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Firm-specific versus systematic momentum

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ABSTRACT

We decompose stock returns into a systematic and a firm-specific component and show that the dynamics of the firm-specific return component drive the well-known stock momentum anomaly. Our results are robust to the use of a variety of prominent factor models for return decomposition. Furthermore, we find that momentum profits are largely unaffected when the investment universe is restricted to stocks with inconspicuous factor loadings. Our empirical findings call into question the transmission mechanism from factor momentum to stock momentum proposed in recent research.

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, momentum has been shown to exist 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; henceforth "EL") 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 empirically test the transmission mechanism proposed by EL, whereby factor momentum translates into stock momentum through autocovariance in factors, amplified by the cross-sectional variation in betas.

To this end, we first investigate the performance of stock-level strategies, using a holding period of one month after a formation period over month $t-1$ ("short-term") or months $t-12$ to $t-2$ ("medium-term"). Our sample consists of monthly U.S. stock returns from CRSP over the period of July 1963 to December 2019. We then sort portfolios by systematic and idiosyncratic stock returns. To do so, 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 returns and expected returns. If EL's

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conjecture about the transmission from factor momentum to stock momentum is correct, systematic returns should be a better predictor for future performance than idiosyncratic returns. We, however, find the opposite: Over a medium-term formation period, systematic returns are not informative about future performance, while idiosyncratic returns are. Alternative rolling window periods for beta estimation and variations in the factor model used for return decomposition yield qualitatively similar results. Moreover, we replicate the results of EL, who double-sort by firm size and idiosyncratic returns to construct "UMD-style" residual momentum strategies. In extensions to this replication, we then find that systematic returns also lack outperformance when using this alternative construction method.

Second, 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 the transmission from factor momentum to stock momentum works as EL hypothesize, 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 betas 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 (Wang and Wu, 2011; Daniel and Moskowitz, 2016) and to a literature that analyzes idiosyncratic momentum and short-term reversal (Gutierrez and Prinsky, 2007; Blitz et al., 2011; Da et al., 2011, 2014). Moreover, our paper relates to Grundy and Martin (2001) who conduct a thorough investigation of the risks and rewards of stock momentum, ruling out dynamic factor exposures, industry effects, or persistent cross-sectional differences in expected returns as primary causes of the strategy's profitability.

The remainder of the paper is organized as follows: Section 2 describes the transmission mechanism proposed by EL, Section 3 describes our data, Section 4 presents our analysis and results, and Section 5 concludes.

2. The transmission from factor momentum and idiosyncratic momentum to stock momentum

Consider a stock momentum strategy that chooses investment weights in proportion to stocks' past returns relative to the cross-sectional mean (Lo and MacKinlay, 1990). If stocks' expected returns are generated by some *F*-factor model, EL show that the following relationship holds for the expected performance of this strategy, implemented in a cross-section of *N* stocks:

$$E\left[\pi_t^{mom}\right] = \sum_{f=1}^{F}\left[cov\left(r^f_{-t},\ r^f_t\right)\sigma^2_{\beta_f}\right] + \frac{1}{N}\sum_{i=1}^{N}\left[cov\left(\varepsilon_{i,-t},\ \varepsilon_{i,t}\right)\right] + \sum_{f=1}^{F}\sum_{g\neq f}^{F}\left[cov\left(r^f_{-t},\ r^g_t\right)cov\left(\beta^f,\ \beta^g\right)\right] + \sigma^2_\eta, \tag{1}$$

where r^f_t is the return of factor f in month t, β^f are stocks' loadings towards factor f, $\varepsilon_{i,t}$ are stocks' idiosyncratic returns, η represents stocks' unconditional expected returns and $-t$ refers to the formation period (e.g., months $t-12$ to $t-2$).

Factor momentum may translate into stock momentum via the first term in Eq. (1), i.e., via the multiplication of factor autocorrelations $cov\left(r^f_{-t},\ r^f_t\right)$ with the cross-sectional variance in betas $\sigma^2_{\beta_f}$. This is the channel proposed by EL. To illustrate this transmission mechanism, assume that expected returns are determined by stocks' loadings against a serially uncorrelated market factor and a positively autocorrelated size factor (SMB). Further assume no autocorrelation in firm-specific returns and no persistent differences in unconditional mean returns. If small-cap stocks then outperform large-cap stocks in the past, they will continue to do so in the following months. Stock momentum may arise in this scenario, because stocks with a large positive (negative) SMB loading tend to be sorted into the top (bottom) momentum portfolio. The strength of this channel depends on the cross-sectional dispersion in betas. For example, one would expect a stock momentum strategy to become less profitable if it is restricted to the subsample of large-cap stocks with similar SMB betas. According to EL, it is therefore the *expected* (i.e., systematic) component of stock returns that picks up autocorrelation in factors and drives stock momentum. We empirically test this conjecture by running a horse race between this first component and the second component in Eq. (1), the latter representing idiosyncratic (or firm-specific) momentum. We thus directly test the relative importance of systematic (or factor) versus idiosyncratic momentum.

3. 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 at any time during the sample period from July 1963 to December 2019. Following Hou et al. (2020), we exclude financial firms 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

[1] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 1
Return-based strategies using 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)

This table shows monthly returns and Fama and French (2015) model alphas of short-term reversal and medium-term momentum strategies using individual stocks. 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.

webpage.[2] Hou et al. (2021) augmented q-model factors are taken from the global-q data library.[3]

4. Empirical results

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

To implement the stock momentum strategy, we rank stocks by their returns over the last year, skipping the month before the ranking ($r_{t-12,t-2}$). To test for short-term reversal, we rank stocks by their returns in the last month (r_{t-1}). We then sort stocks into 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.

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.[4]

4.2. Portfolio sorts by systematic and idiosyncratic returns

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 $\widehat{\beta}^{f}_{i,\,t}$ 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:

$$\text{Short} - \text{term systematic returns} : \widehat{r}_{i,t-1} = \sum_{f=1}^{F} \widehat{\beta}^{f}_{i,\,t} r^{f}_{t-1} \tag{2}$$

$$\text{Short} - \text{term idiosyncratic returns} : \widehat{\varepsilon}_{i,t-1} = r^{e}_{i,t-1} - \widehat{r}_{i,t-1} \tag{3}$$

$$\text{Medium} - \text{term systematic returns} : \widehat{r}_{i,t-12,t-2} = \sum_{j=-12}^{-2} \widehat{r}_{i,t-j} \tag{4}$$

$$\text{Medium} - \text{term idiosyncratic returns} : \widehat{\varepsilon}_{i,t-12,t-2} = \sum_{j=-12}^{-2} \left(r^{e}_{i,t-j} - \widehat{r}_{i,t-j} \right) , \tag{5}$$

where $r^{e}_{i,t}$ are monthly stock returns in excess of the risk-free rate and r^{f}_{t} denotes monthly factor premia. We rank stocks by one of the return measures defined in Eqs. (2) to (5) each month, sort them into value-weighted quintile portfolios and invest long (short) in the top (bottom) quintile portfolio for the subsequent month.

[2] http://finance.wharton.upenn.edu/~stambaug/
[3] http://global-q.org/index.html
[4] 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.

Table 2
Portfolio sorts by systematic and idiosyncratic returns: Baseline results.

Quintile returns		Idiosyncratic returns		Systematic returns	
		Short-term ($\widehat{\varepsilon}_{t-1}$)	Medium-term ($\widehat{\varepsilon}_{t-12,t-2}$)	Short-term ($\widehat{r}_{t-1}$)	Medium-term ($\widehat{r}_{t-12,t-2}$)
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 Eqs. (2)-(5). 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.

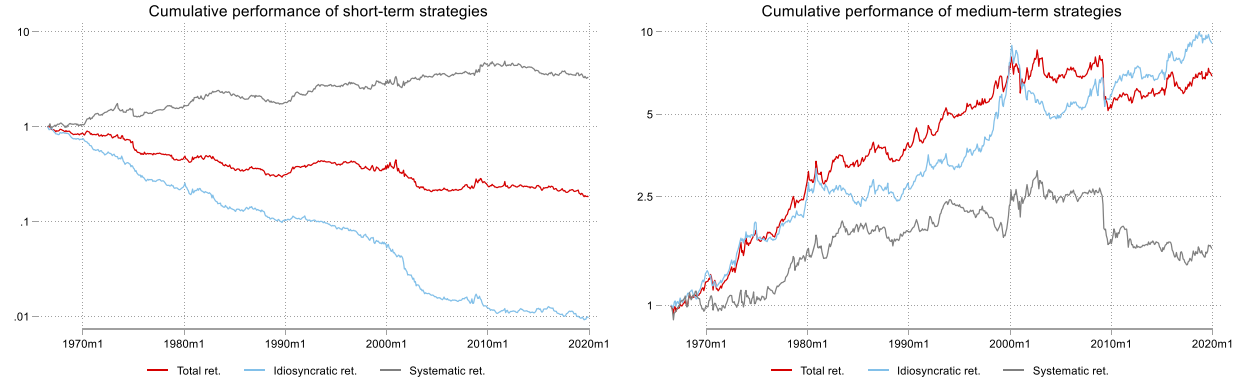

Fig. 1. Cumulative performance of individual-stock investment strategies. This figure shows the performance of a $1 investment into the (value-weighted) individual-stock strategies analyzed in Tables 1 and 2. We adjust the leverage of each strategy to a realized annual volatility of 10 %. The y-axis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

Table 2 reports the returns of the quintile portfolios and of the high-low quintile strategies. Sorting by short-term idiosyncratic returns ($\widehat{\varepsilon}_{i,t-1}$) 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 ($\widehat{r}_{i,t-1}$) results in a statistically significant *positive* return of 0.38 %. Sorting by medium-term idiosyncratic returns ($\widehat{\varepsilon}_{i,t-12,\ t-2}$) 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 ($\widehat{r}_{i,t-12,\ t-2}$), the return of 0.20 % is statistically insignificant. Results are qualitatively identical for the five-factor model alphas.[5] Fig. 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, the results in Table 2 suggest that stock momentum is unlikely to be driven by the transmission mechanism from factor momentum to stock momentum as proposed by EL. Stock momentum rather appears to stem from firm-specific return patterns. 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. Furthermore, Table 2 shows 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.

[5] 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).

Table 3
Portfolio sorts by systematic and idiosyncratic returns: Robustness.

Panel A: Alternative rolling periods					
Q5-Q1		Idiosyncratic returns		Systematic returns	
		Short-term ($\widehat{\varepsilon}_{t-1}$)	Medium-term ($\widehat{\varepsilon}_{t-12,t-2}$)	Short-term ($\widehat{r}_{t-1}$)	Medium-term ($\widehat{r}_{t-12,t-2}$)
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)
Fama & French (2015) beta estimation from t − 36 to t − 1	$\bar{r}$	**-0.694**	**0.513**	0.138	0.321
		(-5.36)	(3.07)	(0.79)	(1.65)
	α^{FF5F}	**-0.483**	**0.852**	0.141	0.230
		(-3.74)	(5.30)	(0.79)	(1.00)
Panel B: Alternative factor models					
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	$\bar{r}$	**-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	$\bar{r}$	**-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 (2017) 4-factor	$\bar{r}$	**-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)

Panel C: UMD-style strategies				
High (SC+LC) - Low (SC+LC)		Estimates from EL (2022) Table 7	Our estimates	
		Idiosyncratic returns	Idiosyncratic returns	Systematic returns
Market model (CAPM)	$\bar{r}$	**0.58**	**0.607**	-0.141
		(4.29)	(4.23)	(-0.77)
Fama & French (1993) 3-factor	$\bar{r}$	**0.44**	**0.478**	0.016
		(3.83)	(3.58)	(0.11)
Fama & French (2015) 5-factor	$\bar{r}$	**0.37**	**0.383**	0.056
		(3.39)	(3.01)	(0.42)

The table presents the results of robustness tests for the strategies analyzed in Table 2. In Panel A, betas against the Fama and French (2015) model factors are determined using rolling window regressions over months $t-72$ to $t-13$ or months $t-36$ to $t-1$. In Panel B, we replace the Fama and French (2015) model with several widely-used factor models when computing systematic and idiosyncratic returns. In the second and third column of Panel C, we implement UMD-style strategies. We form six portfolios by size ($<$ median; $\geq$ median) and past idiosyncratic returns ($<$ P30; $\geq$ P30 & $<$ P70; $\geq$ P70), computed against different factor models over months $t-72$ to $t-13$. We invest long (short) in the best (worst) performing small-cap and large-cap portfolios. The first column shows estimates from Table 7 in Ehsani & Linnainmaa (2022). *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.

4.3. 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 betas using rolling window regressions over months $t-73$ to $t-13$ or months $t-36$ to $t-1$, rather than over months $t-60$ to $t-1$. The results, which are displayed in Panel A of Table 3, are qualitatively similar to those in Table 2.

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

In Table 7 of their paper, EL construct "UMD-style" residual momentum strategies. They interpret the results as evidence for idiosyncratic momentum arising due to "omitted-factor" momentum, since the performance of these strategies decreases when additional factors are added to the factor model used to compute idiosyncratic returns. Comparing our results for the Fama and French

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.

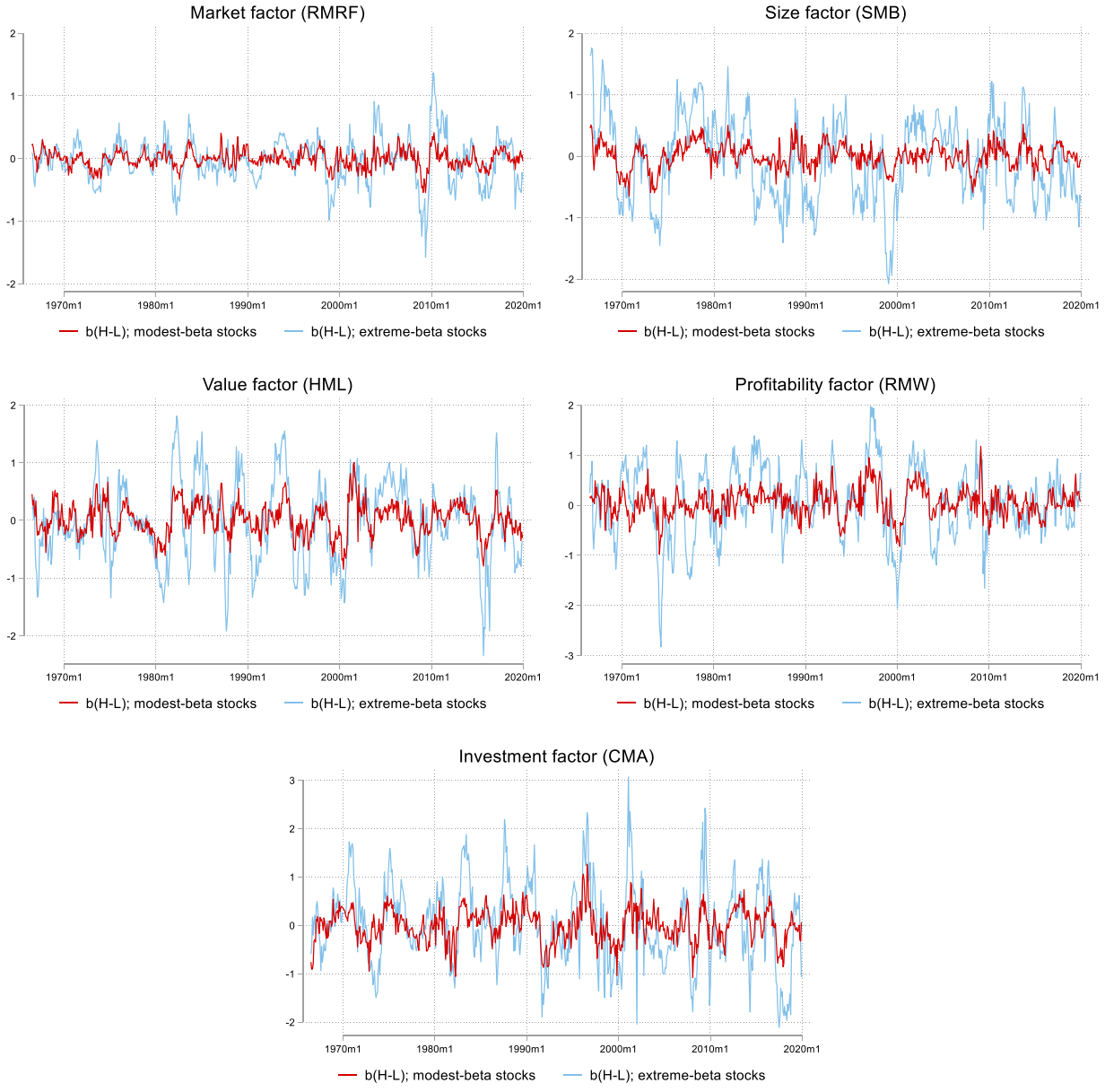

Fig. 2. Factor loadings of momentum in modest-beta and extreme-beta subsamples. This figure shows Fama and French (2015) factor loadings of (value-weighted) momentum strategies, implemented within the "modest-beta" and "extreme-beta" subsamples (see Section 5 and Table 4). We compute the value-weighted 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.

(1993, 2015) three- and five-factor models in Tables 2 and 3, this is not what we find.

To address concerns that the differences between our results and those of EL are due to differences in methodology or sample construction, we replicate their results from Table 7. To this end, we sort stocks into six portfolios by size ($<$ median; $\geq$ median) and past idiosyncratic returns ($<$ P30; $\geq$ P30 & $<$ P70; $\geq$ P70), computed against three different factor models over months $t - 73$ to $t - 13$. We then invest long (short) in the small-cap and large-cap portfolios with the best (worst) performance. Comparing the first two columns in Panel C of Table 3, we find that our estimates for "UMD-style" idiosyncratic momentum are very similar to those of EL. However, the third column shows that "UMD-style" strategies based on *systematic* returns, which are not tested in EL, fail to outperform, which is at odds with the transmission mechanism propagated by EL and suggests that factor momentum may not be the root cause of stock momentum.

4.4. 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 EL 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 80th or below the 20th 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 Fig. 2 illustrates that the momentum strategy implemented in the "extreme-beta" subsample displays a much larger variation in its net factor loadings.

5. Conclusion

EL find that the profitability of stock momentum strategies stems from factor momentum. They explain their finding by aid of a transmission mechanism from factor momentum to stock momentum. In this paper, we empirically test EL's transmission mechanism and present results at odds with it. First, we show that a momentum strategy based on firm-specific (i.e., idiosyncratic) returns yields a 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 drives stock momentum as in EL's transmission mechanism. Second, we find that the cross-sectional dispersion in factor loadings, which should be positively correlated with momentum returns, leaves stock momentum performance largely unaffected. While we do not dispute EL's findings that point to factor momentum being related to stock momentum, our results call into question whether EL's propagated transmission mechanism is responsible for the existence of stock momentum.

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CRediT authorship contribution statement

Frank Graef: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Daniel Hoechle:** Writing – original draft, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Markus Schmid:** Writing – original draft, Visualization, Validation, Supervision, Investigation, Conceptualization.

Data availability

Data will be made available on request.

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