Is factor momentum crash systematic?

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April 2026

A cross-sectional long-short factor momentum portfolio built on 153 U.S. characteristic factors over 1970 through 2024 earns nearly all of its cumulative log return inside five non-overlapping thirty-six-month windows. Every window is followed by a twelve-month reversal of the same sign. The boom-bust pattern is regular. The composition of each boom is not. The factors that lead one window rarely lead another, with pairwise Jaccard overlap of the top-ten contributors bounded by 0.25, and the rolling top-k principal subspace of the factor correlation matrix at these episodes is statistically indistinguishable from the quiet-period reference. Factor momentum crashes are systematic in timing and direction, idiosyncratic in composition and in covariance geometry. A risk lens trained on factor identities or on covariance regimes is unlikely to see them coming.

KEYWORDS factor momentum, momentum crash, regime dependence, principal components, Grassmann distance

1 Setup

We use the monthly value-weighted U.S. factor panel of Jensen et al. (2023): 153 characteristic-sorted long-short portfolios, sign-adjusted so each factor has a nonnegative in-sample mean. The sample runs from January 1970 through December 2024, giving 660 monthly

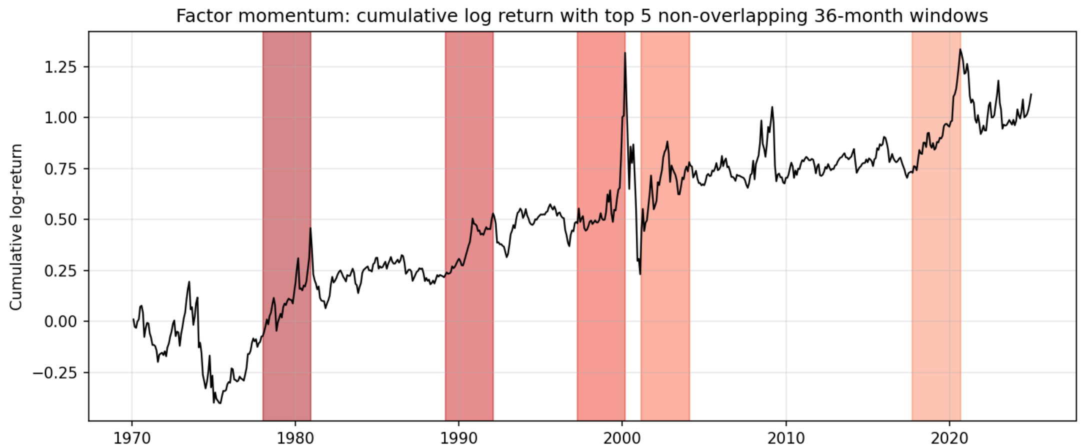

Figure 1. Cumulative log return of a cross-sectional quintile long-short factor momentum strategy formed from 153 U.S. characteristic factors, January 1970 through December 2024. Shaded bands are the five non-overlapping thirty-six-month windows with the highest cumulative log return over the sample.

observations after the signal formation period.

Factor momentum is constructed in the form used by Ehsani and Linnainmaa (2022). For each month t, the signal for factor f is the cumulative log return from month $t-12$ through $t-2$. Factors are ranked cross-sectionally, and the portfolio holds an equally weighted long position in the top quintile and an equally weighted short position in the bottom quintile through month t. The portfolio return in month t is the mean long-leg return minus the mean short-leg return. We require at least thirty factors with complete signal and current-month return.

2 Booms repeat, and each is followed by a reversal

Figure 1 plots the cumulative log return of factor momentum with the five highest non-overlapping thirty-six-month windows shaded. The series is close to a step function: long flat stretches punctuated by sharp ascents. The shaded boom windows together cover 180 months out of 660, or 27 percent of the sample, and contribute 254 percent of the sample's cumulative log return. The 480 months outside the booms produce a Sharpe ratio of -0.20.

Table 1 reports the in-window and post-window cumulative log returns of the factor momentum strategy for each of the five windows. The twelve months that immediately follow every boom are negative. Four of the five windows also post a negative cumulative log return over the subsequent twenty-four months, and for the largest window the reversal in the following year offsets almost the entirety of the boom.

Table 1. Cumulative log return of the factor momentum strategy inside each boom window and in the twelve and twenty-four months that follow.

#	Window	In-window	Post-12m	Post-24m
1	1977-12..1980-11	53%	-37%	-24%
2	1989-02..1992-01	31%	-15%	2%
3	1997-03..2000-02	83%	-87%	-63%
4	2001-02..2004-01	55%	-9%	3%
5	2017-09..2020-08	60%	-36%	-33%

The timing and sign pattern across the five episodes look too regular to be accidental. The question the rest of the note addresses is whether the composition of these booms is equally regular.

3 Compositions do not repeat

For each window we decompose the portfolio return into per-factor contributions:

$$\text{contrib}_{f,w} \;=\; \sum_{t\in w} \big(\omega^{L}_{f,t} - \omega^{S}_{f,t}\big)\, r_{f,t}, \tag{1}$$

where $\omega^{L}_{f,t}$ and $\omega^{S}_{f,t}$ are the long and short leg weights of factor f in month t. Table 2 lists the five largest contributors for three booms spread across the sample.

The three panels barely touch. The 1977–80 boom is carried by a mix of stock-level momentum, volatility characteristics, and dividend yield. The 1997–2000 boom is carried by research intensity, volatility, and valuation multiples, and maps onto the firm characteristics that attracted investor attention during the late 1990s. The 2017–2020 boom is carried almost entirely by valuation multiples and duration, with two profitability factors filling out the top ten.

Table 3 makes the impression quantitative with pairwise Jaccard overlap of top-ten contributors across all five windows. The largest off-diagonal entry is 0.25. Out of the 37 factors that appear in any top-ten list, 26 appear in only one window, 10 appear in two, and only a

Table 2. Top five factor contributors to factor momentum in three boom windows. Contribution is each factor's share of the strategy's log return in the window. Own cum. return is the factor's own cumulative long-short simple return over the thirty-six months.

Factor	Contribution	Own cum. return
Panel A. Window 1: 1977-12..1980-11		
ret_12_1	2.45%	118%
betadown_252d	1.91%	-49%
div12m_me	1.82%	-50%
rvol_21d	1.79%	-45%
ivol_capm_252d	1.78%	-45%
Panel B. Window 3: 1997-03..2000-02		
ni_me	3.16%	-64%
rd_sale	3.13%	202%
rmax5_21d	2.84%	-55%
rd5_at	2.44%	123%
div12m_me	2.41%	-63%
Panel C. Window 5: 2017-09..2020-08		
debt_me	2.32%	-50%
be_me	2.18%	-50%
eq_dur	2.13%	-50%
at_me	1.97%	-51%
bev_mev	1.96%	-50%

single factor (realized volatility, `rvol_21d`) appears in four.

What the windows share is a construction in which momentum was aligned with an episode-specific narrative long enough for that narrative to unwind in the following year. Directional labeling of the individual contributors has to be read with care because many factors rotate between legs within a window and because the relationship between a factor's own return and its contribution to factor momentum depends on how the signal timed those rotations. The aggregate reading is that the twelve-month trend that the signal locks onto is different in each episode.

Table 3. Pairwise Jaccard similarity of the top-ten factor contributors across the five boom windows.

	1	2	3	4	5
1	1.00	0.11	0.18	0.05	0.00
2	0.11	1.00	0.05	0.25	0.00
3	0.18	0.05	1.00	0.18	0.05
4	0.05	0.25	0.18	1.00	0.05
5	0.00	0.00	0.05	0.05	1.00

4 Covariance geometry does not flag the windows

If the boom windows were accompanied by a shift in the factor correlation structure, a rolling principal-component analysis would detect it. For each month t we estimate the sixty-month sample correlation matrix of the 149 factors with complete coverage over the sample, take the top-k eigenvectors, and measure the Grassmann distance to a reference subspace estimated on the 480 quiet-period months, that is, months outside every top-five window. The Grassmann distance between two k-dimensional subspaces is

$$d(U,V) \;=\; \Big(\sum_{i=1}^{k} \theta_i^2\Big)^{1/2}, \tag{2}$$

where $\theta_1,\ldots,\theta_k$ are the principal angles between their column spaces.

Figure 2 plots the resulting distance series for $k=3$ with the boom windows shaded. The in-window and outside-window distributions overlap. Table 4 reports the within-window mean and maximum distance for each of the five windows; the outside-windows mean distance is 1.44 and its maximum is 1.75. Across $k \in \{2,3,5,10\}$, the ratio of the in-boom mean distance to the outside-boom mean distance ranges from 0.95 to 1.10.

Under this metric, the factor correlation geometry at the boom windows is not a regime change. The realized return vector moves toward a subset of pre-existing directions for three years, and the subspace spanned by the dominant correlations remains in place.

5 Implications

Two patterns coexist in the data. The temporal pattern is regular: factor momentum has five large cumulative-return windows in the post-1970 U.S. sample, each followed

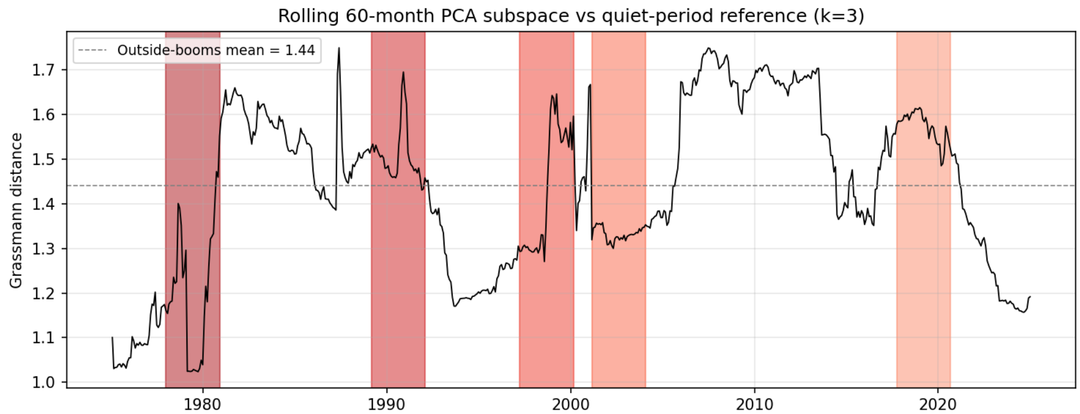

Figure 2. Grassmann distance between the top-three principal subspace of the sixty-month rolling correlation matrix and the top-three principal subspace estimated on the quiet-period months (those outside every top-five boom window). Shaded bands are the boom windows. The dashed line is the outside-booms mean.

Table 4. Grassmann distance at $k = 3$ between the sixty-month rolling principal subspace and the quiet-period reference, summarized inside each boom window. The outside-booms mean is 1.44 and the outside-booms maximum is 1.75.

#	Window	Mean distance	Max distance
1	1977-12..1980-11	1.21	1.55
2	1989-02..1992-01	1.51	1.69
3	1997-03..2000-02	1.44	1.65
4	2001-02..2004-01	1.33	1.36
5	2017-09..2020-08	1.57	1.62

by a reversal. The compositional pattern is not: the factors driving each window barely overlap with those driving the others, and the covariance subspace at these windows is not distinguishable from quiet periods.

For the literature, the first pattern means a full-sample Sharpe ratio or mean return is a statistic about five boom episodes and their reversals, not a stationary premium. The second pattern restricts what can be done about it. A risk model that identifies crashes by the identities of crowded factors, or by a covariance-regime indicator, will learn a pattern that does not generalize; each boom rides a different narrative, and the correlation geometry does not flag the episode. Leaving the booms out at the level of subsample reporting, and running the strategy with the awareness that its headline number depends on the inclusion of a handful of three-year windows, is the handle that the data supports.

Daniel and Moskowitz (2016) showed that individual-stock momentum crashes are predictable from ex-ante market volatility and bear-market indicators. Whether the same approach tames factor momentum's boom-bust cycle, given that its compositions are heterogeneous, is an open question that this note does not attempt to settle.

Acknowledgments

I thank Yeonchan Kang (Sungkyunkwan University) for the conversation that motivated this note.

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