is significantly related to past medium-term performance. Both past medium-term winners and losers with the best short-term performance experience the strongest price continuation. Short-term reversal strategies perform best in the momentum-loser quintile, and momentum strategies perform best in the short-term-winner quintile. The authors' results imply that investors could achieve higher momentum profits by also considering short-term performance and vice versa. The results also suggest that investors adhere to prior dominant beliefs in the face of new* *contradictory information. Short squeezes and fire sales (self-attribution bias) may explain the continued underperformance (outperformance) of momentum losers (winners) with good short-term performance.*

Factor Momentum Everywhere. Tarun Gupta and Bryan Kelly

The Journal of Portfolio Management https://jpm.pm-research.com/content/45/3/13

ABSTRACT: *In this article, the authors document robust momentum behavior in a large collection of 65 widely studied characteristic-based equity factors around the globe. They show that, in general, individual factors can be reliably timed based on their own recent performance. A time-series factor momentum portfolio that combines timing strategies of all factors earns an annual Sharpe ratio of 0.84. Factor momentum adds significant incremental performance to investment strategies that employ traditional momentum, industry momentum, value, and other commonly studied factors. The results demonstrate that the momentum phenomenon is driven in large part by persistence in common return factors and not solely by persistence in idiosyncratic stock performance.*

Fact, Fiction, and Momentum Investing. Clifford Asness, Andrea Frazzini, Ronen Israel, and Tobias Moskowitz

The Journal of Portfolio Management **https://jpm.pm-research.com/content/40/5/75**

ABSTRACT: *It's been more than 20 years since the academic discovery of momentum investing, yet much confusion and debate remains regarding its efficacy and its use as a practical investment tool. In some cases "confusion and debate" is our attempting to be polite, because it is nearly impossible for informed practitioners and academics to still believe some of the myths uttered about momentum—but that impossibility is often belied by real-world statements. In this article, the authors aim to clear up much of the confusion by documenting what we know about momentum and disproving many of the often-repeated myths. They highlight 10 myths about momentum and refute them, using results from widely circulated academic papers and analysis from simple publicly available data.*