Winners Glide, Losers Stumble: A Behavioral Reversal Tilt to Momentum

Juncheng Wen* Taiyang Feng†

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Abstract

Winners trend up smoothly, but losers fall in fits and starts, punctuated by technical rebounds that revert. This asymmetry makes the short (loser) leg the weak, crash-prone side of cross-sectional momentum: losers bounce, and the bounces are where a short position bleeds. This paper studies a parameter-free factor that exploits the asymmetry by tilting the short leg toward the rebounds it should fade. The factor is classic momentum, which skips the most recent month, multiplied stock by stock by that month's gross return, $(1 + r)\,M$. Across a century of U.S. common stocks and twelve international markets, this reversal-tilted factor outperforms classic momentum, and the entire improvement is on the short leg. The premium is not subsumed by standard factors, including the short-term-reversal factor, and it mitigates rather than amplifies momentum crashes. Because it lives in the smaller-capitalization stocks where reversal escapes arbitrage, its magnitude is modest once made tradable: the gross premium, large in the equal-weighted full universe whose absolute levels we do not interpret, narrows to roughly one to two percent per year in the shortable small- to mid-cap range, and to the smaller of those names in recent decades. The contribution is a precise, parameter-free upgrade to momentum's short leg, honestly bounded in size, not a large standalone alpha. The gain comes from how the recent month *scales* momentum, that is, from its interaction with the loser's downtrend, not from the recent return itself.

Keywords: momentum, short-term reversal, limits to arbitrage, factor spanning.

*The Hong Kong University of Science and Technology. Correspondence: `jwen0331@gmail.com`.

†The Hong Kong Polytechnic University. Correspondence: `ftysunny@outlook.com`.

1 Introduction

The path a stock takes up differs from the path it takes down. Winners tend to climb smoothly: an uptrend, once under way, persists with relatively few interruptions. Losers fall more raggedly. A declining stock seldom drops in a straight line; it falls in fits and starts, punctuated by sharp technical rebounds that excite hope but typically reverse, leaving the downtrend intact. The asymmetry is plain in the data. Among past losers, the stocks that rose most last month are the next month's worst performers, a one-month reversal more than three times stronger than the corresponding effect among past winners (Jegadeesh 1990; Lehmann 1990); losing portfolios are also more volatile and more rebound-prone than winning ones. The pattern is the one behavioral models anticipate. Reluctant to accept losses, investors cling to underperforming stocks and drive up their prices at the slightest hint of positive news (the disposition effect described by Shefrin and Statman in 1985). However, the rebound effect fades as negative news resurfaces. The market moves up in an orderly fashion and down in a choppy manner.

This asymmetry has a direct consequence for cross-sectional momentum, the strategy of buying past winners and selling past losers (Jegadeesh and Titman 1993). The long leg inherits the orderly side of the market: winners continue, and the strategy collects that continuation cleanly. The short leg inherits the choppy side: it sells losers, but losers bounce, and the bounces are exactly where a short position bleeds. It is telling that momentum's two best-known infirmities both live on the short leg. The loser leg contributes little of momentum's average profit, and the momentum *crash*, the episodic collapse that defines the strategy's tail risk, is a short-leg event, an explosion of rebounding losers as a bear market turns (Daniel and Moskowitz 2016). The down-side asymmetry is their common source.

If the trouble with the short leg is that losers rebound, the natural remedy is to short the rebound. This paper studies a parameter-free factor that does precisely that: take each stock's classic momentum, the twelve-minus-one momentum that already skips month t, and multiply it by that stock's month-t gross return $1 + r$,

$$B \;\equiv\; \left(\frac{P_t}{P_{t-12}} - 1\right) - \left(\frac{P_t}{P_{t-1}} - 1\right) \;=\; (1+r)\,M \;=\; M + r \cdot M, \tag{1}$$

where $M \equiv P_{t-1}/P_{t-12} - 1$ is classic twelve-minus-one momentum and $r \equiv P_t/P_{t-1} - 1$ is the most recent month's return; the identity holds exactly under simple returns (Section 3 derives it). The multiplier acts on the two legs asymmetrically, just as the market does. For a loser ($M < 0$), a recent *rebound* ($r > 0$) makes $(1 + r)M$ more negative, so the rebounded loser is shorted harder, while a loser still falling is shorted less. In the case of a winner ($M > 0$), for whom momentum and recent month are typically associated with the same sign, the multiplier exerts minimal influence on the ranking. The factor thus concentrates the short leg on the recently rebounded losers that the asymmetry says will give the rebound back, and leaves the orderly long leg essentially intact. This makes a sharp, falsifiable prediction: B should outperform momentum, and the entire improvement should fall on the short leg.

The substance of the paper is concerned with the question of what this multiplicative tilt buys, and where. The present study establishes five results on a century of U.S. data (CRSP, 1927–2025) and across twelve markets.

First, the decile long–short return to B exceeds that of classic momentum M: the annualized Sharpe ratio rises from 0.38 to 0.78 over the full U.S. century, and $B - M > 0$ in every one of the twelve markets examined.

Second, the improvement is *entirely on the short leg*. Splitting the long–short into a long (winner) leg and a short (loser) leg, B and M are statistically indistinguishable on the long leg, while B's short leg dominates M's in every era. The incremental return $B - M$ is, mechanically and empirically, a better way of shorting losers: the factor $(1 + r)$ over-weights losers that have already bounced and de-emphasizes those still falling, harvesting the subsequent reversal of the bounce.

Third, this increment is not a repackaging of known factors. Spanning regressions of the $B - M$ long–short on the Fama–French five factors augmented with the momentum (UMD) and short-term-reversal (STR) factors leave an alpha exceeding 8% per year ($t \approx 6$), and the short-leg increment carries an alpha of 8.4% per year ($t = 6.5$). Fama–MacBeth regressions deliver the same verdict at the stock level: the interaction $r \cdot M$ predicts the cross-section of returns beyond M ($t = 5.7$). The reason the standalone STR factor does not subsume $B - M$ is that B's reversal is *momentum-conditional and concentrated on losers*, a targeted slice that the unconditional reversal factor does not capture.

Fourth, the premium lives where limits to arbitrage are tightest, and survives the tests that matter there. Sorting within size groups, the $B - M$ alpha is overwhelmingly concentrated in small caps, an order of magnitude stronger there than among mid or large caps, where it is at most marginal. This is the expected signature of a reversal-based effect, not a defect. The same concentration bounds what an investor can take: the gross premium of the equal-weighted full universe, whose absolute level we do not interpret, narrows to roughly one to two percent per year once the universe is cut to shortable names, and since 2000 survives only among the smaller of them (Section 8). It is not a transaction-cost illusion. Because $(1 + r)$ only mildly perturbs the momentum ranking, switching from M to B trades only modestly more than momentum itself, so the incremental alpha survives realistic trading costs with a wide margin. Nor is it a bid–ask illusion: imposing a one-week gap between formation and holding, which purges the microstructure bounce while leaving the loser population intact, retains a significant premium, and by construction (1) B excludes the standalone recent return that carries most of that bounce. The premium is large and significant in every subperiod of the century, the 2000–2025 sub-sample included.

Fifth, the tilt improves the tail. Momentum's defining risk is the crash, an episodic collapse of the short leg in rebounding bear markets. Because $(1 + r)$ removes from the short leg precisely the losers most prone to violent rebound, B *mitigates* rather than amplifies momentum crashes: across the worst crash months B is the lighter loser, and the skewness of its long–short return is materially less negative than M's.

The paper's contribution is thus neither a claim that momentum can be universally improved nor the discovery of a new large-capitalization factor. It is a precise, parameter-free characterization of *where and why* a multiplicative reversal tilt helps: it upgrades the short leg of momentum by harvesting a momentum-conditional reversal, in the smaller-cap universe where that reversal is not arbitraged away, at almost no incremental cost, while improving the crash profile. The honest boundaries are themselves part of the result: the effect is concentrated in smaller stocks and attenuates with capitalization; the eight-percent gross figure belongs to the equal-weighted full universe whose absolute levels we never interpret, while the premium one can actually harvest, in the shortable small- to mid-cap range, is roughly one to two percent per year and narrows in the most recent quarter-century to the smaller of those names; and part of it is short-horizon. We document these limits rather than bury them.

The analysis connects two literatures usually kept apart. Relative to the momentum literature (Jegadeesh and Titman 1993; Asness, Moskowitz, and Pedersen 2013), B is the rare modification that touches the short leg rather than the long, and that is motivated algebraically rather than by parameter search. A long line of work respecifies the momentum *signal*, isolating the intermediate-horizon past return (Novy-Marx 2012), the nearness to the fifty-two-week high (George and Hwang 2004), or a blend of moving averages (Han, Zhou, and Zhu 2016); each re-ranks the whole long–short, whereas B keeps classic momentum as its base and re-weights only the short side. Closest in spirit is Da, Gurun, and Warachka (2014), who find momentum stronger when past information arrived continuously rather than in discrete jumps: they read the smoothness of the *winning* path as a driver of continuation, while we read the *roughness* of the losing path, with its rebounds, as the source of short-leg weakness and turn it into a tilt. Relative to Asness (1995), who studies *additive* past-return specifications and concludes that the standalone recent month is largely microstructure, the multiplicative form is the natural object that retains the recent month's *interaction* with momentum while discarding its contaminated level; to our knowledge that interaction $r \cdot M$, and its reading as a reversal tilt on the loser leg, has not been studied. The one-week-gap evidence then shows this object is not merely the bid–ask effect under a new name.

The remainder of the paper proceeds as follows. Section 2 describes the data. Section 3 develops the algebra of B and its relation to the standard decomposition of past returns. Section 4 presents the cross-sectional evidence, both portfolio sorts and Fama–MacBeth regressions. Section 5 dissects the long and short legs and the reversal mechanism. Section 6 reports the factor-spanning tests. Section 7 examines momentum crashes. Section 8 runs the robustness gauntlet, covering size, transaction costs, microstructure, seasonality, and subperiods. Section 9 presents the international evidence. Section 10 concludes.

2 Data

U.S. sample. The primary sample is the universe of U.S. common stocks in the CRSP daily stock file, from January 1926 through December 2025. We keep securities classified as ordinary common shares (CRSP `sharetype` "NS," `securitytype` "EQTY," `securitysubtype` "COM," domestic incorporation), and aggregate daily data to month-end. For each stock and month a total-return index is constructed by compounding daily returns, which include ordinary and special dividends and delisting returns, so that the price relatives used to form signals and to measure holding-period returns are dividend- and split-adjusted. Market capitalization is the CRSP month-end value; the primary listing exchange is used to form New York Stock Exchange (NYSE) breakpoints. A stock enters the cross-section in a given month if it has a positive market capitalization and the twelve months of return history the signals require; to guard against data errors we drop the smallest 0.1% of stocks by month-end capitalization each month, and we drop months with fewer than 100 eligible stocks. We deliberately impose no price screen. A low share price is not a proxy for small size or for illiquidity, since a stock can trade at a low price yet remain large and liquid, so size is governed here by capitalization rather than by price; this follows the universe construction of Asness (1995), who includes all qualifying NYSE, AMEX, and NASDAQ firms with no price filter. The microstructure concern that a price floor is sometimes meant to address is handled instead at the analysis stage: the factor's momentum base already skips month t (Section 3.3), and Section 8 shows the premium survives a one-week gap between formation and holding that bid–ask bounce cannot span. The resulting series spans 1927–2025 (1,187 monthly cross-sections once the twelve-month formation lag is imposed).

Signals. For stock i at month-end t, let P_t denote the total-return index. The four objects studied are

$$\underbrace{M \equiv \frac{P_{t-1}}{P_{t-12}} - 1}_{\text{classic 12-1 momentum}}, \qquad \underbrace{r \equiv \frac{P_t}{P_{t-1}} - 1}_{\text{recent-month return}}, \qquad \underbrace{B \equiv \left(\frac{P_t}{P_{t-12}} - 1\right) - \left(\frac{P_t}{P_{t-1}} - 1\right)}_{\text{the reversal-tilted factor}},$$

and the interaction $r \cdot M$. Classic momentum M skips month t. The factor B keeps that skip, since its momentum base is M itself, and lets month t re-enter only through the multiplicative factor $(1 + r)$. All four use only information through the close of month t; portfolios formed on them are held over month $t + 1$, so there is no look-ahead.

Portfolios. Each month we sort eligible stocks into deciles on the signal and form an equal-weighted long–short portfolio that buys the top decile (winners) and sells the bottom decile (losers), held for one month. Equal weighting and the absence of NYSE breakpoints inflate the *absolute* long–short return, because the smallest stocks receive disproportionate weight; we therefore never interpret absolute levels, and focus throughout on (i) the *relative* comparison of B versus M and (ii) the *decomposition* into long and short legs. Section 8 reports NYSE-breakpoint and capitalization-conditional variants explicitly. In size-conditional tests we sort within NYSE size terciles and use quintiles to keep each cell populated.

Factors. Risk adjustment uses the monthly Fama–French factors from Kenneth French's data library: the three factors (market, size, value) available from 1926, the five-factor extension (adding profitability and investment) available from 1963, the momentum factor (UMD), and the short-term-reversal factor (STR). The STR factor, formed by buying last month's losers and selling last month's winners within size groups, is the standard benchmark for the very effect B is suspected of harvesting, and is central to the spanning tests of Section 6. Standard errors on time-series alphas use the Newey and West (1987) heteroskedasticity- and autocorrelation-consistent estimator with six lags.

International samples. To assess universality (Section 9), we use two further, independently sourced databases that do not overlap the U.S. data. Cross-border evidence for ten markets (Japan, the United Kingdom, Australia, Korea, Taiwan, India, Germany, France, Hong Kong (SAR), and Singapore) comes from Compustat Global's daily security file, with total-return prices constructed from the daily close, adjustment factor, and total-return factor. Chinese A-share evidence comes from the China Stock Market and Accounting Research (CSMAR) database. The construction mirrors the U.S. design: month-end total-return prices, decile long–short sorts, the same removal of the smallest 0.1% of stocks by capitalization in place of any price screen, and a minimum of 100 stocks per cross-section. Each market is defined by listing rather than by incorporation: its universe is the common stocks trading in the market's local currency, reduced to one primary security per firm via the Compustat primary-issue line so that the duplicate cross-listing feeds Compustat carries for the same security do not multiply-count a firm. Defining the market by listing admits the offshore-incorporated firms that trade locally, such as the Cayman-incorporated giants that dominate the Hong Kong market, which a country-of-incorporation screen would wrongly exclude. France and Germany, which share the euro, are identified by country of incorporation in their local currency instead. The international windows open between 1986 and 1994 as coverage begins and run through early 2026, shorter than the U.S. century.

3 The Factor

3.1 An exact identity

The starting point is that B in (1) is *not* eleven-month momentum. The intuition "a year minus a month equals eleven months" holds only when returns add, and simple returns do not. Expanding B under simple returns,

$$B = \left(\frac{P_t}{P_{t-12}} - 1\right) - \left(\frac{P_t}{P_{t-1}} - 1\right) = \frac{P_t}{P_{t-12}} - \frac{P_t}{P_{t-1}} = \frac{P_t}{P_{t-1}}\left(\frac{P_{t-1}}{P_{t-12}} - 1\right) = (1 + r)\,M. \tag{2}$$

The subtraction does not cancel the recent month; it scales eleven-month momentum M by the gross recent-month return $1 + r$. In two data sets spanning the full samples, computing $|B - (1 + r)M|$ in double precision returns a maximum of 1.4×10^{-14}, confirming (1) as an exact algebraic identity rather than an approximation. Under *log* returns the intuition is restored exactly: with $p \equiv \log P$, $(p_t - p_{t-12}) - (p_t - p_{t-1}) = p_{t-1} - p_{t-12}$, so a log-return B *is* eleven-month momentum and selects the same stocks as M. The entire phenomenon studied here is a property of simple returns.

3.2 B keeps the skip; the recent month enters as a tilt

It is tempting to read B as momentum that has abandoned the conventional skip. It has not. The momentum base of B is M itself, the twelve-minus-one momentum that skips month t, and the recent month re-enters only multiplicatively. To see this, contrast B with *no-skip* momentum, which re-admits the recent month *additively*:

$$\frac{P_t}{P_{t-12}} - 1 = (1 + r)(1 + M) - 1 = M + r + r \cdot M, \tag{3}$$

whereas $B = M + r \cdot M$ by (1). The two differ by exactly the standalone recent return:

$$\left(\frac{P_t}{P_{t-12}} - 1\right) - B = r. \tag{4}$$

Classic momentum skips the recent month from the signal; B inherits that skip in its base M and, on top of it, discards the standalone level r, keeping only the *interaction* $r \cdot M$. The hinge of the paper is therefore not *whether* to skip the recent month but *how* it should enter: as a contaminated additive level, which the conventional skip rightly removes and which B removes as well by (4), or as a multiplicative tilt on momentum, which is the one thing B keeps. The distinction matters because the contamination lives entirely in the additive level. In the decomposition studied by Asness (1995), whose PAST$(1,1)$ is the standalone r and whose PAST$(2,12)$ is essentially M, the one-month return is the contrarian signal he finds significant only among small, illiquid, low-priced firms and attributes largely to the bid–ask spread. B never touches that term; it retains only how the recent month *scales* momentum, that is, its asymmetric interaction with the loser's downtrend.

3.3 What the multiplier does

Because $1 + r$ varies across stocks, B and M rank the cross-section differently, and the direction of the re-ranking depends on the sign of M. Table 1 traces the four cases.

Table 1: How the multiplier $(1 + r)$ re-ranks the cross-section

Stock type	M	Recent r	Effect of $(1 + r)$	Change in B-rank
Winner, kept rising	> 0	$r > 0$	$(1{+}r) > 1$, amplifies	further up the ranking
Winner, pulled back	> 0	$r < 0$	$(1{+}r) < 1$, shrinks	slightly down
Loser, kept falling	< 0	$r < 0$	$(1{+}r) < 1$, less negative	out of the short basket
Loser, rebounded	< 0	$r > 0$	$(1{+}r) > 1$, more negative	**deeper into the short basket**

Notes. The multiplier's effect hinges on the sign of momentum M. For winners it barely changes the ranking; for losers it inverts, pushing the recently rebounded losers (last row) deeper into the short basket and easing off those still falling. The last row is the mechanism of the paper.

For a *winner* ($M > 0$), a positive recent month ($r > 0$) makes $(1 + r)M$ larger, pushing the stock further up the ranking; a recent pullback ($r < 0$) pushes it down. For a *loser* ($M < 0$), the economically interesting case, the logic inverts: a loser that has *bounced* ($r > 0$) becomes *more* negative under $(1 + r)$ and is shorted *harder*, whereas a loser that has *kept falling* ($r < 0$) becomes less negative and is shorted less. In one line: relative to M, the factor B concentrates its short leg on losers that have recently rebounded. If those rebounds are transient reversals that subsequently give back, B's short leg should outperform M's, and the gain should arise on the short leg. The remainder of the paper shows that this is exactly what the data deliver, and traces the effect to the segments where reversal survives arbitrage.

4 Cross-Sectional Evidence

Two standard tests bracket a return predictor: a portfolio sort, which measures economic magnitude, and a Fama–MacBeth regression, which measures statistical reliability and lets predictors compete head to head. B passes both, and the multiplicative tilt earns its keep in each.

4.1 Portfolio sorts

Each month we sort the eligible cross-section into deciles on M and, separately, on B, and form the top-minus-bottom (winner-minus-loser) portfolio held for one month. Table 2 reports the resulting long–short performance over the full U.S. century.

Table 2: Decile long–short performance, M versus B (U.S., 1927–2025)

	Ann. return	Ann. volatility	Sharpe ratio	t(return)
Classic momentum M	11.1%	29.2%	0.38	3.83
Reversal-tilted B	18.8%	24.1%	0.78	7.76

Notes. Equal-weighted decile long–short portfolios, formed monthly on each signal and held one month, $n = 1{,}187$ months. Returns are annualized; the t-statistic tests the mean monthly long–short return. Equal weighting inflates the absolute levels, which are not interpreted; the comparison of interest is B versus M.

The tilt improves momentum on every axis at once, and in this broad universe the improvement is large. Relative to classic momentum, B delivers a much higher average return (18.8% versus 11.1% per year) at *lower* volatility (24.1% versus 29.2%), more than doubling the annualized Sharpe ratio from 0.38 to 0.78 and raising the t-statistic from 3.8 to 7.8. Classic momentum is itself fragile in an unscreened all-stock universe, as the momentum literature has long noted; the tilt is what restores it. The long–short return of B *minus* that of M, the incremental portfolio one would trade to convert momentum into B, itself carries a Sharpe ratio of 0.81, foretelling that the difference is a systematic return stream rather than noise. Two questions follow immediately, and organize the next several sections: from which leg does the gain come (Section 5), and does it survive risk adjustment against known factors (Section 6)? The decomposition in Section 3.3 has already foreshadowed the answer to the first: because the multiplier leaves winners largely in place and re-sorts only losers, the improvement should be concentrated in the short leg.

4.2 Fama–MacBeth regressions

Portfolio sorts measure magnitude but discard information by collapsing the cross-section into ten bins. The Fama–MacBeth (1973) regression uses the full cross-section and, by including several predictors at once, asks whether each adds information given the others. Each month we regress stock returns over month $t + 1$ on signals known at t, standardized cross-sectionally to unit standard deviation so that coefficients are comparable returns per one-standard-deviation move; Table 3 reports the time-series average slopes with Newey–West t-statistics.

The regressions confirm the sort and locate the mechanism. Used alone, both momentum measures are strong predictors: B at 0.433% per month per standard deviation ($t = 8.5$), well ahead of M at 0.353% ($t = 5.9$). The recent month r is, on its own, a powerful *reverser*: row (3)'s slope

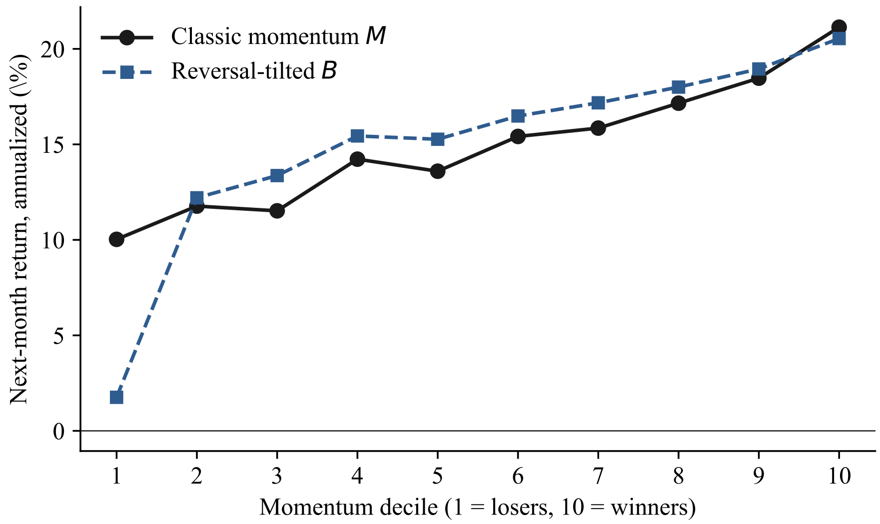

Figure 1: Next-month returns by momentum decile, classic momentum M versus the reversal-tilted factor B (equal-weighted, U.S., 1927–2025). The winner deciles (right) coincide almost exactly; the factors diverge at the loser end (left), where B's bottom decile is deeper. The difference between B and M is a loser-side phenomenon.

of -0.630% ($t = -10.4$) is the short-term reversal of Jegadeesh (1990) and Lehmann (1990), and it strengthens when momentum is held fixed (row 4). The decisive specification is row (5). Writing $B = M + r \cdot M$, the regression of returns on M and the interaction $r \cdot M$ isolates exactly the increment that distinguishes B from classic momentum. The interaction enters positively and significantly (0.376% per month, $t = 5.7$) *on top of* momentum: knowing how a stock's recent month interacts with its momentum predicts returns beyond momentum itself. This is the multiplicative tilt earning its keep at the stock level, and its sign is the asymmetry of Section 3.3: a recent move that contradicts the trend (a rebounding loser, $r \cdot M < 0$) forecasts continuation of the trend, which is why shorting rebounding losers pays. Section 5 shows that this payment is collected almost entirely on the short leg.

5 Anatomy: Where the Gain Lives

Section 4 established that B improves on momentum. This section shows that the improvement comes from a single leg, and traces that fact back to the asymmetry of Section 1 between winning and losing.

Table 3: Fama–MacBeth regressions of month-$t+1$ returns on past-return signals (U.S., 1927–2025)

Specification	M	r	$r \cdot M$	B
(1) B alone				0.433
				(8.47)
(2) M alone	0.353			
	(5.95)			
(3) r alone		−0.630		
		(−10.39)		
(4) M and r	0.361	−0.668		
	(5.60)	(−10.53)		
(5) M and $r \cdot M$	0.372		0.376	
	(5.36)		(5.68)	

Notes. Monthly cross-sectional regressions, 1927–2025. Predictors are winsorized at the 1st and 99th percentiles and standardized to unit cross-sectional standard deviation each month; slopes are in percent per month per one-standard-deviation move. Reported slopes are time-series averages; t-statistics (in parentheses) use the Newey–West estimator with six lags.

5.1 The gain is the short leg

We split each decile long–short into its two halves: the long leg, the top (winner) decile, and the short leg, the bottom (loser) decile entered with a negative sign. Table 4 reports the annualized Sharpe ratio of each leg, for M and for B, over the full sample and four subperiods.

Table 4: Long– and short-leg Sharpe ratios, M versus B (U.S.)

	Long leg (winners, P_{10})		Short leg ($-$losers, $-P_1$)	
Period	M	B	M	B
Full sample, 1927–2025	0.82	0.79	−0.25	−0.05
1927–1962	0.79	0.77	−0.32	−0.14
1963–1989	0.95	0.91	−0.19	0.06
1990–2001	0.98	0.94	−0.33	0.05
2002–2025	0.58	0.60	−0.13	−0.01

Notes. Annualized Sharpe ratio of each leg of the decile sort. The short leg is the bottom (loser) decile entered with a negative sign, so a higher number is a better short.

The pattern is unambiguous. On the *long* leg, M and B are indistinguishable: in every period their winner-decile Sharpe ratios lie within 0.04 of each other, and over the full century both sit near 0.80. The two factors agree almost perfectly on which stocks to buy and earn the same return doing so, which is unsurprising, since for a winner the multiplier $(1+r)$ rarely changes the ranking. On the *short* leg they diverge, and they diverge the same way in all five periods: B's loser leg beats M's without exception. Over the full sample the short leg's Sharpe improves from −0.25 to −0.05, and this improvement accounts for the entire rise in the combined long–short from 0.38 to 0.78. B

is not a better way to buy winners. It is a better way to sell losers.

5.2 Why the short leg: the asymmetry of winning and losing

Why should re-sorting losers help? Because the loser side of the market is where reversal lives, and the multiplier is built to harvest it. Section 1 described the asymmetry informally; Table 5 measures it on the same century of data. Within the past-winner group (top 30% by M) and the past-loser group (bottom 30%), we sort on the recent month r and compare the next-month return of the high-r stocks to the low-r stocks.

Table 5: The asymmetry of winners and losers (U.S., 1927–2025)

	Past winners	Past losers	Loser/winner
One-month reversal: next-month return, high-r minus low-r (t-statistic)	−1.00% (−7.3)	−3.54% (−16.8)	3.5×
Annualized volatility	22.8%	32.9%	1.44×
False-rebound rate: rose this month, fell next	47.0%	54.3%	

Notes. Within each momentum group, stocks are sorted into quintiles on the recent-month return r; "one-month reversal" is the mean next-month return of the top-r minus the bottom-r quintile (negative denotes reversal). Volatility is of the equal-weighted group portfolio. "False-rebound rate" is the fraction of stocks that rose in a month and fell the next.

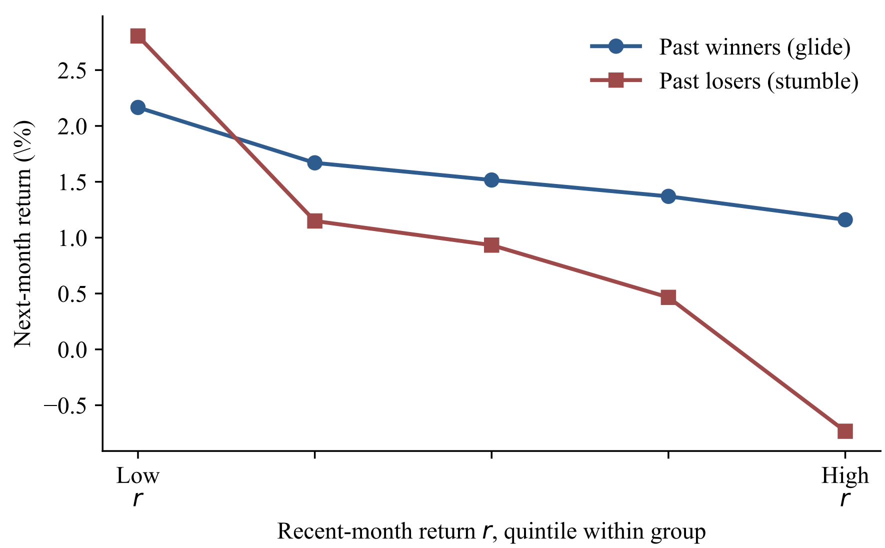

Figure 2: The asymmetry of winning and losing (U.S., 1927–2025). Within past winners and past losers, average next-month return by quintile of the recent-month return r. The winner profile (blue) is nearly flat: winners that rose keep rising. The loser profile (red) slopes down steeply: a loser that rebounded this month tends to fall the next. Reversal is a loser-side phenomenon, the empirical content of "winners glide, losers stumble."

Among winners, a high recent return forecasts a next-month return only 1.00% below that of a low recent return: winners that rose keep rising, with mild give-back. Among losers the same spread is -3.54%, three and a half times larger and overwhelming ($t = -16.8$): a loser that rebounded this month is sharply worse the next. Reversal is a loser-side phenomenon. Two further measures confirm that the down side is the choppy one. Loser portfolios are 1.44 times as volatile as winner portfolios, and the false rebound is more common among losers: of stocks that rose in a given month, 54.3% of losers fall the next versus 47.0% of winners. A rise in a loser is, more likely than not, given back, whereas a rise in a winner more often continues.

This asymmetry is a market regularity with deep roots, which the next section takes up. Whatever its ultimate source, it has a precise consequence for portfolio construction. Classic momentum's short leg sells all losers alike, both those that have just rebounded and are poised to fall further, and those that have already fallen and are due a bounce. The multiplier $(1 + r)$ sorts within the losers exactly along the reversal, shorting the rebounded losers harder (Section 3.3). That is why the gain is on the short leg, and why what B adds to momentum is reversal, not more momentum.

5.3 Why the asymmetry: three reinforcing channels

That losers are choppier than winners is, as a market regularity, well established; what is new here is reading it as the source of momentum's short-leg weakness. Three strands of the literature explain the asymmetry, and they reinforce rather than compete. We motivate the effect with them and do not attempt to identify which dominates.

Information flows asymmetrically. Good news is disclosed promptly; bad news is released grudgingly and travels slowly. In the gradual-information-diffusion theory of Hong and Stein (1999), prices underreact as news spreads through the investor base; Hong, Lim, and Stein (2000) show empirically that momentum profits, the footprint of this slow diffusion, are larger among low-coverage stocks, and that the coverage effect is stronger for past *losers*, whose prices "react more sluggishly to bad news than to good news." Short-sale constraints compound the asymmetry, since pessimism is impounded only as constrained arbitrageurs slowly act on it, which also pushes anomaly returns onto the short leg (Miller 1977; Diether, Malloy, and Scherbina 2002; Stambaugh, Yu, and Yuan 2012). When bad news arrives in pieces, the descent is drawn out and punctuated: in the gaps between disclosures the price drifts up, only to fall again when the next piece lands. The choppiness of the decline is the visible trace of information arriving in installments.

Risk attitudes reverse across the reference point. The prospect-theory value function is concave over gains and convex over losses (Kahneman and Tversky 1979): investors are risk-averse once ahead and risk-seeking once behind. This one asymmetry produces both the disposition effect and, less obviously, the smoothness asymmetry, through the *direction of feedback trading* (Figure 3). In the gain domain, risk-averse holders take profits as a stock rises, selling into strength. That is negative-feedback, stabilizing trading: it dampens upward spikes, and as a standing headwind it slows the rise into a gradual drift, the underreaction of Grinblatt and Han (2005). Winners glide. In the loss domain, risk-seeking holders do the opposite. They refuse to sell, hold, and gamble for resurrection, even adding to losers and chasing any rebound, the lottery demand of Kumar (2009) and the destabilizing positive feedback of De Long, Shleifer, Summers, and Waldmann (1990). With no stabilizing seller to damp the swings and speculative buyers to ignite them, losers stumble. The same value function that makes investors sell winners and hold losers makes them stabilize the gain side and destabilize the loss side.

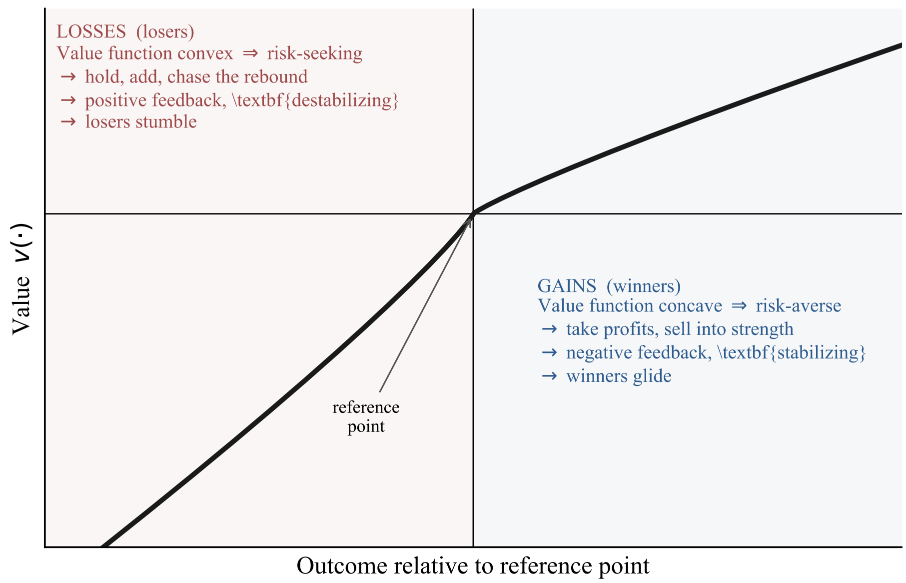

Figure 3: The prospect-theory value function and the direction of feedback trading. Concavity over gains makes investors risk-averse, so they sell winners into strength, a stabilizing (negative-feedback) trade that smooths the ascent. Convexity over losses makes them risk-seeking, so they hold and gamble on losers, a destabilizing trade that roughens the descent. The same value function generates the disposition effect and the smoothness asymmetry.

Volatility and liquidity are asymmetric. Independently of behavior, volatility rises mechanically when prices fall, through the leverage and volatility-feedback effects (Black 1976; Christie 1982; Bekaert and Wu 2000): for a given shock, a down move is followed by more volatility than an up move, so the loser side is the volatile side, as the 1.44 volatility ratio in Table 5 records. Moreover, the reversal that B harvests is, on the leading account, compensation for liquidity provision (Jegadeesh 1990; Lehmann 1990; Nagel 2012): when uninformed or forced selling pushes a stock down, liquidity providers buy and require a rebound in return. Both the selling pressure and the scarcity of liquidity that make this compensation large are concentrated among beaten-down, illiquid losers (Avramov, Chordia, and Goyal 2006; Coval and Stafford 2007), which is precisely where the reversal is strongest.

The three channels overdetermine the asymmetry. Information, behavior, and liquidity each predict that reversal and choppiness concentrate on the loser side, and the data neither can nor need separate them. What matters for the factor is the conclusion they share: the down side of the market is where reversal lives, the multiplier $(1 + r)$ is built to short the rebounds it produces, and so B's gain is, of necessity, a gain on the short leg.

6 Factor Spanning

Section 5 showed that what B adds to momentum is reversal. A natural objection follows at once: short-run reversal is itself a known, tradable factor, so perhaps the $B - M$ return is nothing more than the short-term-reversal (STR) factor wearing momentum's clothes. This section confronts the objection directly, regressing the $B - M$ long–short on standard factors, the STR factor among them.

Panel A of Table 6 introduces the risk models one at a time. The $B - M$ alpha is positive and significant under every specification, and it does not shrink toward zero as factors are added: it is 6.12% per year against the Fama–French three factors, and 8.51% per year ($t = 5.96$) against the full model that adds momentum and STR. Tellingly, the alpha *rises* when the momentum factor is included, because, as Panel B shows, $B - M$ loads *negatively* on momentum ($\beta_{\text{UMD}} = -0.27$, $t = -4.2$). The increment that B adds to momentum is, if anything, slightly anti-momentum in its factor exposure; it is certainly not a second helping of the momentum factor.

Panel B contains the result the section is built around. $B - M$ *does* load on the STR factor, positively, and on the short leg significantly ($\beta_{\text{STR}} = 0.17$, $t = 2.6$). This is not a problem for the paper; it is a confirmation of its mechanism. B's edge is supposed to be reversal, so $B - M$ should be correlated with the reversal factor, and it is. The point is that the correlation is partial: even after this loading, the alpha survives almost intact, at 8.51% per year on the long–short and 8.44% ($t = 6.52$) on the short leg. $B - M$ is short-run reversal, but a *better* one than the standard factor delivers.

The reason is the difference between conditional and unconditional reversal. The STR factor sorts the entire cross-section on last month's return and buys losers against winners *indiscriminately*. B's reversal is conditional: it is applied only within the momentum ranking, and the multiplier concentrates it on the past *losers* that have rebounded, the exact stocks where, as Table 5 showed, reversal is more than three times stronger. Harvesting reversal where it is strongest, rather than

Table 6: Factor-spanning regressions of the $B - M$ long–short (U.S., 1927–2025)

Panel A. Alpha across nested risk models ($B - M$ decile long–short)

	CAPM	FF3	FF3+UMD	FF3+UMD+STR
Alpha (% p.a.)	6.48	6.12	9.29	8.51
(t)	(5.40)	(5.34)	(6.20)	(5.96)
R^2	0.08	0.11	0.29	0.31

Panel B. Full model (FF3+UMD+STR): all loadings

	Alpha (% p.a.)	β_{Mkt}	β_{UMD}	β_{STR}	R^2
$B - M$ long–short	8.51 (5.96)	0.04 (1.3)	−0.27 (−4.2)	0.10 (1.4)	0.31
short leg only	8.44 (6.52)	0.03 (1.2)	−0.24 (−4.3)	0.17 (2.6)	0.33

Notes. Time-series regressions of the monthly $B - M$ long–short return (and its short-leg component) on the Fama–French factors, the momentum factor (UMD), and the short-term-reversal factor (STR). Alphas are annualized; t-statistics (Newey–West, six lags) in parentheses. β_{SMB} and β_{HML} are small and insignificant and are omitted from Panel B for space.

across the whole market, is what the unconditional factor leaves on the table, and is what the surviving alpha measures. The same logic explains why the loading is larger and the alpha sharper on the short leg: that is where both B's tilt and the market's reversal are concentrated.

7 Momentum Crashes

Momentum's average return is bought with a distinctive tail risk. When a bear market turns, the past losers the strategy is short stage violent, correlated rebounds, and the short leg collapses; Daniel and Moskowitz (2016) document these momentum *crashes* as the strategy's defining hazard. Because B differs from momentum only in how it sorts the short leg, the natural question is whether the tilt deepens this hazard or relieves it. A reversal tilt could plausibly do either, so the answer is an empirical matter. It relieves it.

The mechanism points the right way before the data do. A crash is led by the losers most poised to snap back, which are the ones that have *not yet* rebounded. Those losers have low recent returns ($r < 0$), and the multiplier $(1 + r)$ shorts them *less*. By holding a smaller position in exactly the stocks that detonate a crash, B should suffer less when one arrives. Table 7 confirms it.

Over the full century the monthly long–short return of classic momentum has a skewness of −3.68; the tilt cuts this to −2.73, a materially thinner left tail. The improvement concentrates where it matters, in the disasters. In the ten worst crash months for momentum, B loses less in all ten. The single worst month, September 1939, is the exception that proves the rule, costing momentum −85.8% and B a barely better −84.0%; but the second worst, August 1932, cost momentum −85.5% against B's −52.3%, and the third, January 2001, −80.0% against −42.9%, the tilt roughly halving

Table 7: Tail behavior of the momentum and B long–short (U.S., 1927–2025)

	Classic momentum M	Reversal-tilted B
Skewness of monthly return	−3.68	−2.73
Worst month (September 1939)	−85.8%	−84.0%
1st percentile of monthly return	−27.6%	−22.5%
5th percentile of monthly return	−12.2%	−8.7%
Lighter loss in M's ten worst months	B in 10 of 10	

Notes. Statistics of the monthly equal-weighted decile long–short return. "M's ten worst months" are the ten most negative monthly returns to classic momentum; the last row counts those in which B lost less.

the loss. The first-percentile monthly return improves from −27.6% to −22.5%. B does not simply earn a higher average return than momentum. It earns that return with a better-behaved tail, which is the rarer and more valuable of the two improvements.

A last question is whether this tail relief, like the premium itself, is confined to small stocks. It is not, and the reason is instructive. The crash improvement is a property of the short leg's *composition* rather than of the excess return it earns, and composition does not require a surviving mispricing in order to change: whatever the size band, B holds less of the not-yet-rebounded losers that detonate a crash, so its short leg is structurally lighter in the names that snap back hardest. The benefit therefore reaches the large, liquid stocks one can actually short, even where the excess-return premium has been competed away. Forming the universe each month from stocks above the NYSE 40th and 60th percentiles, the equal-weighted long–short still shows the tilt cutting the tail sharply (Table 8): maximum drawdown falls by roughly fifteen percentage points and skewness is nearly halved at both floors, and B again loses less in the major crash episodes, 1932, 2000–2001, and 2009, within these large-cap universes just as in the whole market. These remain unhedged decile spreads spanning the worst momentum crashes, so the drawdown levels are large by construction and describe the factor rather than any implementable portfolio; what the comparison isolates is the gap between M and B, and that gap is wide at every capitalization. The harvestable premium is a small-cap effect, as Section 8 insists, but the improvement in crash shape is not.

8 Robustness

This section subjects the premium to the standard battery: where it sits in the size distribution, whether it survives trading costs, whether it is a microstructure artifact, whether it is seasonal, and whether it has persisted over time. The premium passes each test, within bounds we state plainly.

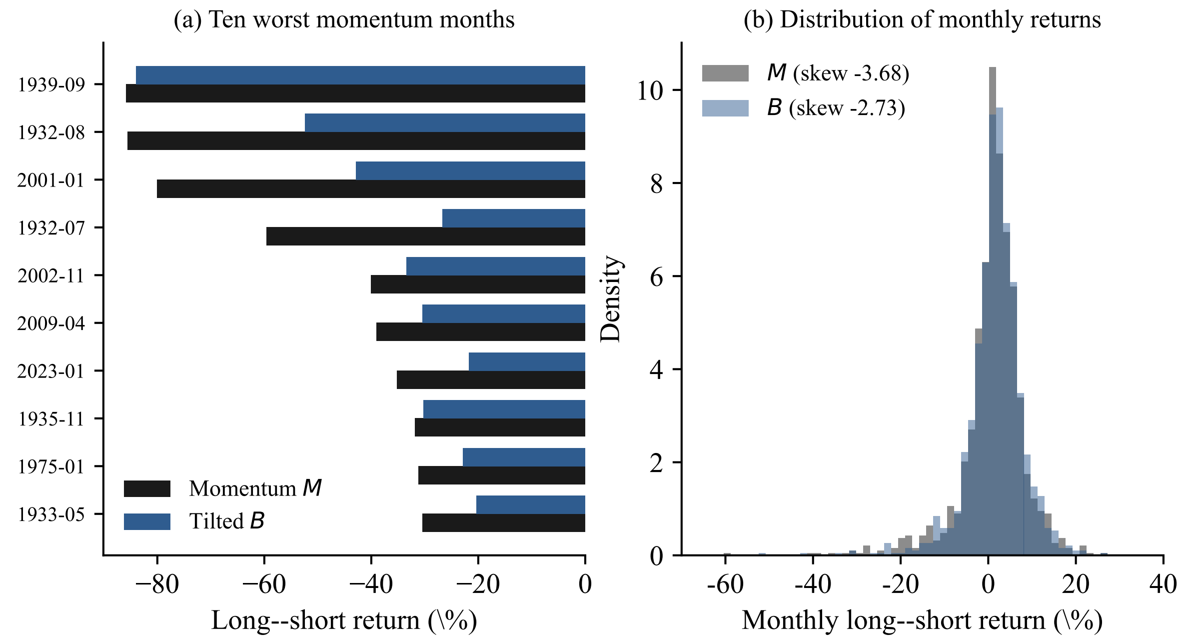

Figure 4: Tail behavior of the momentum and B long–short (U.S., 1927–2025). Panel (a): the ten worst months for classic momentum, and B's return in the same months; B loses less in all ten. Panel (b): the distribution of monthly long–short returns; B's left tail is materially thinner, and its skewness improves from −3.68 to −2.73.

8.1 Size

Sorting within NYSE size terciles, the $B - M$ alpha is overwhelmingly concentrated in small caps. It is 5.68% per year ($t = 4.5$) among small caps, an order of magnitude larger than the 0.40% ($t = 1.6$) among mid caps or the 0.35% ($t = 2.0$) among large caps, with the short leg tracing the same concentration. We read this as locating the effect, not impeaching it. Short-term reversal is itself a small-stock, limits-to-arbitrage phenomenon, strongest where trading frictions keep arbitrageurs away, so a reversal tilt should live in the same place, and it does. The honest statement is that B improves momentum dramatically among small caps and only marginally beyond them; the investability evidence below (Table 10) traces the same decline across cumulative capitalization floors, the short-leg premium shrinking as the floor rises yet remaining statistically present even in the largest universe.

This concentration is what a behavioral reading predicts, and it is worth saying why rather than conceding it as a weakness. The entire gain sits on the short leg (Section 5), and the arbitrage that would erase a short-leg mispricing is short selling, the very trade that is most constrained, most expensive, and often simply impossible among small stocks (Miller 1977; Stambaugh, Yu, and Yuan 2012). The behavioral force that bids up rebounding losers can operate at every size, but the mispricing it leaves survives only where arbitrageurs cannot cheaply sell it back down, which

Table 8: The crash improvement is not a small-cap effect: tail behavior in size-floored universes (U.S., 1927–2025, equal-weighted decile long–short)

	≥ NYSE 40th pct.		≥ NYSE 60th pct.	
	M	B	M	B
Skewness of monthly return	−2.42	−1.36	−2.52	−1.23
Maximum drawdown	−95.2%	−80.7%	−96.2%	−80.3%
Sharpe ratio	0.52	0.62	0.48	0.58

Notes. Each universe is formed each month from the stocks whose formation-month capitalization exceeds the stated NYSE percentile, and the equal-weighted decile long–short is computed inside it. These are unhedged decile spreads spanning the 1932 and 2009 momentum crashes, so the drawdown levels are large by construction and are a property of the factor, not of an implementable strategy; the comparison of interest is the gap between M and B. The improvement holds, more mildly, under value weighting.

is the small, illiquid, costly-to-borrow tail (Shleifer and Vishny 1997). Classic momentum itself behaves this way, larger among small, low-coverage stocks (Hong, Lim, and Stein 2000), and the literature reads that concentration as a sign of its behavioral origin rather than a mark against it. A risk premium would not localize like this; a mispricing throttled by the cost of arbitrage must. The size gradient is not a crack in the behavioral account but its fingerprint, and the investable-universe evidence below (Table 10) shows the same logic in time as well as in the cross section, the large-cap premium thinning in the recent decades when arbitrage capital ran deepest while the full-universe premium, sheltered in the costly-to-arbitrage tail, did not.

The concentration in smaller names raises a sharper question: is the tilt merely a size effect in disguise, with $r \cdot M$ standing in for small capitalization? A cross-sectional control answers it. Returning to the Fama–MacBeth design of Table 3 and adding log market capitalization to the row-(5) specification, the interaction's slope is essentially unchanged, 0.370% per month ($t = 5.7$) with size controlled against 0.376% ($t = 5.7$) without, while size itself carries no significant independent slope ($t = -1.7$). Controlling for the level of capitalization leaves the tilt intact; it is not a relabeled size factor. The same holds when the recent-month reversal r is also held fixed: in the full specification with momentum, the recent month, and size all present, the interaction is if anything stronger (0.339% per month, $t = 7.9$), because separating r from $r \cdot M$ purifies the interaction. The tilt is not momentum, not standalone reversal, and not size; it is the distinct fourth thing that B adds.

What the concentration reflects is an interaction, not a proxy. Adding the cross-term $r \cdot M$ times log size to the regression yields a negative and significant slope on the cross-term ($t = -5.7$), so the tilt's marginal power is indeed stronger among smaller stocks; yet its main effect remains positive and significant at the average capitalization (0.277% per month, $t = 4.8$). The reading is consistent across all three lenses, the portfolio concentration here, the cross-market gradient of Section 9, and this regression: the effect concentrates in smaller names without vanishing in larger ones.

8.2 Value weighting

The concentration in small caps invites the obvious test: does the premium survive value weighting, where the largest stocks dominate the portfolio? It does not, and that is the answer the size evidence predicts. Value weighting de-emphasizes precisely the small, illiquid names in which a limits-to-arbitrage reversal can persist, so it should attenuate the premium, and it does, sharply. Re-estimated value-weighted on the same universe (Table 9), the $B - M$ long–short spanning alpha falls from its equal-weighted 8.5% per year to an insignificant 1.5% ($t = 1.2$), the short-leg increment from 8.4% to 1.9% ($t = 1.5$), and the $B - M$ difference portfolio's Sharpe ratio from 0.81 to 0.23.

Table 9: Equal versus value weighting (U.S. full universe, 1927–2025)

	Equal-weighted		Value-weighted	
$B - M$ increment	Sharpe	α (t)	Sharpe	α (t)
Long–short	0.81	8.51 (5.96)	0.23	1.5 (1.2)
Short leg	0.93	8.44 (6.52)	0.30	1.9 (1.5)

Notes. α is the FF3+UMD+STR spanning alpha of the $B - M$ increment in percent per year (Newey–West, six lags, in parentheses); Sharpe is the increment's annualized Sharpe ratio. Deciles use full-universe breakpoints; the value-weighted columns cap-weight within each decile. The equal-weighted column reproduces Table 6.

We read this as one more size signature, alongside the size terciles above, the cross-market gradient of Section 9, and the size-controlled Fama–MacBeth regression, not as evidence against the effect. Value weighting does not test whether the premium is real; it tests how much of it sits in large stocks, and the honest answer is little. What is invariant to weighting is the structure: even value-weighted, the residual increment is entirely on the short leg (1.9%, against a long-leg alpha indistinguishable from zero, −0.4%, $t = -1.6$), so the short-leg locus on which the paper rests is not an artifact of equal weighting. Whether the small-cap premium is genuine reversal or a microstructure illusion is settled not by weighting but by the one-week-gap test below and the size-controlled regression above, on neither of which value weighting bears.

8.3 Transaction costs

A reversal tilt invites a turnover objection, since reversal signals are fast-moving. The objection dissolves once the right comparison is drawn. The relevant benchmark for B is M, not cash, and momentum is already a high-turnover strategy. Because $(1 + r)$ only mildly perturbs the momentum ranking, B trades only modestly more than M: in the small-cap segment where the premium lives, one-way monthly turnover is 61.8% for M and 67.1% for B, an *incremental* turnover of roughly 64% per year. Even at a punishing 100 basis points one-way, the incremental cost is about 0.6% per year against a gross small-cap premium near 5.7%, so the net premium stays above 5%, and the break-even one-way cost is roughly 880 basis points, far above any realistic small-cap estimate. Converting momentum into B is close to free relative to the premium it adds, the natural consequence of leaving the long leg alone and re-sorting the short.

A factor whose gain is entirely on the short leg invites a sharper version of the same objection: the losers it sells are small and beaten down, the stocks most likely to be expensive to borrow. The answer is again the comparison with M. The increment $B - M$ is not a fresh short position but a re-weighting of one. Both books are fully short the loser decile, in largely the same names, and B only shifts weight from the still-falling losers toward the rebounded ones. The borrow fee is levied on the short notional, which is nearly identical across the two books, so it nearly cancels in the difference: an investor already shorting losers to run momentum captures B's improvement with little additional borrowing, just as it requires little additional trading. Borrow fees do bound the absolute return to holding any short-loser book. The average equity loan fee is modest, a few tens of basis points, but the small, low-priced, distressed names that fill the loser decile skew toward the expensive tail, where fees reach the hundreds of basis points (D'Avolio 2002; Engelberg, Reed, and Ringgenberg 2018). That cost falls on momentum's short leg as a whole, not on the increment B adds, which is what this paper measures.

8.4 Microstructure

Because B uses the recent month, it is fair to ask whether its short-leg edge is bid–ask bounce rather than genuine reversal. By construction B already excludes the standalone recent return that carries most of that bounce (Section 3.3), but a direct test is cleaner. We insert a gap between portfolio formation and holding, which removes the microstructure bounce, a one- to two-day phenomenon, while leaving the loser population unchanged. Skipping the first day of the holding month leaves the small-cap premium at 4.98% ($t = 3.5$); skipping the first week, 2.77% ($t = 2.9$); skipping two full weeks, 0.95% ($t = 1.7$). The premium decays with the gap, as a partly short-horizon effect should, but a statistically significant core survives a one-week separation that no bid–ask bounce, a one- to two-day phenomenon, can span; by two weeks the estimate is positive but only marginal. The edge on the short leg is reversal, not bounce. As expected of a reversal effect, the premium is concentrated in lower-priced stocks, the same beaten-down losers that populate the short leg: imposing a \$5 price floor would retain only 1.26% per year of the small-cap premium ($t = 3.7$), and a \$10 floor essentially none. This locates the effect, it does not impeach it, since the skip-week test above already shows what survives is reversal rather than bounce; it is also the reason the universe screens on capitalization rather than on price.

8.5 Seasonality and subperiods

Short-term reversal is historically concentrated in January, so we check whether $B - M$ is too. It is not. Excluding January, the full-model alpha is 7.22% per year ($t = 5.0$), barely below the all-month figure. The premium is earned year-round. Nor does it show a clear secular decline across the coarse subperiods: it is large and significant in each, at 9.15% per year ($t = 3.4$) over 1927–1962, 5.35% ($t = 4.7$) over 1963–1989, and 10.04% ($t = 4.2$) over 1990–2025, with the most recent quarter-century at 7.55% ($t = 2.9$). A reversal premium that survives a century without being arbitraged away is unusual, and is consistent with its concentration in the small, costly-to-arbitrage stocks documented above.

The premium is uneven across decades, but it does not rest on any one of them. Decade by decade it is positive in nine of the ten since 1927 and significant in the 1930s, 1940s, 1970s, 1980s, 1990s, and 2000s; only the 2010s are slightly negative. It also survives the deletion of its most extreme observations: dropping the single worst month leaves the full-sample alpha at 7.97% ($t = 5.7$), dropping the worst calendar year, 1932, at 7.22% ($t = 6.0$), and dropping the entire 1930s, its strongest decade, at 6.58% ($t = 5.1$). A rolling ten-year alpha is positive in 88% of windows. The Depression decade is the largest single contributor, but the premium does not rest on it.

8.6 Investability and the size of the harvest

The premium is concentrated in smaller stocks under equal weighting, which raises the practical question of whether it can be captured in a universe one can actually short. Part of the gross premium cannot. Stocks below the NYSE 20th percentile, with a median capitalization near $15 million, are more than 40% of the names and carry a $B - M$ short-leg premium above 15% per year: a lottery-like nano-cap segment, of the kind familiar from the small-stock anomaly literature, that no investor can realistically short and that we therefore set aside. The question is what survives in universes one can actually trade. At each formation month we form an *ex ante* universe of the stocks above a chosen NYSE size percentile, run the decile long–short and its short leg inside that universe, and ask whether B still improves on momentum there. Table 10 reports the result for four such universes, both full-sample and over the recent quarter-century.

Two facts frame the magnitudes. The size cut is a *relative* one, an NYSE percentile recomputed each month rather than a fixed dollar figure, so it tracks the secular growth of the market rather than drifting with it; in recent years the NYSE 30th percentile sits near $1.2 billion, a small- to mid-cap universe one can short without difficulty. And the short leg is genuinely small *at formation*,

Table 10: Investability: the premium in ex-ante size-floored universes (U.S.)

	Long–short $B - M$		Short leg only	
Universe (by formation cap)	1927–2025	2000–2025	1927–2025	2000–2025
≥ NYSE 20th percentile	1.99 (2.97)	0.98 (1.89)	2.14 (3.44)	0.98 (2.12)
≥ NYSE 30th percentile	1.75 (3.06)	0.78 (1.52)	1.82 (3.43)	0.82 (1.75)
≥ NYSE 40th percentile	1.40 (2.50)	0.75 (1.48)	1.59 (3.01)	0.66 (1.40)
≥ NYSE 60th percentile	1.49 (2.15)	0.61 (1.23)	1.25 (2.02)	0.11 (0.31)

Notes. Each universe contains the eligible stocks whose formation-month market capitalization exceeds the stated NYSE percentile breakpoint, computed afresh each month so the cut is a constant *relative* size despite the secular growth of the market; within it we form decile long–short and short-leg (−bottom decile) portfolios. Entries are FF3+UMD+STR alphas in percent per year with Newey–West t-statistics in parentheses. In recent years the NYSE 30th, 40th, and 60th percentile breakpoints fall near \$1.2, \$2.1, and \$5.4 billion; the entry universe at the 20th percentile, near \$0.7 billion, is itself liquid and fully shortable.

not merely afterward: the median loser in the bottom decile has a market capitalization near \$80 million when the position is opened, 94% sit below the NYSE 40th percentile, and that median does not fall over the holding month. The premium lives in stocks that are already small when they are shorted, not in mid-caps that collapse into micro-caps later.

The verdict has two halves and we state both. Over the full century the premium, and the short leg that carries it, remain significant across the entire investable range. At the NYSE 20th percentile, near \$0.7 billion in recent years, the short-leg alpha is 2.14% per year ($t = 3.4$); at the NYSE 30th percentile it is 1.82% ($t = 3.4$); at the NYSE 40th percentile 1.59% ($t = 3.0$); and even among the largest stocks, above the NYSE 60th percentile, it is still 1.25% ($t = 2.0$). The binding limit is recent, not cross-sectional: over 2000–2025 only the entry-level NYSE-20th short leg stays significant (0.98%, $t = 2.1$), the larger-cap short legs fading, so the recent premium is concentrated in the smaller of the investable names. A final friction sharpens the boundary, though it bears on the absolute return to the short book rather than on the $B - M$ increment, which, as the transaction-cost discussion above notes, reweights an already-borrowed position and is nearly borrow-neutral. The short leg is built from beaten-down losers, among the names most expensive to borrow, and the fee bites hardest in the smallest of them. The harvestable premium is therefore confined to a capacity-limited, small- and mid-cap, shortable band, captured most cleanly in the larger, cheaper-to-borrow part of that range.

9 International Evidence

A behavioral asymmetry between winning and losing is not a property of the United States, and if B's edge is the asymmetry, it should appear abroad. We repeat the test in eleven markets outside the United States, using the same decile long–short design on independently sourced data. Table 11 reports the improvement in long–short Sharpe ratio, B over M, in each.

Table 11: The reversal tilt across markets (B minus M long–short Sharpe ratio)

Market	$B - M$ (Sharpe)	NW t	Sample
United States	+0.40	n/a	CRSP, 1927–2025
China (A-shares)	+0.05	n/a	CSMAR, 1994–2024
Australia	+0.46	6.4	1986–2026
Hong Kong (SAR)	+0.42	5.7	1990–2026
Singapore	+0.41	5.1	1991–2026
India	+0.32	4.0	1993–2026
Germany	+0.31	3.8	1988–2026
Japan	+0.17	3.9	1986–2026
Korea	+0.16	1.5	1990–2026
United Kingdom	+0.15	3.8	1986–2026
Taiwan	+0.15	2.5	1989–2026
France	+0.06	1.5	1986–2026

Notes. Each non-U.S., non-Chinese market is defined by listing, not by country of incorporation: it is the set of common stocks trading in that market's local currency in Compustat Global, reduced to one primary security per firm via the Compustat primary-issue line, which removes the duplicate cross-listing feeds that would otherwise multiply-count blue chips. This is what lets a market like Hong Kong include the offshore-incorporated giants (for instance Tencent or Alibaba, incorporated in the Cayman Islands) that an incorporation screen would wrongly drop. France and Germany, which share the euro, are instead identified by country of incorporation in their local currency, including the pre-1999 franc and mark. The smallest 0.1% by capitalization is dropped each month. The NW t is a Newey–West (6 lag) statistic on the monthly $(B - M)$ long–short difference. The United States (CRSP) and China (CSMAR A-shares) are the anchor markets carried through the paper; sample windows differ by market as shown. The $B - M$ (Sharpe) entry is the gain in the long–short Sharpe ratio, Sharpe(B) minus Sharpe(M) (for the United States, 0.78 − 0.38), not the Sharpe ratio of the $B - M$ difference portfolio itself (0.81, Section 4).

The improvement is positive in all twelve markets. Among the ten international markets it is statistically significant in eight, with France and Korea the exceptions, and a sign test on the ten positive signs rejects chance at $p = 0.002$. The mechanism travels with the result: in China, where the data permit the decomposition, the gain is again on the short leg, and the one-month reversal is again stronger among losers than winners, here by a factor of 1.9.

The size signature travels as well. In the United States the $B - M$ short-leg premium is strongest among small stocks and weakens as one moves up the size distribution (Section 8). That gradient is itself a cross-market constant. Table 12 re-runs the short-leg test inside progressively larger slices of each market, where the slices are defined by each market's own capitalization percentiles, recomputed monthly: "Full" removes only the smallest 0.1%, while "≥P60" keeps the largest 40% of stocks by local market value. Defining the cut with within-market percentiles, rather than a common dollar threshold, is what makes it comparable across economies of very different size.

Two features recur. First, in most markets the short-leg premium weakens as the size floor rises, confirming that the effect is concentrated in smaller names; the decline is clearest in the

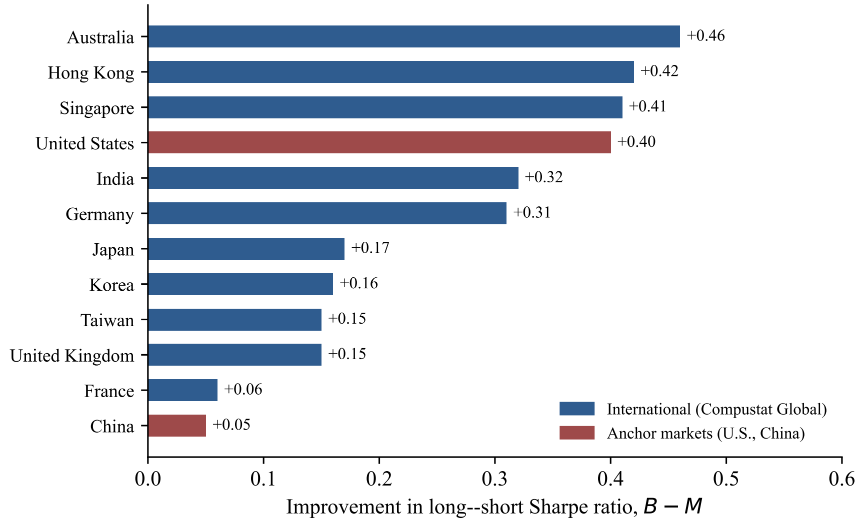

Figure 5: The reversal tilt across markets: the improvement in long–short Sharpe ratio, B minus M, in each of twelve markets. The improvement is positive everywhere. Blue bars are the ten international markets (Compustat Global); gold bars are the U.S. and Chinese anchor markets.

United States, India, Singapore, Australia, and Taiwan, while Japan and Korea are exceptions whose profile stays flat or strengthens toward the large-cap end. Second, the premium does not vanish there. Within the largest 40% of local stocks it remains significant in the United States, Japan, Korea, India, and the United Kingdom, strongly so in the United States and Japan; in China and Hong Kong it stays significant through the upper-middle of the size distribution and is marginal only in the very top slice. Where the premium does fade at the top, the markets are not only the thin ones: they range from deep, liquid markets such as Australia, where the effect is unusually concentrated in small names, to genuinely thin markets such as Taiwan. The recurring shape is concentration in small names with survival into the liquid large-cap tail of the deepest markets, and it appears on every continent tested.

One caveat preserves the distinction from Section 8. The slices here are within-market percentiles, not absolute dollar amounts, so the largest slice of a small market is far smaller in dollar terms than the largest slice of the United States. Table 12 therefore shows that the size signature is universal, not that the premium is harvestable at a common dollar capitalization abroad. The dollar-level question is the one Section 8 answers for the United States with NYSE breakpoints.

Two honest qualifications accompany the breadth. First, the universality is in the *improvement*, not in momentum's profitability. Under the equal-weight decile design, classic momentum is itself weak or negative in several of these markets, as the international momentum literature has long noted; what is robust across borders is that B improves on whatever momentum delivers, and that it does so through the short leg. Second, the Chinese result is evidence of the anomaly's existence,

Table 12: The size signature of the short-leg $B - M$ premium across markets (Newey–West t-statistic)

Market	Full	≥P20	≥P30	≥P40	≥P50	≥P60
United States	6.7	4.6	4.5	4.1	3.5	3.2
China (A-shares)	2.9	3.2	3.0	2.8	2.2	1.9
Japan	4.0	3.4	3.5	3.7	3.6	4.0
Korea	1.9	3.2	2.5	3.2	3.1	2.8
India	3.9	3.7	2.6	2.6	1.9	2.2
United Kingdom	3.5	1.3	1.3	1.9	2.0	2.4
Singapore	6.3	3.7	2.8	2.2	2.4	1.0
Australia	7.1	3.1	2.6	2.0	1.7	1.1
Hong Kong (SAR)	4.9	3.5	2.9	2.5	2.4	1.9
Germany	4.5	2.0	1.6	1.6	1.2	1.6
Taiwan	3.1	2.2	1.9	1.5	1.1	0.7
France	1.5	2.2	3.0	2.6	1.3	0.9

Notes. Each cell is the Newey–West (6 lag) t-statistic on the monthly short-leg $(B - M)$ return difference, computed inside a size slice of the market. Slices are cumulative within-market capitalization percentiles recomputed each month: "Full" removes the smallest 0.1%, "≥P20" keeps stocks above the local 20th percentile, and so on to "≥P60," the largest 40% by local market value. Universes are listing-based and primary-security deduplicated exactly as in Table 11. All twelve markets use the same decile long–short design and the same percentile scheme, so the columns are comparable across economies of different absolute size. The U.S. row uses within-market percentiles, so its dollar cutoffs differ from the NYSE breakpoints of Table 10.

not of its harvestability: short selling of A-shares is tightly constrained, so the short-leg premium that B identifies is difficult to capture there in practice.

10 Conclusion

Momentum buys winners and sells losers, and it inherits the asymmetry of the two. Winners glide; the long leg is clean. Losers stumble, rebounding and reverting on the way down; the short leg is treacherous, and it is where momentum is weakest and where it crashes. This paper has studied a single, parameter-free response to that asymmetry: multiply classic momentum by the most recent month's gross return, $B = (1 + r)M$. The multiplier keeps momentum's skip in its base and adds only the recent month's *interaction* with the trend, which sorts the short leg along the reversal, shorting rebounded losers harder and not-yet-rebounded losers less.

The evidence assembled here is consistent and bounded. Across a century of U.S. data and twelve markets, B outperforms classic momentum, and the entire gain is on the short leg. The increment is not explained by the Fama–French factors, by momentum, or even by the short-term-reversal factor, against which it loads but which it beats, because it harvests reversal conditionally, among the losers where reversal is more than three times stronger, rather than across the whole market. The premium survives transaction costs, since converting momentum into B is nearly free, and it survives a microstructure gap that rules out bid–ask bounce. It improves momentum's defining tail risk, cutting the skewness of the crash and losing less in all ten of momentum's worst months. Its boundaries are equally clear and equally part of the finding: the effect lives mostly in small caps, is an order of magnitude smaller and at best marginal beyond them, and carries a short-horizon component. We have documented these limits rather than hidden them.

The reading we favor is behavioral. The asymmetry B exploits, smooth ascents and choppy descents with hope-driven rebounds that fade, is the kind the disposition effect predicts, and the premium lives exactly where limits to arbitrage would let such mispricing survive. Whatever its ultimate source, the asymmetry is real, and in the small- and mid-cap, shortable segment where limits to arbitrage preserve it, a multiplicative tilt is the natural, parameter-free way to put the recent month back to work without readmitting the noise that the skip was designed to remove. Winners glide and losers stumble; B is a way of shorting the stumble.

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