Firm-specific versus systematic momentum

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Abstract

We revisit prior findings that the profitability of stock momentum strategies is driven by factor momentum and present evidence to the contrary. We decompose stock returns into a systematic and a firm-specific component and show that momentum in firm-specific returns drives stock momentum. Our results are robust to using several prominent factor models for return decomposition. Momentum profits remain largely unaffected when restricting the investment universe to stocks with inconspicuous factor loadings. Overall, our results suggest that individual stock momentum and factor momentum are largely independent of each other and thus warrant separate explanations.

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1. Introduction

Stock momentum (e.g., Jegadeesh and Titman, 1993) appears to be at odds with the weakest form of market efficiency, according to which future returns should not be predictable based on historical price movements. Since prominent factor models fail to explain momentum profits, behavioral explanations have been proposed. However, it is known that momentum also exists in the cross-section of characteristics-sorted portfolios that contain a large number of stocks and, as noted by Lewellen (2002), biased reactions to firm-specific news arguably cannot explain momentum as a portfolio-level phenomenon. Against this background, Ehsani and Linnainmaa (2022) propose an alternative explanation for the existence of stock momentum: They find that momentum originates at the level of equity risk factors and that this *factor momentum* transmits into the cross-section of stock returns.

In this paper, we present results that are difficult to reconcile with stock momentum arising from factor momentum. We consistently find that stock momentum is driven by momentum in *firm-specific* returns and that its performance does not hinge on the timing of autocorrelated factors. Overall, our results suggest that stock momentum and factor momentum are largely independent of each other, and thus separate explanations for their existence are required.

First, we investigate the performance of stock-level and factor-level strategies, using a formation period of month $t-1$ ("short-term") or months $t-12$ to $t-2$ ("medium-term"), and a holding period of one month. Our sample consists of monthly U.S. stock returns from CRSP and annual accounting information from Compustat over the period of July 1963 to December 2019. To implement factor momentum, we use data on 133 anomaly portfolios analyzed by Hou et al. (2020). We find a striking discrepancy at the one-month horizon, where short-term reversal in individual stocks (e.g., Jegadeesh, 1990; Lehmann, 1990) contrasts with short-term factor momentum.

Next, to empirically test the transmission mechanism proposed by Ehsani and Linnainmaa (2022), we sort portfolios by systematic and idiosyncratic stock returns. We estimate Fama and French (2015) five-factor model betas on a rolling basis and compute expected (i.e., systematic) returns. Firm-specific (i.e., idiosyncratic) returns then correspond to the difference between total (excess) returns and expected returns. If stock momentum is caused by factor momentum, systematic returns should be a better predictor for future performance than idiosyncratic returns, yet we find the exact opposite: Over a medium-term formation period, systematic returns are not informative about future performance, while idiosyncratic returns are. Using several widely-used factor models for return decomposition, we obtain qualitatively similar results.

Finally, we split our sample into two subsamples. The first subsample includes all stock-months with very large (> 80th percentile) or very small (< 20th percentile) loadings on at least one of the five Fama and French (2015) factors. The second subsample consists of all remaining observations. If factor momentum drives stock momentum, we would expect momentum profits to be higher, when there is large variation in stocks' betas. However, we find that momentum profits in the two subsamples are quite similar.

We contribute to the literature on factor momentum (Gupta and Kelly, 2019; Ehsani and Linnainmaa, 2022; Arnott et al., 2023), by showing that stock momentum is driven by momentum in firm-specific returns and that the dispersion in betas does not affect momentum performance. Our finding that a larger fluctuation in the factor loadings of a momentum strategy does not necessarily imply better performance also contributes to a literature that examines the time varying risk exposures of momentum strategies (Grundy and Martin, 2001; Wang and Wu, 2011; Daniel and Moskowitz, 2016) as well as to the literature that analyzes the profitability of idiosyncratic momentum and short-term reversal (Gutierrez and Prinsky, 2007; Blitz et al., 2011; Da et al., 2011, 2014).

The remainder of the paper is organized as follows: Section 2 describes our data, Section 3 investigates return-based strategies using individual stocks and factor portfolios, Section 4 analyzes portfolio sorts by systematic and idiosyncratic returns, Section 5 examines the relationship between momentum profits and dispersion in betas, and Section 6 concludes.

2. Data and factor construction

We merge monthly U.S. stock returns from CRSP with annual accounting information from Compustat. We collect data for all NYSE, AMEX, and Nasdaq securities listed as ordinary common stock any time during the sample period from July 1963 to December 2019. Following Hou et al. (2020), we exclude financial firms (SIC code starting with "6") and firms with negative book equity. To avoid a look-ahead bias, we lag Compustat accounting information by six months, such that year-end figures become available at the end of June of next year (Fama and French, 1992). We use CSRP delisting returns. If delisting returns are missing and the delisting is performance-related, we set them to -30% (Shumway, 1997; Beaver et al., 2007). We retrieve factor returns of the Fama and French (1993, 2015) three- and five-factor models from Ken French's webpage.[1] Stambaugh and Yuan (2017) mispricing factors are obtained from Robert Stambaugh's webpage.[2] Hou et al. (2021) augmented q-model factors are taken from

[1] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[2] http://finance.wharton.upenn.edu/~stambaug/

the global-q data library.[3] From the latter source, we also collect returns for 186 anomaly portfolios analyzed in Hou et al. (2020), covering the period from January 1967 to December 2019.[4] We exclude 53 anomalies that are based on past returns and thus are mechanically related to momentum strategies, leaving a total of 133 anomalies.[5] Finally, we construct factors from these anomaly portfolios by taking the average return of the two small-cap and large-cap portfolios, which rank "high" (> 80th percentile) in the anomaly variable and deducting it from the average return of the two small-cap and large-cap portfolios, which rank "low" (< 20th percentile) in the anomaly variable.

3. Return-based strategies using individual stocks and factor portfolios

To implement stock momentum, we rank stocks in our sample each month according to their past returns over the last year, skipping the month before the ranking ($r_{t-12,t-2}$). To implement short-term reversal, we rank stocks according to their returns in the last month (r_{t-1}). Stocks are then sorted into value-weighted or equal-weighted quintile portfolios. In the value-weighted specification, we use NYSE breakpoints and compute value-weighted average returns for each quintile, using stocks' lagged market equity. In the equal-weighted specification, we use unconditional breakpoints. To compute strategy returns, we go long (short) the top (bottom) quintile portfolio for the current month, with monthly rebalancing.

Panel A of Table 1 reports the results. The value-weighted momentum (short-term reversal) strategy achieves a statistically significant monthly return of 0.66% (-0.34%). After adjusting for exposure to the Fama and French (2015) factors, momentum returns increase, whereas short-term reversal returns become smaller and statistically insignificant. In the equal-weighted setup, momentum (short-term reversal) performance amounts to 0.85%. (-1.55%) per month, with a statistically significant alpha.[6]

Next, we analyze momentum in 133 long-short factor portfolios, constructed from Hou et al. (2020) anomaly data. We rank factors according to their past short-term (r_{t-1}), or medium-term ($r_{t-12,t-2}$) return and make an equal-weighted long (short) investment into the 20% of factors with the best (worst) performance. Long and short portfolios are rescaled to unit leverage and rebalanced on a monthly basis. In addition, we analyze a simple strategy that

[3] http://global-q.org/index.html
[4] The set of anomaly portfolios we use in our study was released in April 2021.
[5] Similar to Arnott et al. (2023), we exclude 41 anomalies listed in the momentum category, eight seasonality measures, three measures related to long-term reversal, and one measure related to short-term reversal.
[6] We report short-term reversal returns with a negative sign for analytical reasons. Of course, by switching the long and short positions, we get an equivalent positive return.

invests in the size (SMB), value (HML), profitability (RMW), and investment (CMA) factors of Fama and French (2015), going long (short) the two best (worst) performing factors.

Results are reported in Panel B of Table 1. Using a short-term (medium-term) formation period, the first and broader factor momentum strategy yields 1.09% (0.65%) per month, while the simple strategy that invests in a small set of only four factors yields 0.63% (0.23%). In each case, the Fama and French (2015) alphas exceed the raw returns.

In stark contrast to the short-term reversal found in individual stocks, factor momentum thus exhibits positive returns over *both* formation periods, with the short-term strategies consistently being more profitable than the medium-term strategies.

4. Portfolio sorts by systematic and idiosyncratic returns

4.1. Return decomposition and baseline results

Next, we decompose stock returns into a systematic and an idiosyncratic component, where the former represents the expected return, given stocks' current factor loadings, and the latter represents the firm-specific return that is unexplained by factor loadings. We estimate firms' loadings $\hat{\beta}_{i,t}^{f}$ against the $F = 5$ factors of Fama and French (2015), using a five-year rolling period from month $t-60$ to $t-1$. Each beta estimate is based on at least 36 past-return observations. Systematic and idiosyncratic returns are computed as follows:

Short-term systematic returns: $$\hat{r}_{i,t-1} = \sum_{f=1}^{F} \hat{\beta}_{i,t}^{f} r_{t-1}^{f} \tag{1}$$

Short-term idiosyncratic returns: $$\hat{\varepsilon}_{i,t-1} = r_{i,t-1}^{e} - \hat{r}_{i,t-1} \tag{2}$$

Medium-term systematic returns: $$\hat{r}_{i,t-12,t-2} = \sum_{j=-12}^{-2} \hat{r}_{i,t-j} \tag{3}$$

Medium-term idiosyncratic returns: $$\hat{\varepsilon}_{i,t-12,t-2} = \sum_{j=-12}^{-2} r_{i,t-j}^{e} - \hat{r}_{i,t-j}\ , \tag{4}$$

where $r_{i,t}^{e}$ are monthly stock returns in excess of the risk-free rate and r_{t}^{f} denotes monthly factor premia. We rank stocks by one of the return measures defined in Equations (1) to (4) each month, sort them into value-weighted quintile portfolios and invest long (short) in the top (bottom) quintile portfolio for the subsequent month.

Table 2 reports the returns of the quintile portfolios and of the high-low quintile strategies. Sorting by short-term idiosyncratic returns ($\hat{\varepsilon}_{i,t-1}$) delivers a statistically significant short-term reversal return of -0.78% per month, which is more than twice as large compared to the conventional value-weighted short-term reversal strategy analyzed in Table 1. In contrast, sorting by short-term systematic returns ($\hat{r}_{i,t-1}$) results in a statistically significant *positive* return of 0.38%. Sorting by medium-term idiosyncratic returns ($\hat{\varepsilon}_{i,t-12,t-2}$) yields a statistically significant return of 0.57%, which is only slightly smaller than the 0.66% return of the conventional value-weighted momentum strategy in Table 1. When we instead sort by medium-term systematic returns ($\hat{r}_{i,t-12,t-2}$), the return of 0.20% is statistically insignificant. Results are qualitatively identical for the five-factor model alphas.[7] Figure 1 tracks the cumulative performance of a \$1 investment into the (value-weighted) individual-stock strategies analyzed in Tables 1 and 2.

The finding of statistically insignificant returns and alphas when we sort by medium-term systematic returns is noteworthy: If stock momentum is caused by factor momentum, we would expect positive predictability for exactly this measure. However, this is not what we find. To the contrary, sorting by medium-term idiosyncratic returns largely captures the performance of a conventional momentum strategy.

Taken together, these results suggest that stock momentum is not driven by factor momentum, but rather by firm-specific return patterns. More specifically, the results in Table 2 suggest that if there is a spillover from factor momentum to stock momentum, it is limited to a one-month time frame, as evidenced by significant short-term systematic momentum. However, the results in Table 2 also show that this effect is dominated by strong short-term reversal in idiosyncratic returns, leading to an overall negative alpha of the short-term reversal strategy in Table 1.

4.2. Robustness

In this section, we conduct a series of robustness tests. First, we test whether our results are sensitive to the estimation window over which betas are estimated. To this end, we repeat the analysis in Table 2. However, we now estimate the factor exposures using rolling window regressions over months $t-73$ to $t-13$, rather than over months $t-60$ to $t-1$. The estimation results, which are displayed in Panel A of Table 3, are qualitatively similar to those in Table 2.

Second, we test the robustness of our results against the choice of the factor model used for the return decomposition. In particular, we use the CAPM, the Fama and French (1993) three-factor model, the augmented q-factor model of Hou et al. (2021), and the Stambaugh and Yuan (2017) mispricing factor model to derive systematic and idiosyncratic returns. We then re-

[7] For the strategies with a significant positive (negative) performance, portfolio returns increase (decrease) fairly monotonously from Q1 to Q5, making it less likely that the results are spurious (Patton and Timmermann, 2010).

estimate the analysis in Table 2. Results in Panel B of Table 3 show that medium-term systematic returns ($\hat{r}_{i,t-12,t-2}$) consistently lack any return predictability, whereas medium-term idiosyncratic momentum ($\hat{\varepsilon}_{t-12,\mathrm{t}-2}$) returns and alphas are positive and statistically significant for all factor models.

5. Dispersion in betas and momentum performance

In this section, we examine the relationship between momentum profits and the cross-sectional dispersion in betas. The transmission mechanism proposed by Ehsani and Linnainmaa (2022) implies lower (higher) momentum profits when stocks in the investment universe are characterized by similar (widely varying) factor exposures.

To empirically test this hypothesis, we perform a monthly ranking of stocks by their loadings against each of the five Fama and French (2015) factors (i.e., each stock receives five different ranks). We then construct an "extreme-beta" subsample by selecting all stock-months, which rank above the 80^{th} or below the 20^{th} percentiles in terms of their exposures against at least one factor. All remaining observations with non-missing factor loadings are included in the "modest-beta" subsample. We then re-estimate the value-weighted momentum and short-term reversal strategies analyzed in Table 1 within these two subsamples.

Results in Table 4 show that momentum returns are only marginally higher in the "extreme-beta" subsample (0.58%), compared to the "modest-beta" subsample (0.54%). The same holds true for the risk-adjusted returns. In contrast, the performance of the short-term reversal strategies differs substantially across the two subsamples.

In other words, we find that the cross-sectional variation in betas does *not* significantly affect the profitability of stock momentum, even though Figure 2 illustrates that the momentum strategy implemented in the "extreme-beta" subsample displays a much larger variation in its net factor loadings.

6. Conclusion

In this paper, we present evidence at odds with Ehsani and Linnainmaa (2022), who find that the profitability of stock momentum strategies (e.g., Jegadeesh and Titman, 1993) stems from factor momentum. In particular, we show that a momentum strategy based on firm-specific (i.e., idiosyncratic) returns delivers statistically significant outperformance, while a strategy based on expected (i.e., systematic) returns does not. This outcome is the opposite of what we would expect if factor momentum was responsible for stock momentum. Moreover, we find that the cross-sectional dispersion in factor loadings leaves the profitability of stock momentum largely unaffected, which conflicts with factor momentum being its root cause.

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Table 1

Return-based strategies using individual stocks and factor portfolios.

Panel A: Momentum and short-term reversal in individual stocks

Investment universe	Investment rule		Short-term returns (r_{t-1})	Medium-term returns ($r_{t-12,t-2}$)
Individual stocks (value-weighted)	High quintile - Low quintile (Q5-Q1)	$\bar{r}$	**-0.337**	**0.660**
			(-2.19)	(3.05)
		α^{FF5F}	-0.190	**0.755**
			(-1.06)	(2.83)
Individual stocks (equal-weighted)	High quintile - Low quintile (Q5-Q1)	$\bar{r}$	**-1.548**	**0.846**
			(-7.87)	(3.52)
		α^{FF5F}	**-1.518**	**0.765**
			(-5.21)	(2.45)

Panel B: Momentum in long-short factor portfolios

Investment universe	Investment rule		Short-term returns (r_{t-1})	Medium-term returns ($r_{t-12,t-2}$)
Hou et al. (2020) factors (133 in total)	High 20% - Low 20%	$\bar{r}$	**1.085**	**0.652**
			(6.52)	(3.57)
		α^{FF5F}	**1.161**	**0.733**
			(5.86)	(3.33)
Fama-French (2015) SMB, HML, RMW, and CMA	High two - Low two	$\bar{r}$	**0.629**	**0.233**
			(5.51)	(2.00)
		α^{FF5F}	**0.675**	**0.328**
			(4.96)	(2.49)

Panel A of this table shows monthly returns and Fama and French (2015) model alphas of short-term reversal and medium-term momentum strategies using individual stocks. Panel B shows the performance of short-term and medium-term factor momentum strategies. The sample period is July 1966 to December 2019. The starting date for Hou et al. (2020) factor momentum is January 1968. t-values (in parentheses) are based on Newey-West standard errors with three lags. Bold numbers indicate statistical significance at the 5% level or higher.

Table 2

Portfolio sorts by systematic and idiosyncratic returns: Baseline results.

Quintile returns		Idiosyncratic returns		Systematic returns	
		Short-term ($\hat{\varepsilon}_{t-1}$)	Medium-term ($\hat{\varepsilon}_{t-12,\mathrm{t}-2}$)	Short-term ($\hat{r}_{t-1}$)	Medium-term ($\hat{r}_{t-12,\mathrm{t}-2}$)
Q1		1.357	0.635	0.828	0.831
Q2		1.227	0.985	0.930	1.001
Q3		0.926	0.864	1.063	1.064
Q4		0.789	0.926	1.083	1.084
Q5		0.575	1.206	1.211	1.031
Q5-Q1	$\bar{r}$	**-0.783**	**0.571**	**0.383**	0.200
		(-6.13)	(3.24)	(2.19)	(1.00)
	α^{FF5F}	**-0.579**	**0.937**	**0.414**	0.040
		(-4.41)	(5.65)	(2.35)	(0.17)

This table shows monthly returns of quintile portfolios sorted on idiosyncratic or systematic stock returns, as well as the performance of the corresponding high-low quintile strategies. We compute systematic and idiosyncratic returns according to Equations (1)-(4). The sample period is July 1966 to December 2019. t-values (in parentheses) are based on Newey-West standard errors with three lags. Bold numbers indicate statistical significance at the 5% level or higher.

Table 3

Portfolio sorts by systematic and idiosyncratic returns: Robustness.

Panel A: Alternative rolling period

Q5-Q1		Idiosyncratic returns Short-term ($\hat{\varepsilon}_{t-1}$)	Idiosyncratic returns Medium-term ($\hat{\varepsilon}_{t-12,t-2}$)	Systematic returns Short-term ($\hat{r}_{t-1}$)	Systematic returns Medium-term ($\hat{r}_{t-12,t-2}$)
Fama & French (2015) beta estimation from $t-72$ to $t-13$	$\bar{r}$	**-0.730**	**0.476**	**0.570**	0.126
		(-5.62)	(2.74)	(3.56)	(0.74)
	α^{FF5F}	**-0.567**	**0.744**	**0.610**	-0.056
		(-4.14)	(3.94)	(3.72)	(-0.28)

Panel B: Alternative factor models

Q5-Q1		Idiosyncratic returns Short-term ($\hat{\varepsilon}_{t-1}$)	Idiosyncratic returns Medium-term ($\hat{\varepsilon}_{t-12,t-2}$)	Systematic returns Short-term ($\hat{r}_{t-1}$)	Systematic returns Medium-term ($\hat{r}_{t-12,t-2}$)
Market model (CAPM)	$\bar{r}$	**-0.564**	**0.701**	**0.570**	-0.126
		(-3.87)	(3.71)	(2.55)	(-0.50)
	α^{FF5F}	**-0.410**	**0.889**	**0.727**	-0.205
		(-2.36)	(3.87)	(2.93)	(-0.73)
Fama & French (1993) 3-factor model	$\bar{r}$	**-0.758**	**0.537**	**0.539**	0.191
		(-5.87)	(3.11)	(2.69)	(0.93)
	α^{FF5F}	**-0.607**	**0.738**	**0.681**	0.145
		(-4.55)	(3.82)	(3.12)	(0.66)
Hou et al. (2021) 5-factor model	$\bar{r}$	**-0.657**	**0.458**	**0.383**	0.227
		(-5.11)	(2.76)	(2.16)	(1.23)
	α^{FF5F}	**-0.471**	**0.701**	**0.550**	0.198
		(-3.40)	(4.01)	(3.03)	(0.95)
Stambaugh & Yuan (2016) 4-factor model	$\bar{r}$	**-0.690**	**0.496**	**0.476**	0.047
		(-5.48)	(2.65)	(2.50)	(0.23)
	α^{FF5F}	**-0.506**	**0.849**	**0.503**	-0.156
		(-3.49)	(4.10)	(2.50)	(-0.73)

The table presents the results of robustness tests for the high-low quintile strategies analyzed in Table 2. In Panel A, stocks' loadings against the Fama and French (2015) model factors are determined using rolling window regressions over months $t-72$ to $t-13$. In Panel B, we replace the Fama and French (2015) model with several widely-used factor models when computing systematic and idiosyncratic returns. t-values (in parentheses) are based on Newey-West standard errors with three lags. Bold numbers indicate statistical significance at the 5% level or higher.

Table 4

Strategy performance in modest-beta and extreme-beta subsamples.

		"Modest-beta" sample		"Extreme-beta" sample	
		Short-term total returns (r_{t-1})	Medium-term total returns ($r_{t-12,t-2}$)	Short-term total returns (r_{t-1})	Medium-term total returns ($r_{t-12,t-2}$)
Q5-Q1	$\bar{r}$	**-0.821**	**0.544**	**-0.360**	**0.585**
		(-5.45)	(2.83)	(-2.27)	(2.61)
	α^{FF5F}	**-0.637**	**0.642**	-0.181	**0.682**
		(-3.95)	(2.90)	(-1.00)	(2.45)

This table shows the performance of the (value-weighted) individual-stock momentum and short-term reversal strategies analyzed in Table 1, implemented within two different subsamples. The "extreme-beta" subsample is defined as all stock-months, for which at least one of the Fama and French (2015) model factor loadings ranks above the 80th or below the 20th percentile. The "modest-beta" subsample consists of all remaining observations with non-missing factor loadings. The sample period is July 1966 to December 2019. t-values (in parentheses) are based on Newey-West standard errors with three lags. Bold numbers indicate statistical significance at the 5% level or higher.

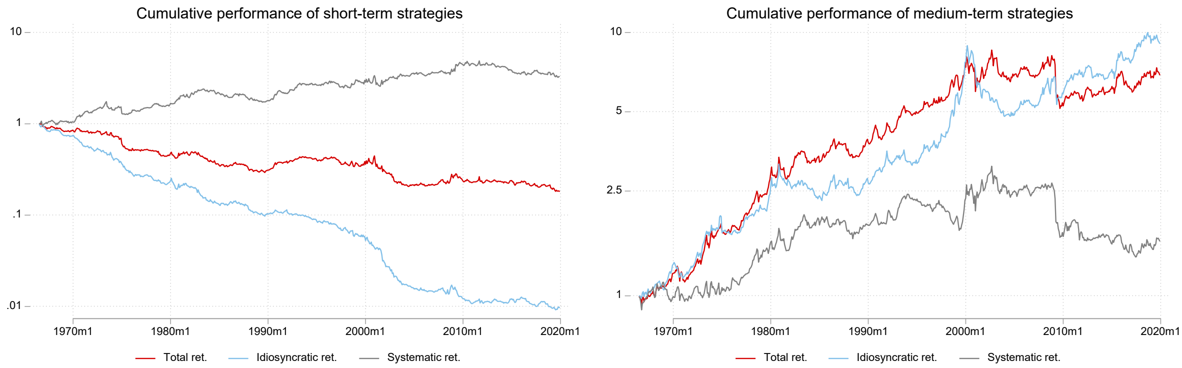

Fig. 1. Cumulative performance of individual-stock investment strategies. This figure shows the performance of a $1 investment into the (value-weighted) individual-stock strategies analyzed in Tables 1 and 2. We adjust the leverage of each strategy to a realized annual volatility of 10%. The y-axis is shown in logarithmic scale. The sample period is July 1966 to December 2019.

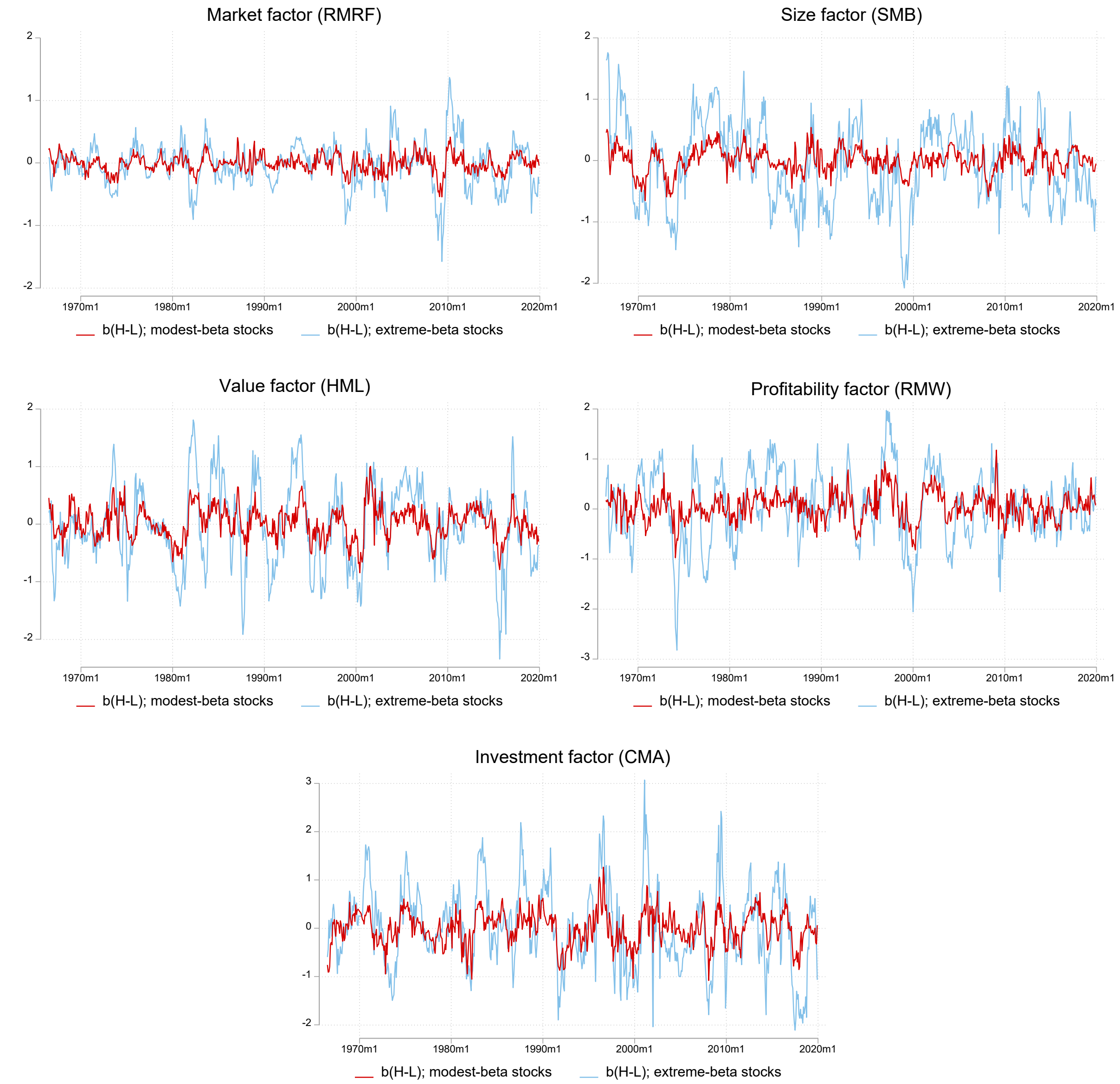

Fig. 2. Factor loadings of momentum in modest-beta and extreme-beta subsamples. This figure shows Fama and French (2015) factor loadings of (value-weighted) momentum strategies, implemented within the "modest-beta" and "extreme-beta" subsamples (see Section 5 and Table 4). We compute the value-weighted average loadings of composite stocks against each factor for the high and low momentum quintiles (β_H and β_L). Net loadings then correspond to $\beta_{H-L} = \beta_H - \beta_L$. The sample period is July 1966 to December 2019.