Intermediate-Term Reversal

Abstract

Long-term reversal is widely regarded as a fragile anomaly: the premium is concentrated in small and distressed firms and does not survive the standard risk adjustment. We ask whether this verdict reflects how the overreaction is measured rather than whether it occurs. Because the overreaction is an episode in the price path rather than a condition on its endpoints, we rank stocks on the maximum drawdown—the deepest peak-to-trough decline over a window that skips the most recent year—in place of the cumulative return. The sorts uncover an *intermediate-term reversal* that sits between the momentum continuation and the classic long-horizon effect: the high-minus-low decile portfolio earns 1.16% per month, with an eight-factor alpha of 0.87% per month. Unlike the conventional strategy, the premium survives value weighting, persists among the stocks above the NYSE median capitalization, strengthens after 2000, and remains significant once the inference is corrected for the search across seventeen measurement horizons. It is not subsumed by momentum, the firm fundamentals, or a broad set of return predictors, and it concentrates in the stocks that are costly to arbitrage.

Keywords: Overreaction, intermediate-term reversal, maximum drawdown, market efficiency, limited arbitrage.
JEL classification: G10, G11, G12.

1 Introduction

Does the stock market overreact? This has been one of the major empirical questions in the study of behavioral finance ever since De Bondt and Thaler (1985, 1987) argued that investors overreact to news over a prolonged period of time. To support the long-term overreaction hypothesis, De Bondt and Thaler form trading strategies that hold the stocks which have been underperforming over the past 3 to 5 years and short those which have been outperforming during the same period, and they show that such strategies earn positive abnormal returns as the stock prices reverse to correct the mispricing. Together with the momentum effect of Jegadeesh and Titman (1993), this evidence gave rise to the familiar horizon structure of return predictability: the stock returns continue over the intermediate horizon of up to one year and reverse over the long horizon of 3 to 5 years. The two legs of this structure, however, have not aged equally well. While the momentum effect has spawned a voluminous literature and withstood decades of scrutiny, the long-term reversal has been progressively dismissed as a risk premium in disguise, a tax-induced seasonal, or an artifact of the smallest stocks.

The dismissal rests on three well-documented facts. Fama and French (1996) show that the stocks which have been losing their market value over the past 3 to 5 years are concentrated among the small-cap and distressed firms, and that the abnormal returns associated with the long-term reversal strategies vanish after the risk adjustment. Grinblatt and Moskowitz (2004) find that the reversal of the long-term losers occurs mostly in January, which points to the tax-loss selling behavior rather than the correction of overreaction, and George and Hwang (2007) find no evidence of reversal outside January. Furthermore, Jegadeesh and Titman (2001); Blackburn and Cakici (2017) document that the long-term reversal is absent among the large-cap stocks. We argue that this collective verdict may convict the measurement rather than the hypothesis. The literature evaluates the overreaction exclusively through the cumulative return over a ranking window, a statistic that is determined by the two endpoint prices alone. The overreaction, however, is

an episode in the price path: a prolonged accumulation of selling pressure that drives the price from a temporary peak to a trough below the fundamental value. The cumulative return discards the path, conflates the overreaction episode with the run-ups that precede it and the recoveries that follow it, and is mechanically sensitive to the placement of the window endpoints—a choice that theory leaves to the researcher and that the recent literature on the multiplicity of anomalies teaches us to treat with suspicion (Harvey et al., 2016; Chordia et al., 2020). Consistent with the view that the summary statistic matters, recent studies document that alternative characterizations of the past price path—the continuing overreaction measure of Chen et al. (2022), the left-tail momentum of Eom et al. (2023), and the 52-week high anchor (Lin, 2024)—contain predictive information that the simple cumulative return misses, and Chui et al. (2022) show that the momentum and the reversal phenomena can coexist within the very same firms, accruing to different investor clienteles.

In this paper, we revisit the overreaction hypothesis with a measure that targets the episode itself. Instead of using the cumulative returns over a given time period, we define the loser stocks as the ones that have the greatest maximum drawdown, the largest peak-to-trough decline of the price path over the measurement window. When a negative information shock arrives, investors react by piling up selling pressure on the stock price at its peak; if the investors overreact to the news for a prolonged period of time, then the market value of the stock drops deeply and persistently before any correction begins. The maximum drawdown records the amplitude of exactly this trajectory. It is invariant to moderate shifts of the window endpoints whenever the episode lies inside the window, and it retains the stocks whose prices have already begun to rebound—the stocks that the endpoint-based classification rotates out of the loser portfolio precisely when the correction of the mispricing is underway.

Our central finding is what we call the *intermediate-term reversal*: a large and robust reversal premium that resides at the horizon between the momentum continuation and

the classic long-term reversal. Sorting stocks on the maximum drawdown measured from 24 to 12 months before the portfolio formation, the high-minus-low decile portfolio earns 1.16% per month (t-statistic=5.51) in the sample that excludes micro-cap stocks and 1.07% per month (t-statistic=5.15) among large-cap stocks, with the eight-factor alphas of 0.87% per month in both universes; the value-weighted spreads of 0.72% and 0.82% per month remain significant, with the alphas of 0.61% and 0.83%. We emphasize the performance in the large-cap universe: whereas the price-based anomalies typically concentrate in the small and illiquid stocks and are difficult to exploit at scale (Jegadeesh and Titman, 2001; Blackburn and Cakici, 2017), the intermediate-term reversal is as strong among the stocks above the NYSE median market capitalization as it is in the broader sample. The premium doubles in the post-2000 subperiod. To ensure that these figures do not reflect a fortunate choice of the measurement window, we evaluate the entire menu of seventeen lookback horizons jointly and adjust the inference for the false discovery rate (Benjamini and Hochberg, 1995). The premium survives the correction, and its term structure is informative: it concentrates in the windows that skip the most recent year and reach one to three years into the past, and it dissipates at the 4-to-5-year horizons where De Bondt and Thaler (1985) originally looked. The overreaction correction, in other words, is an intermediate-term phenomenon, and the conventional strategies miss it on both ends: the cumulative return sort over the identical window delivers a spread that is confined to the equal-weighted portfolios of smaller stocks, while the classic 5-to-1-year reversal sort produces neither a value-weighted spread nor a large-cap alpha.

The intermediate-term reversal is neither a relabeled momentum nor a repackaging of the known firm characteristics. Because the stocks with large maximum drawdown could have rebounded by the time of portfolio construction, the premium might in principle reflect the momentum continuation rather than the overreaction correction. The conditional sorts reject this possibility: the maximum drawdown premium is significantly positive within every momentum quintile, whereas the momentum effect conditional on a large

maximum drawdown is absent and even reverses sign at the 12-month holding period, a finding that also holds in the sample period with fewer momentum crashes (Daniel and Moskowitz, 2016). The premium is equally robust to the firm fundamentals: it stays significant within every quintile of the sorts on profitability, valuation, leverage, accruals, and turnover. Moreover, in the Fama-MacBeth regressions the predictive power of the maximum drawdown survives the inclusion of twenty lagged characteristics—including size, book-to-market, liquidity, idiosyncratic volatility, momentum, the 52-week high, and the capital gains overhang—while the conventional long-term reversal measure loses its own significance in the same specification.

While the eight-factor risk adjustment absorbs the comovement of the strategy with the traded factors, there still remains unexplained positively significant risk-adjusted returns. We consider two alternative behavioral explanations for the persistence of the premium: (1) the abnormal profit is related to the disposition effect (Grinblatt and Han, 2005); (2) the systematic mispricing in stocks with high maximum drawdown is due to the limited arbitrage capital (McLean, 2010). We find that the overall evidence is in favor of the costly arbitrage explanation, in which the idiosyncratic risk and the illiquidity serve as the proxies for the arbitrage cost. That is, the maximum drawdown premium concentrates in the stocks with high idiosyncratic volatility and high illiquidity—the stocks that are the most difficult to arbitrage—while the variation in the capital gains overhang leaves the premium intact.

This paper contributes to the empirical asset pricing literature in three ways. First, we document a new and robust leg in the horizon structure of reversal. Measured with the cumulative returns, the long-term overreaction does not constitute an anomaly as strong as the intermediate-term momentum, because the reversal premium is either explained by the distress risk factor or disappears in the large-cap stocks universe. Measured with the maximum drawdown, the overreaction correction emerges as an intermediate-term reversal premium that is larger than the conventional reversal premium and robust to

the weighting scheme, the exclusion of the smaller stocks, the risk adjustment, and the subperiods—in short, a strictly better reversal strategy. Second, our approach separates the overreaction hypothesis from its measurement. The combination of a path-based sorting variable with a false discovery rate correction across the full menu of measurement horizons guards the inference against both the endpoint contamination and the specification search, and it offers a template for re-examining other anomalies whose construction requires an arbitrary window. Third, we provide evidence on why the mispricing survives. As noted by Pontiff (2006); McLean (2010), the presence of arbitrage cost does not eliminate the profitable investment opportunity as the liquidity and transaction cost do. Instead, the limited arbitrage capital imposes holding cost for investors to take large position such that the mispricing, and with it the intermediate-term reversal, persists in the market.

The rest of this paper is organized as follows. Section 2 explains the data and methodology. In Section 3, we report the main results and investigate what drives the maximum drawdown premium. Section 4 provides the conclusion for this study.

2 Data and Methodology

The main variable of interest in this study is the maximum drawdown of a stock over the time horizon $[t-p, t-q]$, where $p > q \geq 0$ denote the start and the end of the measurement window in months prior to the portfolio formation time t. Let P_τ denote the stock price, adjusted for splits and distributions, on trading day τ. Specifically, we calculate the maximum drawdown of a stock at the portfolio formation time t as

$$\text{MaxDD}_t = \max_{\tau \in [t-p, t-q]} \frac{HWM_\tau - P_\tau}{HWM_\tau}, \tag{1}$$

where $HWM_\tau = \max_{s \in [t-p, \tau]} P_s$ is the high-water mark at time τ. MaxDD reflects the largest loss, measured from a temporary peak to the subsequent trough, that a buy-and-

hold investor could have experienced over the horizon $[t-p, t-q]$; a loss of such magnitude is most likely to be induced by a sustained accumulation of selling pressure. We define the "losers" in our strategy as the stocks whose MaxDD is in the top decile or quintile group.

The stock price movement measured by MaxDD is the direct consequence of negative demand by investors after the stock price reaches a local maximum. The greater the magnitude of the adverse movement until a trough is reached, the more likely the investors have overreacted to the negative news or shocks. We argue that MaxDD is a more faithful measurement of the long-term overreaction than the cumulative return conventionally used to identify the long-term losers, because the overreaction is an episode in the price path rather than a condition on its endpoints. Under the behavioral theories of De Bondt and Thaler (1985); Daniel et al. (1998); Hong and Stein (1999), an overreacting market drives the stock price from a local peak to a level below the fundamental value through a prolonged accumulation of selling pressure, and the price subsequently reverses as the mispricing is corrected. The amplitude of this episode is precisely what MaxDD records. The cumulative return, in contrast, is a function of the two endpoint prices alone: it discards the entire price path between them, and it conflates the overreaction episode with whatever run-up precedes it or recovery follows it inside the window. Two stocks with the same cumulative return can therefore embody very different histories of overreaction, and only the path-based measure distinguishes between them.

The endpoint dependence also renders the cumulative return mechanically sensitive to the placement of the measurement window. Whenever the peak-to-trough episode lies strictly inside the window, a moderate shift of either endpoint leaves MaxDD unchanged, whereas the cumulative return varies with every such shift because it is re-anchored to the new endpoint prices. Since the horizon over which investors overreact is not observable and must be chosen by the researcher, a sorting variable that is robust to this choice is preferable; we formalize this argument as a multiple testing problem across the lookback

windows in Section 3.2. To illustrate how the rankings diverge, suppose $P_{t-q} = P_{t-p}$, with a peak that occurs before the trough is formed during the window. The cumulative return is zero while MaxDD is strictly positive, so the conventional sort would not classify the stock as having an episode of long-term overreaction despite the deep drawdown in its past. The omission is the most costly for the stocks that have already begun to rebound by the time of portfolio formation: the partial recovery pulls the cumulative return toward zero and rotates these stocks out of the loser portfolio precisely when the correction of the mispricing is underway, even though the reversal could continue for a sustained period in the future (see, e.g., Daniel et al., 1998; Wu and Mazouz, 2016; Conrad and Yavuz, 2017).

The distinction between the two measures is not merely conceptual. As shown in Section 3.1, sorting stocks on the cumulative return measured over the same window as our maximum drawdown measure produces a loser-minus-winner spread that is confined to the equal-weighted portfolios of smaller stocks, whereas the maximum drawdown premium survives value weighting, the restriction to large-cap stocks, and the risk adjustment. Because the two sorting variables share an identical measurement window, the difference in performance can only originate from the information contained in the price path. In this regard, MaxDD is the appropriate measure for revisiting the long-term overreaction hypothesis: it is less sensitive to the choice of the time horizon, and it captures the stocks which have experienced the long-term overreaction events but would escape the endpoint-based classification.

To compute the maximum drawdown, we use the CRSP daily data. For ease of presentation, we use the notation $[-p, -q]$ to denote the choice of window at the monthly frequency to calculate the variable of interests. For instance, maximum drawdown strategy MaxDD[-24, -12] means that the MaxDD is calculated using the daily stock price series over the past 24 months but excluding the data from the most recent 12 months.[1] Here the time index 0 is the portfolio formation end-of-month. The return-based anomalies

[1]The price path within each window is reconstructed from the CRSP daily returns, so the prices are adjusted for stock splits, dividends, and other distributions.

literature has shown that stock prices tend to exhibit intermediate momentum and long-term reversal. The popular view suggests that stock prices of the losers over the past 36 to 60 months reverse, and the stocks that have performed greatly over the past 12 months continue to perform well. Following the literature, we exclude the stock prices over the past 12 months so that the maximum drawdown measure is not confounded by the intermediate momentum.

We follow Jegadeesh and Titman (1993) to examine the trading strategies based on maximum drawdown by forming overlapping portfolios in each month. Specifically, at the end of each month, we sort the stocks into ten decile groups in ascending order based on MaxDD$[-p,-q]$. In each group, we form the equally and the value weighted portfolios, where the value weights are given by the market capitalization in the month prior to the return measurement, and hold them for K periods. Since the portfolio formation process is repeated every month, then there are additional $K-1$ portfolios from the previous months as well as the portfolios formed in the current month. Therefore, in any given month the strategy simultaneously holds the K portfolios with weight $1/K$. The baseline analysis rebalances the portfolios every month ($K = 1$); Table 4 reports the results for the holding periods of one quarter, six months, and one year.

The trading strategies in this paper differ from Jegadeesh and Titman (1993)'s in two ways. First, the K-month holding period portfolios are not rebalanced monthly to maintain equal weight. Second, the stocks that have micro market capitalization at the time of portfolio formation are excluded. We follow Fama and French (2008) to define the micro-cap stocks as the ones whose market capitalization are below the NYSE's bottom 20% quantile. The two modifications are made to avoid the high transaction costs associated with frequent rebalancing and trading illiquid stocks.

The market data are retrieved from CRSP database. The accounting data is obtained from Compustat North America database. The portfolio construction process considers only the U.S. incorporated common stocks that are trading at NYSE, AMEX, or NASDAQ.

The monthly returns in the updated CRSP files incorporate the delisting returns, so the portfolio returns are free of the delisting bias documented by Beaver et al. (2007).[2] Our sample covers the period from July 1963 to December 2024. Because the longest measurement window requires five years of prior price data, the portfolio return series in the empirical analysis starts in July 1968. For the risk factor returns, the factor returns in the Fama-French 5-factor model, the momentum factor, and the short-term and long-term reversal factors are obtained from Prof. Kenneth French's webpage.[3]

3 Results

3.1 The performance of maximum drawdown strategy

We begin the empirical investigation with the performance analysis of maximum drawdown strategy. For the comparison purpose, we follow Jegadeesh and Titman (1993) to form the momentum portfolios (MOM12) by sorting stocks ascendingly based on their cumulative returns over the past year but skipping the most recent month. Similarly, we construct the traditional long-term reversal portfolios (LTR) by sorting stocks in ascending order based on the negative cumulative returns from 5 years to 1 year before the portfolio formation end-of-month. Tables 1 and 2 additionally report the sorts on the cumulative return measured over the same window as the maximum drawdown (MOM24) and on the short-term reversal measure (STR). In this subsection, our discussion focuses on the maximum drawdown portfolios that are formed with MaxDD measured within the time horizon [-24, -12]; Section 3.2 examines the sensitivity of the premium to this choice of the lookback window. The discussion proceeds from the single sorts of Tables 1 and 2 to the subsample analysis of Table 3 and the holding period analysis of Table 4.

As Tables 1 and 2 show, apart from the bottom decile, the average excess return in-

[2] If a stock is delisted during the holding period, we assume it is sold and allocate the proceeds proportionally to the rest of the stocks in the portfolio.

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

creases nearly monotonically as the magnitude of maximum drawdown becomes greater, and the pattern holds under both weighting schemes and market capitalization universes. In the equal-weighted sample excluding micro-cap stocks, the average excess return rises from 0.86% per month in the second decile to 2.36% per month in the top decile, and the value-weighted decile returns climb from 0.47% to 1.20% per month; the eight-factor alphas in Panel B trace out the same gradient. The only departure from monotonicity is the elevated average return of the bottom decile, the stocks with the shallowest historical drawdowns, whose prices have barely deviated from their high-water marks. Meanwhile, the increasing pattern does not emerge for the momentum and traditional reversal strategies. In particular, the momentum sorts exhibit a pronounced U-shaped pattern of average returns across decile groups, so that the return differential between the two extreme momentum deciles is statistically indistinguishable from zero in the equal-weighted sample that excludes micro-cap stocks. The traditional long-term reversal sort produces the familiar decile pattern in which the past long-horizon losers earn the highest equal-weighted average returns, but the decile spread flattens out considerably once the portfolios are value weighted. There are two ways on how the maximum drawdown measure resurrects the long-term overreaction effect. First, it restores the increasing relation between the magnitude of price reversal and the extent of investor overreaction. Second, it increases the return differential between the two extreme decile groups.

Table 1 examines the returns of long-short decile monthly rebalanced portfolios for each strategy, in the sample that excludes the micro-cap stocks and in the large-cap universe. Panel A reports the average returns and Panel B reports the eight-factor alphas. For the full sample analysis, the momentum strategy earns only 0.39% monthly premium (t-statistic=1.45) once the micro-cap stocks are excluded, and the risk adjustment turns the momentum alpha significantly negative at −0.45% per month. This finding is consistent with Daniel and Moskowitz (2016).[4] The traditional long-term reversal sort delivers

[4]Daniel and Moskowitz (2016) show that a series of momentum crash episodes causes the portfolio of past losers to increase in value by 163% and the portfolio of past winners gain by only 8%. In line with this

a loser-minus-winner spread of 1.10% per month (t-statistic=5.83) with an eight-factor alpha of 0.73% per month in the equal-weighted sample excluding micro-cap stocks. The conventional reversal premium, however, is fragile: the value-weighted counterpart in Table 2 is an insignificant 0.26% per month, and among large-cap stocks the equal-weighted alpha shrinks to 0.06% per month (t-statistic=0.60). The MOM24 sort, which ranks stocks on the cumulative return measured over the same $[-24, -12]$ window as the maximum drawdown, tells a similar story: its equal-weighted loser-minus-winner spread of 0.83% per month (t-statistic=4.44) excluding micro-cap stocks shrinks to an insignificant 0.39% per month under value weighting, and its large-cap alpha is indistinguishable from zero. The contrast between the two sorts on the identical window isolates the contribution of the price path information embedded in MaxDD.

Comparing the three classes of strategies, the maximum drawdown strategy generates the largest return premium which remains unexplained by the risk factors. Sorting on MaxDD[-24, -12] delivers a high-minus-low spread of 1.16% per month (t-statistic=5.51) in the sample excluding micro-cap stocks and 1.07% per month (t-statistic=5.15) among large-cap stocks, with the eight-factor alphas of 0.87% per month in both universes. The premium is not an artifact of equal weighting: Table 2 shows that the value-weighted spread remains a sizable 0.72% per month (t-statistic=2.84) excluding micro-cap stocks and 0.82% per month (t-statistic=3.44) among large-cap stocks, with the eight-factor alphas of 0.61% and 0.83% per month. In contrast, the value-weighted momentum alpha is statistically indistinguishable from zero, and the value-weighted long-term reversal sort produces neither a significant spread nor a significant alpha. It is also worth noting that the long leg positions of MaxDD portfolios, which consist of stocks that investors have overreacted to the bad news, yield significantly large positive excess returns at above 2% per month on average.

To further show the robustness of maximum drawdown effect, we report in Tables 1 and

evidence, the subsample analysis in Table 3 shows that the equal-weighted momentum premium is 1.10% per month (t-statistic=3.98) in the pre-2000 period but becomes indistinguishable from zero afterwards.

2 the results for portfolio of large-cap stocks only. The firms with market capitalizations below the median NYSE stocks at the time of portfolio formation are excluded. Previous studies (see, e.g., Jegadeesh and Titman, 2001; Blackburn and Cakici, 2017) have argued based on the historical cumulative returns that there is no long-term reversal pattern in the large-cap stocks universe, and thus suggested that the long-term overreaction prevails only in small-cap stocks. The results confirm these findings by the previous works. The traditional long-term reversal strategy provides little evidence of overreaction in the large-cap stocks sample: the equal-weighted loser-minus-winner spread of 0.55% per month loses all significance after the risk adjustment (alpha of 0.06% per month), and the value-weighted spread is indistinguishable from zero even without any risk adjustment. On the other hand, the stocks with MaxDD in the top decile group consistently outperform those in the bottom decile group by large margin. The eight-factor alphas of the high-minus-low MaxDD[-24, -12] portfolios in the large-cap universe are 0.87 (t-statistic=5.34) under equal weighting and 0.83 (t-statistic=4.55) under value weighting. These results highlight the fact that the stocks with large maximum drawdown exhibit price reversals, indicating investor overreaction in the past, and this fact is not specific to small-cap stocks or explained by the standard risk factors. The survival of the premium among the largest and most liquid stocks distinguishes the intermediate-term reversal from the conventional reversal and from many price-based anomalies, whose premia concentrate in the small-cap segment where the implementation costs are the highest, and it implies that the strategy is exploitable at scale; a comparable large-cap robustness has recently been documented for the cash-based profitability-to-price value strategy of Wang (2024).

Table 3 splits the sample into the pre-2000 (July 1968–December 1999) and post-2000 (January 2000–December 2024) subperiods for both the equal- and value-weighted portfolios. The maximum drawdown premium is present in both halves of the sample and, if anything, strengthens over time. In the equal-weighted sample excluding micro-cap stocks, the high-minus-low spread doubles from 0.79% per month (t-statistic=3.14) in the

pre-2000 period to 1.63% per month (t-statistic=4.77) afterwards, and the corresponding eight-factor alphas rise from 0.50% to 1.36% per month. The same pattern emerges among large-cap stocks and under value weighting, where the post-2000 alphas of 1.10% and 1.09% per month remain highly significant; the only specification in which the premium loses significance is the pre-2000 value-weighted spread in the sample excluding micro-cap stocks (0.49%, t-statistic=1.55). The strengthening of the premium in the more recent decades suggests that the maximum drawdown effect is not an artifact of the early sample and has not been arbitraged away.

The return-based sorting variables fare differently across the two subperiods. The equal-weighted momentum premium of 1.10% per month (t-statistic=3.98) in the pre-2000 period disappears entirely afterwards (−0.51%, t-statistic=−1.04), reflecting the momentum crash episodes documented by Daniel and Moskowitz (2016). The conventional long-term reversal spread, in contrast, remains confined to the equal-weighted portfolios: the value-weighted LTR spreads are statistically indistinguishable from zero in both subperiods. The comparison reinforces the conclusion from Tables 1 and 2 that the maximum drawdown measure captures a dimension of the long-term overreaction that the conventional return-based sorts do not.

Finally, Table 4 reports the return analysis for the maximum drawdown strategy when the portfolios are held for one quarter, six months, or one year. Sorting stocks with MaxDD continues to produce large return spread at the lower rebalancing frequencies. For instance, the equal-weighted portfolios excluding micro-cap stocks yield the premia of 1.03%, 0.95%, and 0.82% per month for the quarterly, semiannual, and annual holding periods, respectively, all with t-statistics near 5, and the corresponding eight-factor alphas of 0.72%, 0.80%, and 0.64% per month remain highly significant. The value-weighted spreads are smaller in magnitude but retain the statistical significance; among large-cap stocks the annual holding period strategy still earns 0.69% per month with an eight-factor alpha of 0.69% per month (t-statistic=4.45). The slow decay of the premium in the holding

period indicates that the price correction following the long-term overreaction unfolds gradually rather than being confined to the formation month.[5]

3.2 The lookback horizon and multiple testing

The evidence so far fixes the measurement window of the maximum drawdown at $[-24, -12]$, yet this window is not pinned down by theory. Because the pair $[p, q]$ is selected by the researcher rather than dictated by an economic restriction, an inference drawn from the single most favorable window would overstate the reliability of the maximum drawdown premium, a concern that a growing literature has raised for the anomalies documented in the cross-section of stock returns (Harvey et al., 2016; Chordia et al., 2020). In this subsection, we address this concern by treating the choice of horizon as a multiple testing problem and by evaluating the entire collection of specifications jointly in Figures 1 through 4. Specifically, we consider the seventeen windows reported on the horizontal axis of the figures, sort stocks into deciles on each of three price path variables—the maximum drawdown, the maximum rebound, and the past cumulative return—and form the high-minus-low decile portfolio for each variable under both equal and value weighting.[6] Within a given market capitalization universe and sample period this procedure yields a family of $17 \times 3 \times 2 = 102$ long-short strategies. For every strategy we compute the t-statistic of the average monthly excess return and the t-statistic of the intercept from the time-series regression of the long-short return on the eight traded factors—the Fama and French (2015) five factors augmented with the momentum, the short-term reversal, and the long-term reversal factors—in both cases using the heteroskedasticity- and autocorrelation-robust covariance estimator of Newey and West (1987) with data-driven

[5] Blackburn and Cakici (2017); Zaremba et al. (2020) suggest that the traditional long-term reversal premia could not be explained by the book-to-market ratio (value factor) using the Fama-Macbeth regression. Our methods are in line with Fama and French (1996)'s who use factor portfolio returns to explain the anomalous returns. This is also consistent with the asset pricing theory which suggests that the return co-movement should be the proper measure of risk.

[6] We define the maximum rebound, in a similar manner to maximum drawdown, as the maximum gain from trough to peak over the window $[p, q]$.

lag selection.

Denote by t_j the resulting statistic for strategy j and by $\Phi(\cdot)$ the standard normal cumulative distribution function. We convert each statistic into the two-sided p-value $p_j = 2\left[1 - \Phi\left(\left|t_j\right|\right)\right]$ and apply the step-up procedure of Benjamini and Hochberg (1995) to the 102 p-values, which controls the false discovery rate, the expected share of spurious rejections among the discoveries, rather than the family-wise error rate. The false discovery rate criterion is the appropriate choice in this setting because the measurement windows overlap heavily and the corresponding test statistics are therefore strongly dependent, so that a family-wise correction such as the Bonferroni bound would be severely conservative (Harvey et al., 2016). The average return and the alpha statistics are treated as two separate families and adjusted independently. Letting p_j^{BH} denote the adjusted p-value and $\hat{\theta}_j$ the estimated premium or alpha, we map the outcome back onto the conventional scale as

$$\tilde{t}_j = \operatorname{sgn}\left(\hat{\theta}_j\right)\left|\Phi^{-1}\left(p_j^{BH}/2\right)\right|. \tag{2}$$

It is this adjusted statistic that is printed above each bar in Figures 1 through 4, so that a reported value exceeding 1.96 in absolute terms identifies a strategy which survives the correction for the horizon search at the 5% level.

Figures 1 and 2 report the equal- and the value-weighted results over the full sample, and Figures 3 and 4 repeat the exercise for the post-2000 subperiod; in each figure the top panel plots the average monthly high-minus-low return and the bottom panel the corresponding alpha. Two features of the evidence stand out. First, the equal-weighted maximum drawdown premium is positive at every horizon we consider, and the adjusted statistics indicate that its significance is not an artifact of the specification search; under value weighting the premium concentrates in the windows of two years or longer, in particular those that skip the most recent year, while the spreads at the shortest horizons are close to zero. For the equal-weighted portfolios formed on the window $[-24, -12]$,

which the preceding tables adopt, the average return is 1.16% per month with an adjusted statistic of 4.99 when micro-cap stocks are excluded and 1.07% per month with an adjusted statistic of 4.59 among large-cap stocks; the corresponding alphas of 0.87% per month retain adjusted statistics of 4.26 and 5.02. Second, the premium attenuates as the measurement window recedes further into the past. While the raw spreads remain positive at the longest horizons, the alphas on the windows $[-48, -12]$ and $[-60, -12]$ carry adjusted statistics of 1.48 and 1.56 in the sample excluding micro-cap stocks, and of 0.39 and -0.42 among large-cap stocks, and thus cannot be distinguished from zero once the multiplicity of the horizon choice is taken into account. The evidence therefore validates the choice of an intermediate window in Section 3.1: the long-term overreaction is best measured over a horizon that excludes the most recent year but does not extend to the longest history available.

3.3 Cross-sectional regressions

The portfolio sorts in Section 3.1 control for one characteristic at a time. To examine whether the maximum drawdown contains predictive information beyond the known determinants of the cross-section of stock returns, we estimate Fama–MacBeth regressions of the one-month-ahead excess returns on MDD and a comprehensive set of lagged firm characteristics. In each month, every regressor is transformed into its cross-sectional percentile rank, so that a slope coefficient measures the difference in the expected next-month return, in percent, between the stocks at the top and at the bottom of the ranking of that characteristic. Table 5 reports the time-series averages of the monthly coefficient estimates for six nested specifications in the large-cap universe.

The univariate regression in column (1) assigns to MDD a premium of 1.19% per month (t-statistic=5.53), in line with the decile spreads of Table 1. Controlling for the market beta, size, and book-to-market in column (2) roughly halves the coefficient to 0.61%, and the successive additions of the profitability and investment characteristics,

the liquidity and idiosyncratic risk proxies, and the price-path variables reduce it further. Nevertheless, in the full specification of column (6), which includes twenty control characteristics—among them momentum, the 52-week high, the capital gains overhang, the short-term and long-term past returns, and the maximum daily return—the MDD coefficient remains a statistically significant 0.29% per month (t-statistic=2.37). The estimates on the controls carry the familiar signs: the size and illiquidity ranks command strongly negative premia, momentum enters positively, and the most recent month return enters negatively, consistent with the short-term reversal. We conclude that the maximum drawdown is not a repackaging of the known return predictors, and its premium survives the characteristic controls that subsume the conventional long-term reversal measure, whose own coefficient in column (6) is an insignificant -0.17 (t-statistic=-1.55).

3.4 The maximum drawdown effect controlling for momentum

The theoretical models developed in Daniel et al. (1998); Hong and Stein (1999) imply that the momentum and reversal effects are related due to the cyclical nature of investor's under- and overreaction. The empirical evidence shown by Conrad and Yavuz (2017) also suggest that the time-series pattern of intermediate-horizon momentum and long-horizon reversal could be linked. More recently, Chui et al. (2022) attribute the coexistence of the two phenomena to distinct investor clienteles, and Zeng et al. (2025) show that conditioning the momentum signal on the firm characteristics materially alters its profitability. Therefore, it is possible that the stock price reversal observed in maximum drawdown sorting strategy is a continuing effect of intermediate-horizon momentum. This subsection examines such possibility by revisiting the maximum drawdown effect for stocks that show no momentum at the time of portfolio formation.

To examine whether maximum drawdown effect persists after controlling for past intermediate momentum, we use conditional sorts (see, e.g., Grinblatt and Han, 2005; Asness et al., 2019, among many others). Specifically, in each month we first group the

stocks into momentum quintiles, and then sort the stocks based on MaxDD[-24, -12] within each of the momentum groups. The results in Table 6 show that the maximum drawdown premium stays statistically significant after controlling for momentum. In the sample excluding micro-cap stocks, the high-minus-low MaxDD spread ranges from 0.50% to 1.35% per month across the momentum quintiles, with the largest premia observed in the two extreme quintiles, and the corresponding eight-factor alphas remain significantly positive. The same pattern emerges in the large-cap universe and for the sorts conditional on the short-term and long-term reversal measures.

Consistent with the prior literature (e.g., De Bondt and Thaler, 1985; Conrad and Yavuz, 2017), our empirical results also suggest that the price reversal effect due to long-term overreaction could persist beyond 12 months. For instance, Table 7 shows that the stocks in the high maximum drawdown group with the strongest past 12-month performance continue to earn 2.38% per month under monthly rebalancing and 1.68% per month over the subsequent 12-month holding period based on the full sample. This finding is a further evidence to show the strength of maximum drawdown effect.

Table 7 shows that the momentum effect becomes fragile once we control for the maximum drawdown. Within the top quintile of maximum drawdown, the momentum sort produces a pronounced U-shaped pattern of excess returns, with the two extreme momentum quintiles both earning more than 2.3% per month, so that the full sample high-minus-low momentum spread is an insignificant 0.05% per month under monthly rebalancing. When the portfolios are held for 12 months, the spread turns significantly negative at −0.49% per month, which indicates that the long-term reversal eventually dominates the momentum continuation among the stocks with large maximum drawdown. In the bottom quintile of maximum drawdown, the monthly rebalanced momentum spread is a modest 0.41% per month, well below the unconditional momentum premium. The conditional momentum spreads are larger in the pre-2000 subperiod, at 0.76% and 0.88% per month for the high and low maximum drawdown groups, consistent with the concen-

tration of the momentum crash episodes in the later sample; yet even there the 12-month holding period spreads shrink to −0.19% and 0.31% per month.

To summarize, the maximum drawdown sorts generate statistically significant return premium regardless of whether there exists intermediate momentum or not in the past. On the contrary, the momentum effect conditional on maximum drawdown is weak: it is absent among the stocks with large maximum drawdown in the full sample and even reverses sign once the holding period is extended to 12 months.

3.5 Firm fundamentals and the behavioral explanations

As shown in Section 3.1, the strong return premium associated with maximum drawdown sorts presents a challenge to the traditional risk-based theories. In this section, we first examine whether the premium merely reflects the firm fundamentals and investment characteristics, and we then consider two behavioral theories—the disposition effect and the costly arbitrage—for explaining why the long-term overreaction premium persists. The behavioral channel is plausible a priori, as the recent international evidence shows that the sentiment-driven overpricing is followed by predictable return reversals (Ahn and Hambusch, 2024).

3.5.1 Controlling for firm fundamentals and investment characteristics

The stocks that have experienced a deep drawdown may simply be the firms with deteriorating fundamentals, in which case the maximum drawdown premium would merely repackage the anomalies based on the accounting characteristics. To examine this possibility, we repeat the conditional sorts of the previous subsection with the firm fundamentals and investment characteristics as the controls: accruals, asset turnover, book-to-market, leverage, gross profitability, price-to-sales, and return on equity. Within each control quintile, the stocks are further sorted into quintiles of MaxDD[-24, -12], and Table 8 reports the high-minus-low spreads.

The maximum drawdown premium is positive and statistically significant within every quintile of every characteristic we consider; in the sample excluding micro-cap stocks the spreads range from 0.41% to 1.71% per month, and the eight-factor alphas display the same pattern. Two features of the conditional premia are worth noting. First, the premium concentrates among the least profitable firms: within the bottom quintile of return on equity the spread reaches 1.71% per month (t-statistic=6.18), against 0.60% per month (t-statistic=3.33) in the top quintile, and the gross profitability sorts exhibit a similar, albeit weaker, gradient. Second, the premium is somewhat U-shaped across the valuation quintiles, being the strongest among the extreme value and the extreme growth stocks in both the book-to-market and the price-to-sales sorts. The overall evidence indicates that the long-term overreaction premium is distinct from the fundamental-based anomalies, although its magnitude covaries with the characteristics associated with weak profitability and valuation uncertainty, which are precisely the firms for which investors are most prone to overreact to negative news.

3.5.2 The disposition effect

Another well-known psychological bias is the investors' disposition to hold on losing stocks in their portfolio for too long and sell winners too early (see, e.g., Shefrin and Statman, 1985; Grinblatt and Han, 2005). According to the disposition effect theory, investors possess mental accounting that causes the gain/loss status of a stock in their portfolio, in addition to the stock's fundamental value, to be an important factor that influence the investment decision making. Therefore, when there exists a fraction of investors with such mental accounting in the market, the stocks which have experienced losses would face less selling pressure in the future, and hence have larger expected returns than they should be under the market with fully rational investors.

We follow Grinblatt and Han (2005) to compute the capital gains overhang at a weekly

frequency,

$$CGO_{i,t} = \frac{P_{i,t-2} - R_{i,t-1}}{P_{i,t-2}}, \tag{3}$$

where $P_{i,t-2}$ is the weekly closing price of stock i lagged two weeks, to avoid the microstructure effects, and $R_{i,t-1}$ is the proxy for the reference price. The reference price is defined as the weighted average of weekly closing prices over the past five years,

$$R_{i,t-1} = \frac{1}{k} \sum_{n=1}^{260} \left(V_{i,t-1-n} \prod_{\tau=1}^{n-1} [1 - V_{i,t-1-n+\tau}] \right) P_{i,t-1-n}, \tag{4}$$

where $V_{i,t}$ is the weekly turnover ratio and k is the normalizing constant such that the weights sum to one. Following the previous sections, we use 5×5 conditional sort to examine the maximum drawdown premium with CGO as the means of controlling the disposition effect. At the end of each month, the most recent week CGO is used in the portfolio construction process.

The measure CGO has been adopted by the prior literature and shown to have powerful predictive information in explaining anomalous cross-sectional stock returns. Grinblatt and Han (2005) show that CGO explains the variability of momentum profit because investors have reference-dependent preference and underreact to new information. An et al. (2020) also assume the same investor behavior and employ CGO to explain anomalies that are related to investment in lottery-type stocks. If the maximum drawdown anomaly is subsumed by the disposition effect, then we should expect to see the maximum drawdown premium disappears for the stocks in the low CGO group. The results in Table 9 show that sorting stocks based on MaxDD[-24, -12], regardless of the CGO clusters, consistently generate positive and significant premium. In addition, the maximum drawdown premia in the low CGO group are even moderately greater than those in the high CGO group. For instance, excluding the micro-cap stocks, the return spread between high and low MaxDD portfolios is 1.27% per month for the lowest quintile CGO stocks, while the H-L difference is 0.87% per month for the highest quintile CGO stocks.

Our results suggest that the variation in CGO is unable to explain maximum drawdown premium. However, we should note that because Grinblatt and Han (2005) make the additional assumption of investor underreaction to negative news, it may be incorrect to reject the entire disposition effect theory. In fact, the long-term overreaction and disposition effects might coexist to explain the maximum drawdown premium. This is because the long-term overreaction to firm-specific negative news induces excessive selling of the stocks in the past. Absent the investors with unrealized gains and losses, the stock price would revert to its fundamental value as the large maximum drawdown has exhausted the downward pressure. Therefore, one could also conclude that the variable MaxDD is a proxy for capital losses overhang.

3.5.3 The effect of costly arbitrage

Finally, we consider the theory of limited arbitrage capital to explain the persistence of long-term overreaction premium. Pontiff (2006); McLean (2010) argue that the risk-averse investors' optimal weight on an asset is inversely proportional to the asset's idiosyncratic risk. Therefore, even if the asset could deliver a significant risk-adjusted return, the high idiosyncratic volatility would incur large holding cost and prevent the investors from allocating too many of the available capital into the asset. As a consequence, for the investment opportunity with large holding cost, there is only limited capital to arbitrage away the abnormal profit. The theory delivers a sharp cross-sectional prediction: if the intermediate-term reversal premium reflects mispricing, then the return spread should be the greatest for the stocks that are the most difficult to arbitrage, where the mispricing can accumulate without being traded away. Wang (2024) apply the same logic to the value strategy and document that the conditional premia line up with the limits to arbitrage proxies; we follow this line of argument here.

We examine two limits to arbitrage measures. The first is the idiosyncratic volatility (IVOL), the dominant holding cost in the taxonomy of Pontiff (2006), which we estimate

from the Fama-French-Carhart 4-factor model: at the time of portfolio formation, we regress the monthly stock excess returns on the returns on the four factor portfolios using the prior 36 monthly observations, and the square root of the regression mean square error is obtained as the end of month idiosyncratic risk. The second is the Amihud (2002) illiquidity ratio (ILLIQ), which captures the transaction cost dimension of the arbitrage cost. The method to analyze the conditional effect is similar to that used for Table 6: we calculate the average long-short maximum drawdown quintile portfolio returns within each IVOL and each ILLIQ quintile. If the maximum drawdown effect is the result of the arbitrage costs limiting the arbitrage activity, then the premium should increase in both proxies and concentrate in the most constrained quintiles.

The results in Table 10 bear out both predictions. Along the holding cost dimension, the long-short portfolios that sort the stocks based on MaxDD[-24, -12] earn statistically significant premia of 1.00% per month in the top IVOL quintile of the sample excluding micro-cap stocks and 0.95% per month among large-cap stocks, with the corresponding eight-factor alphas of 0.91% and 0.79% per month; applying the same strategy in the three lowest IVOL quintiles produces the return spreads of no more than 0.25% per month, which are insignificant after the risk adjustment. Along the transaction cost dimension, the premium rises nearly monotonically from an insignificant 0.20% per month in the most liquid ILLIQ quintile to 2.34% per month (t-statistic=10.54) in the least liquid quintile, with the eight-factor alphas climbing from 0.18% to 2.21% per month; the same gradient appears in the large-cap universe, where the spread reaches 1.74% per month in the least liquid quintile. The alignment of the conditional premia with both arbitrage cost proxies strongly supports the limits to arbitrage interpretation, in line with McLean (2010) and Wang (2024).

In summary, the limited arbitrage capital plays a key role in the continuation of mispricing arising from the long-term overreaction effect. Here we should emphasize the difference between transaction cost and holding cost. As noted by Pontiff (2006), the

transaction cost is paid once per trade, whereas the holding cost accrues for as long as the arbitrage position stays open; a sophisticated arbitrageur can therefore still trade the mispriced securities profitably subject to the willingness to bear the holding cost of undiversified risk. The concentration of the premium in the illiquid stocks indicates that the transaction cost channel also binds, but it cannot be the whole story: the premium survives among the large-cap stocks, where the trading costs are the lowest, and within that universe it still concentrates in the high IVOL quintile. The evidence thus points to the holding cost as the margin that sustains the mispricing, so that the intermediate-term reversal persists in equilibrium precisely where the arbitrage capital is the most limited.

4 Conclusion

The momentum effect in the cross-section of asset returns is a pervasive and widely studied phenomena, in which investors' intermediate-term underreaction is often cited as the major theory supporting the anomaly. Meanwhile, the long-term overreaction is relatively less popular, and such anomaly is sometimes refuted as a behavioral bias to the extent that the return premium associated with the long-term reversal is either explained by the distress risk factor or only limited to the small-cap stocks. Measuring the long-term overreaction with maximum drawdown over a fixed time horizon, this paper provides the evidence that a large and persistent reversal premium emerges because of investors' long-term overreaction to negative shocks. These results are robust to various risk adjustment and the exclusion of smaller market capitalization stocks. Additionally, given the fact that the significance of the return on long-short maximum drawdown portfolio does not dissipate after controlling for price momentum and disposition effect, the persistence of the reversal premium is unlikely due to the investors' underreaction to new positive information arrival.

A further analysis shows that the maximum drawdown premium is not subsumed

by the firm fundamentals and investment characteristics, and it is the most pronounced among the stocks with low profitability. Finally, we find that the maximum drawdown premium is not arbitraged away because of the holding cost faced by the risk averse arbitrageurs. That is, given the unwillingness to aggressively load on the large idiosyncratic risk when investing in the large maximum drawdown stocks, investors would opt to allocate smaller size of capital for this investment opportunity, and thus the abnormal profit continues to exist due to the limited arbitrage capital.

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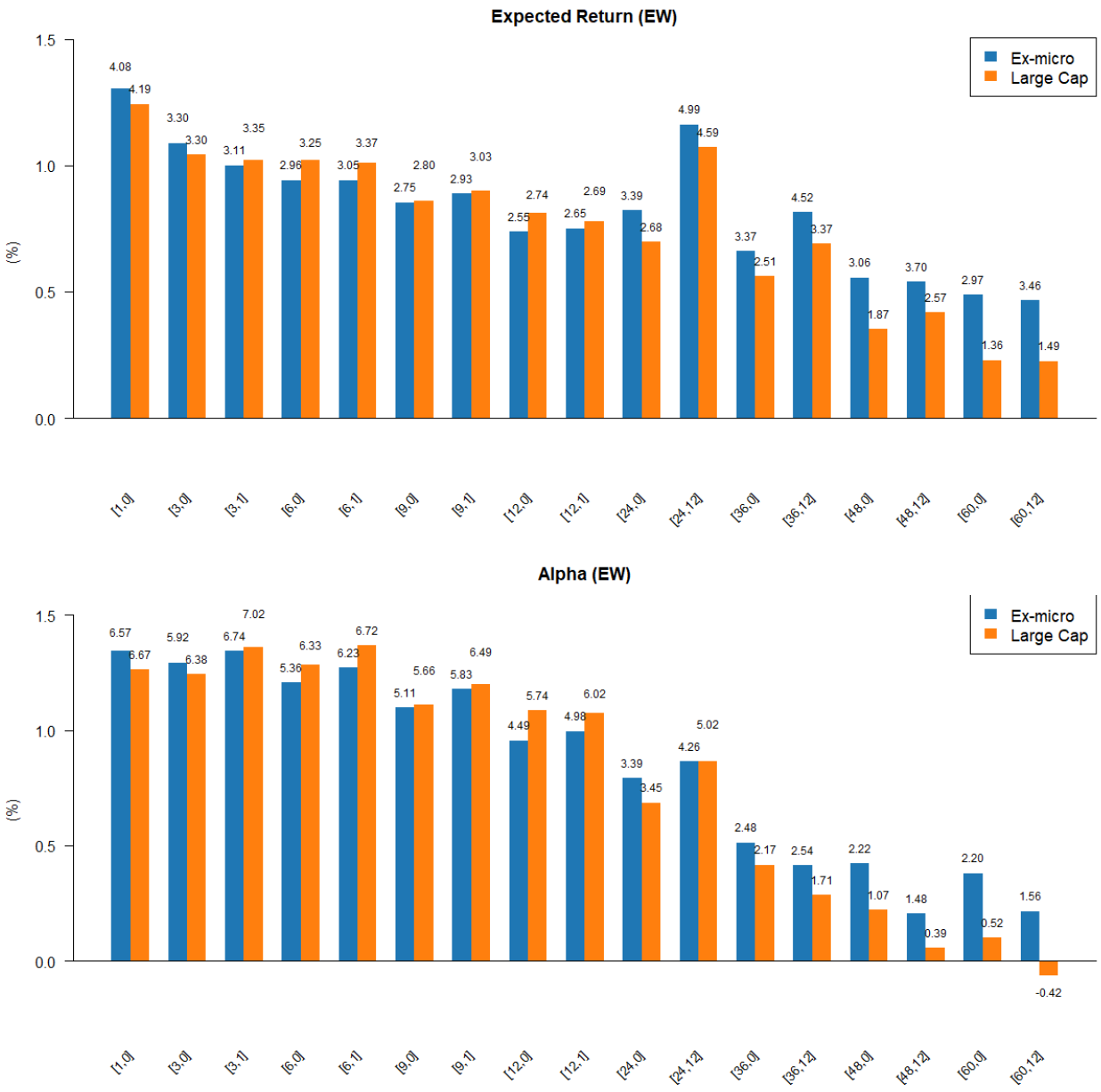


Figure 1: MDD **Portfolios over Different Lookback Horizons for Equal-Weighted Portfolios.** This figure presents bar plots of equal-weighted average monthly returns (top panel) and eight-factor model alphas (bottom panel) for decile high-minus-low MDD portfolios formed using different lookback horizons. The alphas are the intercepts from the time-series regression of the high-minus-low returns on the Fama–French five factors augmented with the momentum, short-term reversal, and long-term reversal factors. At each month-end t, NYSE/Amex/Nasdaq common stocks are sorted into deciles based on maximum drawdown (MDD) measured over the interval $[p, q]$, where p and q denote the start and end months prior to t. "Ex-micro" (blue bars) excludes stocks in the bottom 20% of NYSE market capitalization, while "Large Cap" (orange bars) includes stocks above the NYSE median. Bar labels report the multiple-testing adjusted t-statistics for the high-minus-low spread, computed with the Benjamini–Hochberg procedure described in Section 3.2. The sample period is from July 1968 to December 2024.

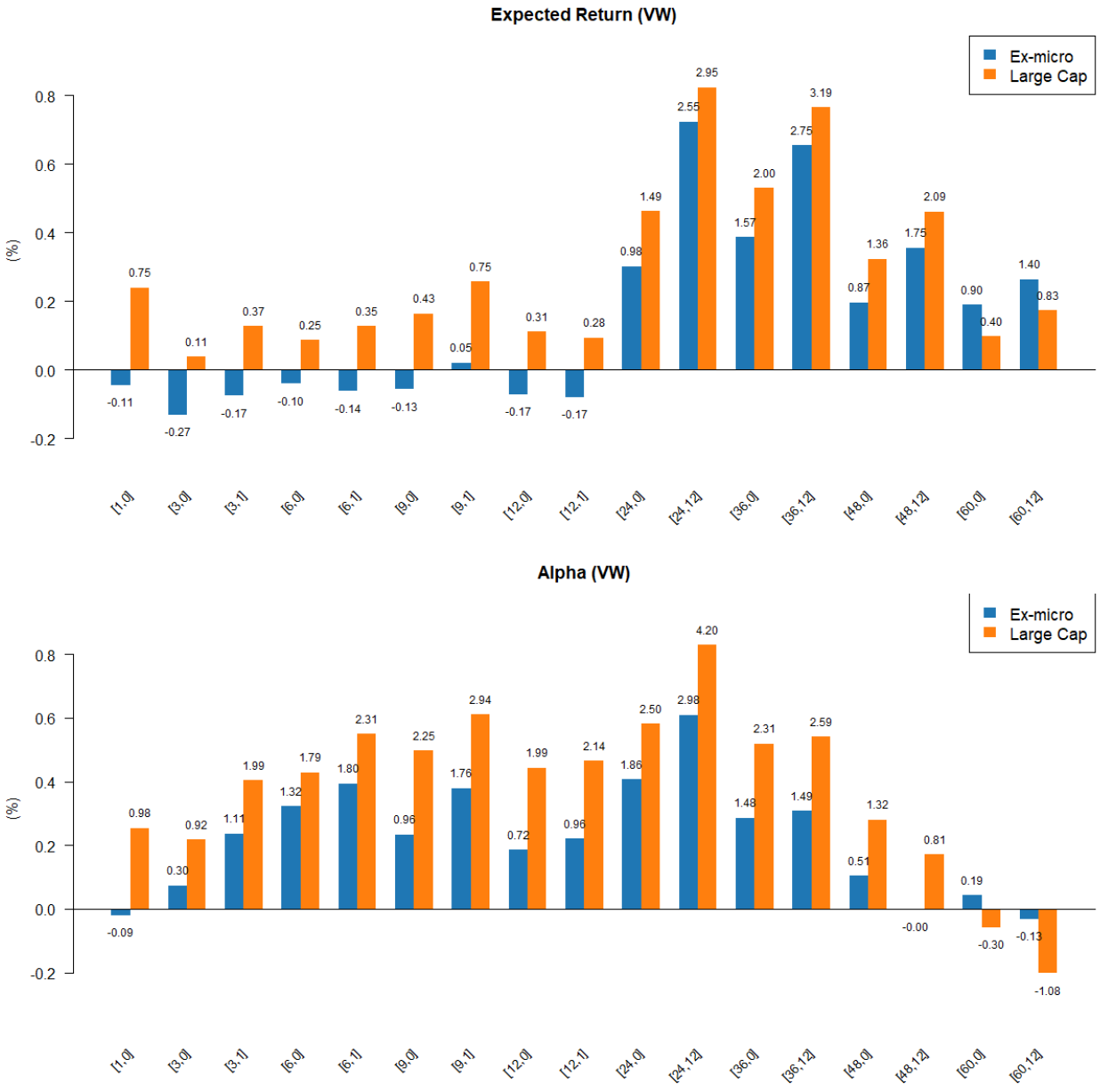


Figure 2: MDD **Portfolios over Different Lookback Horizons for Value-Weighted Portfolios.** This figure presents bar plots of value-weighted average monthly returns (top panel) and eight-factor model alphas (bottom panel) for decile high-minus-low MDD portfolios formed using different lookback horizons. At each month-end t, NYSE/Amex/Nasdaq common stocks are sorted into deciles based on maximum drawdown (MDD) measured over the interval $[p, q]$, where p and q denote the start and end months prior to t. "Ex-micro" (blue bars) excludes stocks in the bottom 20% of NYSE market capitalization, while "Large Cap" (orange bars) includes stocks above the NYSE median. Bar labels report the multiple-testing adjusted t-statistics for the high-minus-low spread, computed with the Benjamini–Hochberg procedure described in Section 3.2. The sample period is from July 1968 to December 2024.

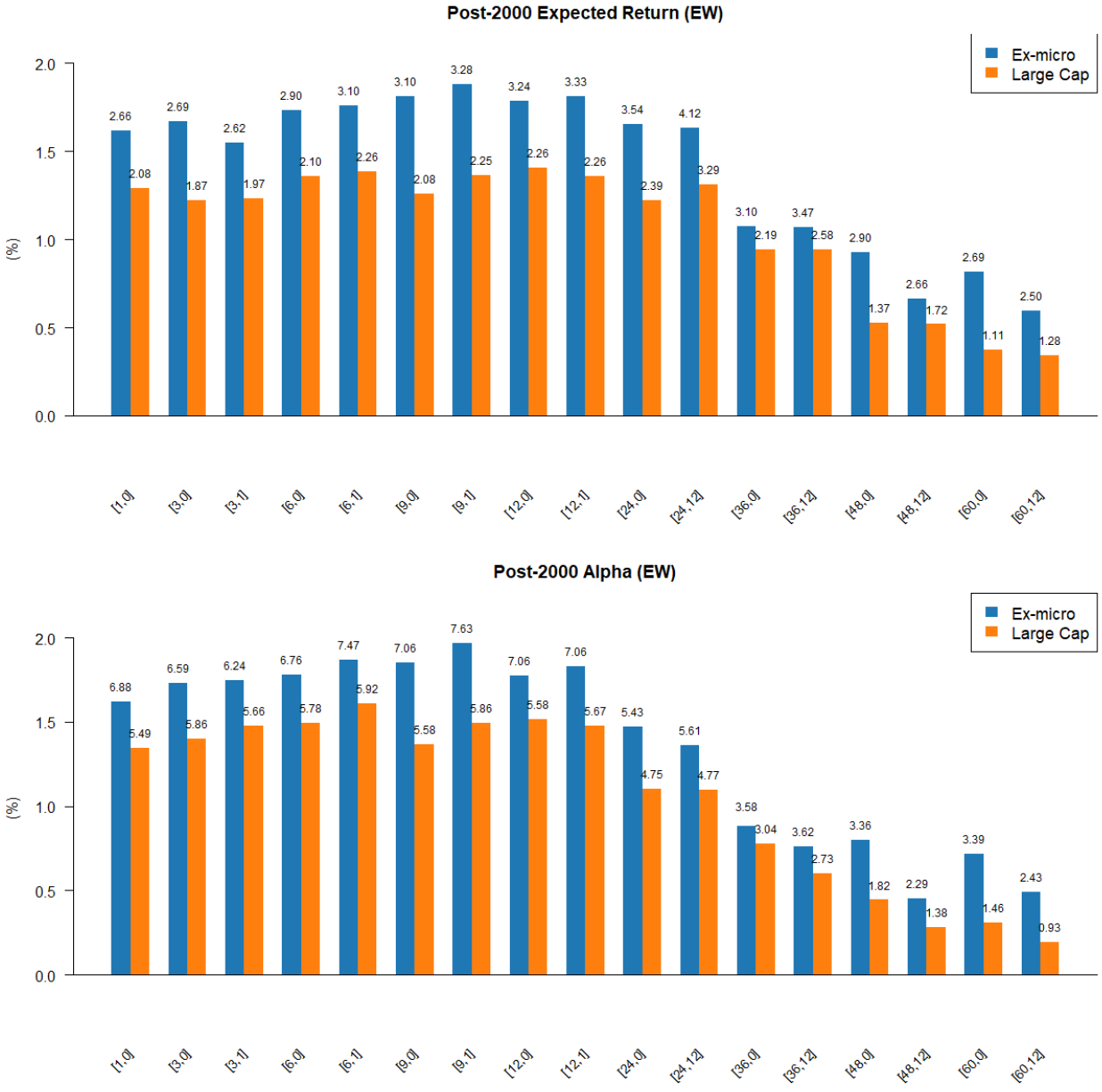


Figure 3: MDD **Portfolios over Different Lookback Horizons for Equal-Weighted Portfolios in the Post-2000 Period.** This figure presents bar plots of equal-weighted average monthly returns (top panel) and eight-factor model alphas (bottom panel) for decile high-minus-low MDD portfolios in the post-2000 sample period. At each month-end t, NYSE/Amex/Nasdaq common stocks are sorted into deciles based on maximum drawdown (MDD) measured over the interval $[p, q]$, where p and q denote the start and end months prior to t (shown on the x-axis). "Ex-micro" (blue bars) excludes stocks in the bottom 20% of NYSE market capitalization, while "Large Cap" (orange bars) includes stocks above the NYSE median. Bar labels report the multiple-testing adjusted t-statistics for the high-minus-low spread, computed with the Benjamini–Hochberg procedure described in Section 3.2. The post-2000 sample period covers January 2000 to December 2024.

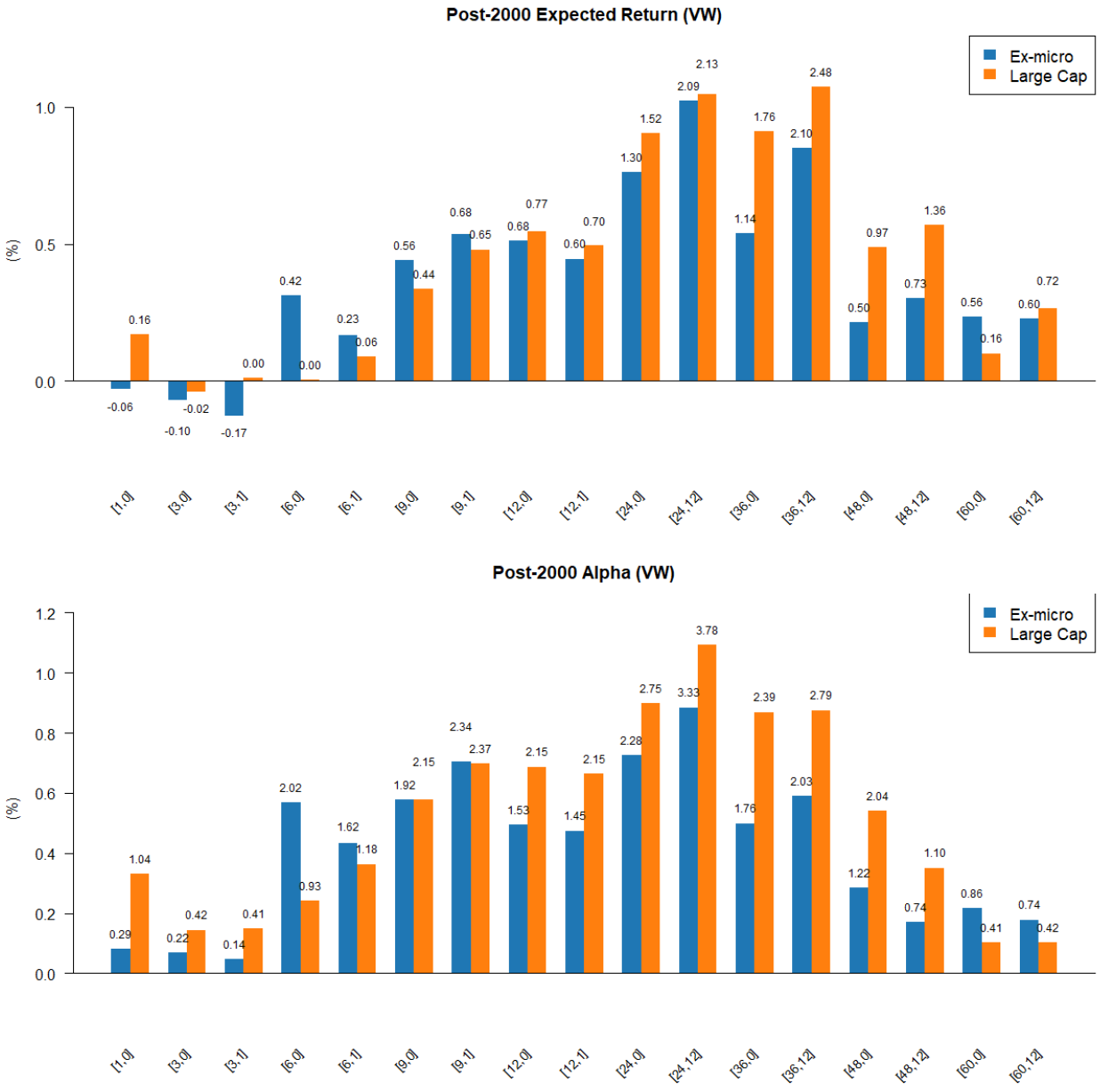


Figure 4: MDD **Portfolios over Different Lookback Horizons for Value-Weighted Portfolios in the Post-2000 Period.** This figure presents bar plots of value-weighted average monthly returns (top panel) and eight-factor model alphas (bottom panel) for decile high-minus-low MDD portfolios in the post-2000 sample period. At each month-end t, NYSE/Amex/Nasdaq common stocks are sorted into deciles based on maximum drawdown (MDD) measured over the interval $[p, q]$, where p and q denote the start and end months prior to t (shown on the x-axis). "Ex-micro" (blue bars) excludes stocks in the bottom 20% of NYSE market capitalization, while "Large Cap" (orange bars) includes stocks above the NYSE median. Bar labels report the multiple-testing adjusted t-statistics for the high-minus-low spread, computed with the Benjamini–Hochberg procedure described in Section 3.2. The post-2000 sample period covers January 2000 to December 2024.

Table 1: Equal-Weighted Portfolio Returns Sorted on Maximum Drawdown and Return-Based Measures.

This table reports equal-weighted average monthly returns (Panel A) and eight-factor model alphas (Panel B)—the intercepts from the time-series regression of the portfolio returns on the Fama–French five factors augmented with the momentum, short-term reversal, and long-term reversal factors—for extreme decile portfolios sorted on five characteristics: maximum drawdown (MDD), long-term momentum ($MOM24$), short-term momentum ($MOM12$), short-term reversal (STR), and long-term reversal (LTR). MDD is the maximum drawdown over months $t-24$ to $t-12$; $MOM24$ is the cumulative return from $t-24$ to $t-12$; $MOM12$ is the cumulative return from $t-12$ to $t-1$; STR is the return over the most recent month; and LTR is the cumulative return from $t-60$ to $t-12$. Since STR and LTR rank stocks by their past returns, a negative $H-L$ spread on these sorts indicates short-term and long-term reversal, respectively. At each month-end t, NYSE/Amex/Nasdaq common stocks are independently sorted into ten deciles for each characteristic, with "Ex-micro" excluding stocks in the bottom 20% of NYSE market capitalization and "Large Cap" including stocks above the NYSE median. Panel A reports average returns for the lowest (L) and highest (H) deciles and the high-minus-low ($H-L$) spread; Panel B reports the corresponding alphas. The sample period is from July 1968 to December 2024. t-statistics (in parentheses) are reported only for $H-L$ and are computed using Newey–West heteroskedasticity- and autocorrelation-robust standard errors.

	Ex-micro					Large Cap				
	MDD	$MOM24$	$MOM12$	STR	LTR	MDD	$MOM24$	$MOM12$	STR	LTR
Panel A. Average Returns										
L	1.20	2.15	1.64	2.11	2.04	1.09	1.81	1.40	1.88	1.68
2	0.86	1.47	1.10	1.59	1.37	0.85	1.35	1.07	1.46	1.17
3	0.95	1.22	1.07	1.40	1.18	0.92	1.10	1.02	1.32	1.03
4	0.96	1.12	0.99	1.25	1.01	0.95	1.05	0.99	1.21	1.09
5	1.05	1.01	1.00	1.19	1.06	1.05	0.97	0.95	1.10	1.00
6	1.07	1.01	1.04	1.08	1.00	1.10	1.00	0.97	1.13	1.00
7	1.17	1.02	1.11	0.98	1.00	1.12	0.96	1.02	0.99	1.00
8	1.42	1.05	1.20	1.02	0.99	1.26	1.01	1.13	0.93	1.01
9	1.62	1.10	1.41	0.92	1.01	1.54	1.11	1.34	0.92	1.05
H	2.36	1.33	2.03	1.36	0.94	2.16	1.43	2.04	1.28	1.13
$H-L$	1.16	-0.83	0.39	-0.75	-1.10	1.07	-0.38	0.63	-0.60	-0.55
	(5.51)	(-4.44)	(1.45)	(-3.93)	(-5.83)	(5.15)	(-1.91)	(2.38)	(-3.09)	(-2.97)
Panel B. Eight-factor model α										
L	0.90	1.51	1.55	1.32	1.20	0.69	1.15	1.26	1.09	0.81
2	0.19	0.80	0.72	0.76	0.56	0.19	0.66	0.63	0.61	0.42
3	0.24	0.53	0.54	0.60	0.42	0.23	0.39	0.46	0.52	0.26
4	0.22	0.37	0.36	0.46	0.25	0.25	0.31	0.36	0.46	0.34
5	0.30	0.28	0.29	0.46	0.31	0.33	0.25	0.28	0.37	0.27
6	0.34	0.27	0.29	0.40	0.29	0.39	0.27	0.22	0.44	0.28
7	0.43	0.31	0.31	0.40	0.29	0.42	0.29	0.22	0.41	0.34
8	0.73	0.38	0.35	0.50	0.31	0.55	0.36	0.31	0.43	0.34
9	1.02	0.45	0.55	0.51	0.38	0.93	0.52	0.52	0.50	0.44
H	1.77	0.81	1.11	1.14	0.47	1.56	0.95	1.18	1.06	0.75
$H-L$	0.87	-0.70	-0.45	-0.18	-0.73	0.87	-0.20	-0.08	-0.04	-0.06
	(4.59)	(-3.57)	(-3.25)	(-1.53)	(-6.31)	(5.34)	(-1.14)	(-0.56)	(-0.37)	(-0.60)

Table 2: Value-Weighted Portfolio Returns Sorted on Maximum Drawdown and Return-Based Measures.

This table reports value-weighted average monthly returns (Panel A) and eight-factor model alphas (Panel B) for extreme decile portfolios sorted on the same five characteristics defined in Table 1. At each month-end t, NYSE/Amex/Nasdaq common stocks are independently sorted into ten deciles for each characteristic, with "Ex-micro" excluding stocks in the bottom 20% of NYSE market capitalization and "Large Cap" including stocks above the NYSE median. Panel A reports average returns for the lowest (L) and highest (H) deciles and the high-minus-low ($H-L$) spread; Panel B reports the corresponding alphas. The sample period is from July 1968 to December 2024. t-statistics (in parentheses) are reported only for $H-L$ and are computed using Newey–West heteroskedasticity- and autocorrelation-robust standard errors.

	Ex-micro					Large Cap				
	MDD	$MOM24$	$MOM12$	STR	LTR	MDD	$MOM24$	$MOM12$	STR	LTR
Panel A. Average Returns										
L	0.47	1.02	0.33	0.74	0.96	0.50	1.04	0.48	0.91	1.00
2	0.60	0.86	0.48	0.78	0.83	0.61	0.84	0.62	0.81	0.75
3	0.61	0.80	0.62	0.75	0.75	0.66	0.78	0.62	0.72	0.65
4	0.54	0.71	0.57	0.74	0.61	0.53	0.65	0.55	0.84	0.78
5	0.63	0.55	0.53	0.63	0.71	0.64	0.57	0.55	0.60	0.60
6	0.65	0.64	0.58	0.68	0.64	0.68	0.62	0.59	0.66	0.66
7	0.72	0.61	0.70	0.54	0.65	0.70	0.61	0.66	0.62	0.69
8	0.80	0.58	0.66	0.53	0.63	0.74	0.55	0.71	0.50	0.61
9	0.89	0.66	0.79	0.45	0.51	0.94	0.72	0.73	0.50	0.56
H	1.20	0.63	1.31	0.62	0.71	1.32	0.76	1.34	0.68	0.78
$H-L$	0.72	-0.39	0.97	-0.12	-0.26	0.82	-0.28	0.87	-0.22	-0.23
	(2.84)	(-1.68)	(3.36)	(-0.57)	(-1.14)	(3.44)	(-1.21)	(3.13)	(-1.13)	(-1.01)
Panel B. Eight-factor model α										
L	0.08	0.43	0.26	-0.05	0.21	0.04	0.46	0.37	0.15	0.18
2	0.01	0.26	0.27	-0.02	0.00	0.02	0.23	0.33	0.00	0.03
3	0.01	0.16	0.22	-0.05	0.05	0.06	0.12	0.17	-0.04	-0.08
4	-0.06	0.04	0.06	0.08	-0.12	-0.06	0.00	0.03	0.17	0.09
5	0.00	-0.09	-0.08	-0.03	-0.01	0.01	-0.09	-0.05	-0.04	-0.11
6	0.02	-0.03	-0.11	0.10	-0.06	0.08	-0.04	-0.09	0.06	-0.05
7	0.10	-0.08	-0.08	0.06	-0.03	0.10	0.00	-0.12	0.14	0.06
8	0.28	0.02	-0.16	0.15	-0.04	0.13	-0.04	-0.08	0.09	-0.02
9	0.41	0.09	-0.03	0.12	-0.12	0.44	0.22	-0.03	0.16	-0.03
H	0.69	0.24	0.46	0.46	0.31	0.87	0.38	0.52	0.49	0.43
$H-L$	0.61	-0.19	0.20	0.50	0.10	0.83	-0.08	0.15	0.34	0.25
	(3.30)	(-0.97)	(1.57)	(4.41)	(0.80)	(4.55)	(-0.41)	(1.06)	(3.57)	(2.08)

Table 3: Subsample Analysis of Portfolio Returns Sorted on Maximum Drawdown and Return-Based Measures.

This table reports equal-weighted (EW) and value-weighted (VW) average monthly returns (Panel A) and eight-factor model alphas (Panel B) for extreme decile portfolios sorted on the same five characteristics defined in Table 1. The sample is split into two subperiods: July 1968–December 1999 (Pre-2000) and January 2000–December 2024 (Post-2000). At each month-end t, NYSE/Amex/Nasdaq common stocks are independently sorted into ten deciles for each characteristic, with "Ex-micro" excluding stocks in the bottom 20% of NYSE market capitalization and "Large Cap" including stocks above the NYSE median. Panel A reports average returns for the high-minus-low ($H-L$) spread; Panel B reports the corresponding alphas. t-statistics (in parentheses) are reported and are computed using Newey–West heteroskedasticity- and autocorrelation-robust standard errors.

Portfolio		Pre-2000					Post-2000				
		MDD	*MOM*24	*MOM*12	*STR*	*LTR*	*MDD*	*MOM*24	*MOM*12	*STR*	*LTR*
Panel A. Average Returns											
EW	Ex-micro	0.79	-0.60	1.10	-0.85	-0.90	1.63	-1.12	-0.51	-0.63	-1.35
		(3.14)	(-2.88)	(3.98)	(-3.77)	(-4.04)	(4.77)	(-3.33)	(-1.04)	(-1.98)	(-4.36)
	Large Cap	0.88	-0.15	1.14	-0.74	-0.52	1.31	-0.67	0.00	-0.42	-0.59
		(3.34)	(-0.70)	(3.85)	(-3.14)	(-2.35)	(4.06)	(-1.87)	(0.00)	(-1.33)	(-1.91)
VW	Ex-micro	0.49	-0.16	1.32	-0.28	-0.35	1.02	-0.69	0.53	0.08	-0.14
		(1.55)	(-0.60)	(3.76)	(-1.05)	(-1.31)	(2.46)	(-1.67)	(1.08)	(0.23)	(-0.37)
	Large Cap	0.64	-0.03	1.22	-0.35	-0.28	1.05	-0.60	0.43	-0.06	-0.16
		(2.22)	(-0.11)	(3.61)	(-1.39)	(-1.06)	(2.73)	(-1.41)	(0.93)	(-0.19)	(-0.43)
Panel B. Eight-factor model α											
EW	Ex-micro	0.50	-0.54	0.02	-0.18	-0.36	1.36	-0.96	-0.84	-0.21	-1.06
		(2.84)	(-2.79)	(0.14)	(-1.15)	(-3.19)	(5.87)	(-3.65)	(-3.77)	(-1.15)	(-7.42)
	Large Cap	0.74	-0.03	0.19	-0.08	-0.01	1.10	-0.51	-0.31	-0.07	-0.22
		(4.16)	(-0.17)	(1.11)	(-0.46)	(-0.13)	(5.11)	(-2.30)	(-1.48)	(-0.40)	(-1.70)
VW	Ex-micro	0.45	-0.02	0.01	0.60	0.19	0.88	-0.65	0.26	0.32	-0.03
		(1.95)	(-0.08)	(0.05)	(4.18)	(1.27)	(3.60)	(-2.55)	(1.65)	(1.76)	(-0.13)
	Large Cap	0.69	0.07	0.13	0.50	0.25	1.09	-0.57	0.08	0.14	0.05
		(3.07)	(0.32)	(0.67)	(3.30)	(1.63)	(4.16)	(-2.26)	(0.48)	(1.00)	(0.30)

Table 4: Portfolio Returns for Different Holding Periods.

This table reports equal-weighted (EW) and value-weighted (VW) average monthly returns (Panel A) and eight-factor model alphas (Panel B) for high-minus-low ($H-L$) decile portfolios sorted on the same five characteristics defined in Table 1, but constructed using different holding periods. Portfolios are formed at the end of each month t and held for one quarter, six months, or one year, with overlapping returns when the holding period exceeds one month. "Ex-micro" excludes stocks in the bottom 20% of NYSE market capitalization, while "Large Cap" includes stocks above the NYSE median. The sample period is from July 1968 to December 2024. t-statistics (in parentheses) are reported only for $H-L$ and are computed using Newey–West (1987) heteroskedasticity- and autocorrelation-robust standard errors.

Portfolio		Quarter	Semiannual	Annual
Panel A. Average Returns				
EW	Ex-micro	1.03	0.95	0.82
		(5.24)	(5.11)	(4.87)
	Large Cap	1.00	0.90	0.82
		(5.12)	(4.85)	(4.68)
VW	Ex-micro	0.64	0.60	0.57
		(2.64)	(2.56)	(2.57)
	Large Cap	0.71	0.57	0.69
		(3.35)	(3.18)	(3.35)
Panel B. Eight-factor model α				
EW	Ex-micro	0.72	0.80	0.64
		(4.26)	(5.21)	(4.21)
	Large Cap	0.70	0.50	0.62
		(4.84)	(3.91)	(4.42)
VW	Ex-micro	0.53	0.51	0.46
		(2.99)	(3.02)	(2.90)
	Large Cap	0.81	0.75	0.69
		(4.84)	(4.62)	(4.45)

Table 5: Fama–MacBeth Regressions.

This table reports Fama–MacBeth regressions of one-month-ahead excess stock returns (in percent) on lagged firm characteristics. Independent variables are maximum drawdown (MDD), market beta (β_{MKT}), size ($SIZE$), book-to-market (BM), price-to-sales (PS), return on equity (ROE), gross profitability ($GPROF$), asset turnover ($ATURN$), accruals ($ACCRUAL$), debt-to-equity (DE), Amihud illiquidity ($ILLIQ$), average turnover ($AVGTURN$), idiosyncratic volatility ($IVOL$), information discreteness (ID), recency ratio ($RRATIO$), 52-week high ($HIGH52W$), 12-month momentum ($MOM12$), capital gains overhang (CGO), long-term past return (LTR), most recent month return (STR), and maximum daily return (MAX). All regressors are transformed into cross-sectional percentile ranks in each month, so that a coefficient measures the difference in the expected next-month excess return between the top- and bottom-ranked stocks. The sample consists of stocks with market capitalization above the NYSE median. t-statistics (in parentheses) are computed from the time series of the monthly coefficient estimates using Newey–West standard errors with 12 lags. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
MDD	1.19***	0.61***	0.57***	0.32**	0.26**	0.29**
	(5.53)	(3.18)	(3.36)	(2.48)	(2.05)	(2.37)
β_{MKT}		0.21	0.22	0.27**	0.08	0.08
		(1.35)	(1.54)	(2.00)	(0.70)	(0.77)
$SIZE$		-2.43***	-2.47***	-5.52***	-5.67***	-5.99***
		(-12.12)	(-12.43)	(-11.86)	(-11.75)	(-12.10)
BM		-0.24	-0.57**	-0.60***	-0.21	-0.12
		(-1.27)	(-2.48)	(-2.89)	(-1.03)	(-0.60)
PS			-0.96***	-0.97***	-0.55***	-0.49***
			(-3.78)	(-3.82)	(-3.01)	(-2.83)
ROE			0.33**	0.32**	0.28**	0.30**
			(2.36)	(2.37)	(2.14)	(2.32)
$GPROF$			0.44**	0.28*	0.29*	0.23
			(2.50)	(1.65)	(1.81)	(1.53)
$ATURN$			-0.96***	-0.97***	-0.66***	-0.56***
			(-4.27)	(-4.26)	(-3.59)	(-3.17)
$ACCRUAL$			-0.48***	-0.42***	-0.43***	-0.45***
			(-5.38)	(-4.53)	(-4.82)	(-5.11)
DE			-0.29*	-0.34**	-0.18	-0.16
			(-1.73)	(-2.04)	(-1.21)	(-1.13)
$ILLIQ$				-3.52***	-3.70***	-4.11***
				(-9.86)	(-10.08)	(-10.67)
$AVGTURN$				-0.87***	-1.12***	-1.30***
				(-5.03)	(-6.47)	(-7.11)
$IVOL$				0.50***	0.18	0.18
				(3.58)	(1.22)	(1.36)
ID					-0.09	-0.12*
					(-1.41)	(-1.88)
$RRATIO$					0.08	0.15*
					(0.95)	(1.71)
$HIGH52W$					-1.56***	-0.76***
					(-7.99)	(-4.60)
$MOM12$					1.15***	0.50**
					(6.03)	(2.52)
CGO						0.38**
						(2.32)
LTR						-0.17
						(-1.55)
STR						-1.07***
						(-6.79)
MAX						0.69***
						(8.03)

Table 6: Double Sort Portfolios on MDD and Return-based Controls (EW).

This table reports equal-weighted average monthly returns (Panel A) and eight-factor model alphas (Panel B) for portfolios double-sorted on MDD and a return-based control variable. At each month-end t, NYSE/Amex/Nasdaq common stocks are independently sorted into quintiles (Q1–Q5) based on the control variable, and within each quintile stocks are further sorted into quintiles based on MDD. For each control variable quintile, the table reports the return spread between the highest and lowest MDD quintiles ($H-L$). "Ex-micro" excludes stocks in the bottom 20% of NYSE market capitalization; "Large Cap" includes stocks above the NYSE median. t-statistics (in parentheses) are computed using Newey–West (1987) heteroskedasticity- and autocorrelation-robust standard errors. Control variables include *MOM12*, *LTR*, and *STR*. The sample period is July 1968–December 2024.

	Ex-micro					Large Cap				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Panel A. Average Returns										
$MOM12$	1.35	0.50	0.67	0.69	1.17	1.06	0.37	0.54	0.67	1.12
	(5.44)	(2.67)	(3.81)	(3.96)	(5.98)	(4.87)	(2.13)	(3.18)	(4.00)	(5.91)
LTR	1.50	0.80	0.69	0.58	0.46	1.28	0.74	0.80	0.57	0.73
	(6.28)	(4.04)	(3.54)	(3.01)	(2.21)	(6.36)	(3.97)	(3.95)	(3.17)	(3.38)
STR	1.04	0.64	0.66	0.91	1.31	1.04	0.71	0.69	0.80	1.18
	(4.17)	(3.25)	(3.32)	(4.32)	(5.74)	(4.75)	(3.80)	(3.53)	(4.28)	(5.78)
Panel B. Eight-factor model α										
$MOM12$	1.42	0.28	0.49	0.54	0.99	1.05	0.18	0.42	0.55	0.97
	(7.08)	(2.39)	(3.57)	(4.45)	(6.90)	(4.89)	(1.41)	(2.94)	(4.25)	(5.72)
LTR	1.37	0.77	0.56	0.61	0.69	1.12	0.65	0.63	0.48	1.01
	(6.98)	(4.79)	(4.18)	(4.52)	(4.73)	(6.61)	(4.43)	(4.32)	(3.57)	(5.39)
STR	0.91	0.55	0.51	0.76	1.24	0.82	0.60	0.49	0.70	1.21
	(4.76)	(4.14)	(3.78)	(5.62)	(6.67)	(4.95)	(4.27)	(3.08)	(3.79)	(7.10)

Table 7: Momentum Portfolios Conditional on Maximum Drawdown.

This table examines whether the intermediate-horizon momentum effect survives after conditioning on maximum drawdown. At each month-end t, stocks are first classified into "High" and "Low" MDD groups using the top and bottom quintile breakpoints of the maximum drawdown measured over months $t-24$ to $t-12$, and within each group stocks are further sorted into five portfolios based on momentum, defined as the cumulative return from $t-12$ to $t-1$. The table reports equal-weighted average monthly excess returns for each momentum quintile, from the lowest (L) to the highest (H), together with the high-minus-low ($H-L$) momentum spread. The monthly rebalancing rows reform the portfolios every month; the 12-month holding period rows average the returns of the twelve overlapping portfolio vintages, whose constituent weights drift with the buy-and-hold returns. Micro-cap stocks, whose market capitalization falls below the NYSE bottom 20% quantile, are excluded before sorting. The symbols *, **, and *** indicate significance of the $H-L$ return at the 10%, 5%, and 1% level, respectively, based on Newey–West heteroskedasticity- and autocorrelation-robust standard errors.

		Momentum					
	MDD	L	2	3	4	H	$H-L$
Panel A. Full sample (July 1968–December 2024)							
Monthly rebalancing	High	2.33	1.76	1.70	1.83	2.38	0.05
	Low	1.11	0.86	0.80	0.85	1.52	0.41**
12-month holding period	High	2.17	1.69	1.55	1.54	1.68	−0.49***
	Low	1.23	0.87	0.81	0.88	1.15	−0.07
Panel B. Before momentum crashes (July 1968–December 1999)							
Monthly rebalancing	High	1.62	1.38	1.44	1.71	2.38	0.76***
	Low	0.84	0.75	0.69	0.80	1.72	0.88***
12-month holding period	High	1.70	1.46	1.34	1.39	1.51	−0.19
	Low	0.89	0.73	0.67	0.80	1.21	0.31**

Table 8: Double Sort Portfolios on MDD and Fundamentals & Investment (EW).

This table reports equal-weighted average monthly returns (Panel A) and eight-factor model alphas (Panel B) for portfolios double-sorted on MDD and a fundamental or investment-related characteristic. At each month-end t, NYSE/Amex/Nasdaq common stocks are independently sorted into quintiles (Q1–Q5) based on the characteristic, and within each quintile stocks are further sorted into quintiles based on MDD. For each characteristic quintile, the table reports the return spread between the highest and lowest MDD quintiles ($H-L$). "Ex-micro" excludes stocks in the bottom 20% of NYSE market capitalization; "Large Cap" includes stocks above the NYSE median. t-statistics (in parentheses) are computed using Newey–West (1987) robust standard errors. Fundamental and investment-related characteristics include *ACCRUAL*, *ATURN*, *BM*, *DE*, *GPROF*, *PS*, and *ROE*. The sample period is July 1968–December 2024.

	Ex-micro					Large Cap				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Panel A. Average Returns										
ACCRUAL	1.42	0.83	0.74	0.95	0.71	1.07	0.89	0.72	0.74	0.89
	(5.36)	(3.85)	(3.56)	(4.95)	(3.46)	(4.76)	(4.49)	(3.60)	(4.22)	(4.51)
ATURN	0.99	0.94	0.82	1.03	0.88	1.06	0.86	0.79	0.84	0.80
	(3.77)	(3.47)	(3.86)	(5.43)	(4.93)	(4.60)	(3.75)	(3.81)	(4.60)	(4.76)
BM	1.06	0.73	0.73	0.91	1.39	1.02	0.81	0.66	0.85	1.19
	(3.94)	(3.40)	(3.51)	(4.32)	(5.57)	(4.96)	(4.22)	(3.76)	(4.06)	(4.98)
DE	0.98	0.81	0.87	1.04	0.99	1.00	0.61	0.63	0.96	0.96
	(4.68)	(3.82)	(3.82)	(4.30)	(4.48)	(5.29)	(3.25)	(3.20)	(4.52)	(5.08)
GPROF	1.22	1.02	0.73	0.75	0.98	1.03	0.93	0.57	0.67	0.88
	(4.33)	(3.84)	(3.81)	(3.86)	(4.70)	(4.62)	(4.03)	(3.14)	(3.55)	(4.91)
PS	1.26	0.76	0.80	0.46	1.10	0.92	0.72	0.66	0.61	1.12
	(6.06)	(4.33)	(3.83)	(1.99)	(4.02)	(5.11)	(4.16)	(3.24)	(2.93)	(5.43)
ROE	1.71	0.79	0.70	0.41	0.60	1.44	0.67	0.77	0.48	0.73
	(6.18)	(3.84)	(4.02)	(2.72)	(3.33)	(5.80)	(3.38)	(4.67)	(3.17)	(4.31)
Panel B. Eight-factor model α										
ACCRUAL	1.32	0.69	0.55	0.99	0.71	0.98	0.74	0.57	0.69	0.86
	(6.25)	(4.89)	(3.68)	(7.15)	(4.71)	(4.61)	(5.18)	(3.52)	(5.33)	(5.67)
ATURN	1.01	0.84	0.76	1.03	0.71	0.89	0.77	0.88	0.89	0.62
	(5.15)	(3.77)	(5.05)	(7.45)	(5.84)	(4.44)	(4.07)	(4.77)	(6.24)	(4.76)
BM	1.22	0.84	0.69	0.68	1.07	1.14	0.93	0.66	0.64	0.94
	(5.87)	(5.31)	(5.89)	(4.69)	(5.51)	(7.03)	(4.94)	(4.66)	(3.66)	(4.85)
DE	1.14	0.87	0.65	0.69	0.63	1.06	0.67	0.42	0.63	0.66
	(7.20)	(5.30)	(4.45)	(4.33)	(3.36)	(5.45)	(4.41)	(2.80)	(3.80)	(4.17)
GPROF	1.37	0.71	0.72	0.80	0.87	0.91	0.72	0.59	0.73	0.81
	(6.05)	(3.74)	(4.50)	(5.09)	(6.52)	(5.29)	(3.97)	(3.41)	(4.50)	(5.75)
PS	1.01	0.57	0.59	0.35	1.33	0.77	0.58	0.45	0.50	1.23
	(6.78)	(4.30)	(4.19)	(2.03)	(6.15)	(5.25)	(3.86)	(2.73)	(2.97)	(6.65)
ROE	1.61	0.61	0.51	0.26	0.47	1.35	0.47	0.62	0.36	0.69
	(6.62)	(4.00)	(4.19)	(2.29)	(3.31)	(5.86)	(2.85)	(4.73)	(2.92)	(4.65)

Table 9: Double Sort Portfolios on MDD and Behavioral & Lottery Signals (EW).

This table reports equal-weighted average monthly returns (Panel A) and eight-factor model alphas (Panel B) for portfolios double-sorted on MDD and a behavioral or lottery-related signal. At each month-end t, NYSE/Amex/Nasdaq common stocks are independently sorted into quintiles (Q1–Q5) based on the signal, and within each quintile stocks are further sorted into quintiles based on MDD. For each signal quintile, the table reports the return spread between the highest and lowest MDD quintiles ($H-L$). "Ex-micro" excludes stocks in the bottom 20% of NYSE market capitalization; "Large Cap" includes stocks above the NYSE median. t-statistics (in parentheses) are computed using Newey–West (1987) robust standard errors. Behavioral and lottery-related signals include *CGO*, *HIGH52W*, *ID*, *MAX*, and *RRATIO*. The sample period is July 1968–December 2024.

	Ex-micro					Large Cap				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Panel A. Average Returns										
CGO	1.27	0.58	0.48	0.61	0.87	1.03	0.56	0.45	0.62	0.87
	(5.63)	(2.64)	(2.62)	(3.29)	(4.78)	(4.94)	(2.99)	(2.60)	(3.50)	(5.10)
HIGH52W	1.13	0.46	0.76	0.84	0.68	1.02	0.59	0.63	0.73	0.73
	(4.71)	(2.51)	(3.83)	(4.19)	(3.57)	(4.59)	(3.55)	(3.60)	(3.61)	(4.28)
ID	1.02	1.00	0.84	1.04	1.06	0.98	0.87	0.99	0.96	0.78
	(4.14)	(4.67)	(4.08)	(4.91)	(4.48)	(4.36)	(4.40)	(5.21)	(5.12)	(3.88)
MAX	0.39	0.42	0.63	1.05	1.63	0.54	0.42	0.43	0.94	1.31
	(2.76)	(2.82)	(3.80)	(5.70)	(6.21)	(3.12)	(2.75)	(2.86)	(5.51)	(5.99)
RRATIO	1.03	0.87	0.79	0.92	1.33	0.89	0.80	0.92	0.79	1.10
	(4.70)	(4.26)	(3.99)	(3.87)	(5.59)	(4.96)	(4.19)	(4.89)	(3.91)	(5.20)
Panel B. Eight-factor model α										
CGO	1.13	0.27	0.28	0.53	0.80	0.87	0.27	0.31	0.54	0.84
	(5.33)	(2.02)	(2.26)	(3.83)	(5.44)	(4.40)	(1.80)	(2.16)	(3.71)	(5.06)
HIGH52W	1.12	0.32	0.63	0.74	0.56	0.94	0.45	0.55	0.61	0.70
	(5.40)	(2.47)	(4.72)	(4.69)	(2.91)	(4.18)	(3.43)	(3.90)	(3.47)	(4.55)
ID	1.16	0.86	0.68	0.89	0.93	1.06	0.71	0.85	0.89	0.66
	(6.16)	(5.99)	(4.71)	(6.23)	(6.14)	(5.72)	(5.00)	(5.51)	(6.34)	(4.05)
MAX	0.14	0.24	0.49	0.94	1.58	0.33	0.23	0.24	0.78	1.26
	(1.39)	(2.37)	(3.84)	(5.57)	(7.24)	(2.55)	(1.80)	(2.01)	(4.75)	(6.32)
RRATIO	0.85	0.68	0.63	0.90	1.30	0.80	0.69	0.76	0.72	1.10
	(5.35)	(4.19)	(4.00)	(5.20)	(7.08)	(4.83)	(4.17)	(4.58)	(4.54)	(5.59)

Table 10: Double Sort Portfolios on MDD and Uncertainty & Liquidity (EW).

This table reports equal-weighted average monthly returns (Panel A) and eight-factor model alphas (Panel B) for portfolios double-sorted on MDD and an uncertainty or liquidity proxy. At each month-end t, NYSE/Amex/Nasdaq common stocks are independently sorted into quintiles (Q1–Q5) based on the proxy, and within each quintile stocks are further sorted into quintiles based on MDD. For each proxy quintile, the table reports the return spread between the highest and lowest MDD quintiles ($H-L$). "Ex-micro" excludes stocks in the bottom 20% of NYSE market capitalization; "Large Cap" includes stocks above the NYSE median. t-statistics (in parentheses) are computed using Newey–West (1987) robust standard errors. Uncertainty and liquidity proxies include *AVGTURN*, *ILLIQ*, *IVOL*, and β_{MKT}. The sample period is July 1968–December 2024.

	Ex-micro					Large Cap				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Panel A. Average Returns										
AVGTURN	0.77	0.81	0.77	0.93	1.20	0.50	0.38	0.54	0.65	1.19
	(4.78)	(4.61)	(4.49)	(4.96)	(5.01)	(3.48)	(2.65)	(3.65)	(3.82)	(5.46)
ILLIQ	0.20	0.17	0.27	1.17	2.34	0.19	0.31	0.68	1.34	1.74
	(1.00)	(0.75)	(1.20)	(4.76)	(10.54)	(0.92)	(1.57)	(3.15)	(6.31)	(9.19)
IVOL	0.22	0.14	0.25	0.38	1.00	0.25	0.15	0.17	0.31	0.95
	(1.80)	(1.25)	(2.02)	(2.49)	(4.82)	(1.91)	(1.18)	(1.30)	(2.01)	(4.72)
β_{MKT}	1.10	0.88	0.61	0.66	1.24	1.11	0.71	0.49	0.68	1.05
	(4.86)	(4.11)	(3.63)	(3.57)	(5.68)	(5.80)	(4.04)	(3.18)	(4.29)	(5.24)
Panel B. Eight-factor model α										
AVGTURN	0.58	0.67	0.69	0.93	1.13	0.31	0.20	0.39	0.56	1.03
	(5.26)	(4.95)	(5.00)	(6.18)	(6.24)	(2.66)	(1.58)	(3.09)	(3.68)	(4.91)
ILLIQ	0.18	0.07	0.16	1.11	2.21	0.25	0.23	0.54	1.25	1.59
	(1.19)	(0.49)	(1.16)	(5.92)	(11.02)	(1.47)	(1.49)	(3.05)	(7.67)	(8.83)
IVOL	0.04	0.02	0.10	0.24	0.91	0.05	0.00	0.03	0.14	0.79
	(0.37)	(0.20)	(1.01)	(1.76)	(5.06)	(0.42)	(0.00)	(0.28)	(1.00)	(4.16)
β_{MKT}	1.00	0.82	0.58	0.70	1.32	1.04	0.61	0.50	0.73	1.10
	(6.40)	(5.51)	(4.68)	(4.40)	(6.77)	(6.22)	(4.21)	(4.01)	(4.48)	(5.62)

Appendix A Value-Weighted Double Sorts

The conditional sorts reported in Section 3 are equal weighted, which places a comparatively large weight on the smaller stocks within each portfolio. This appendix reports the value-weighted analogs of Tables 6 through 10, in which the constituents of every portfolio are weighted by the market capitalization of the month preceding the return measurement. Table A1 corresponds to the return-based controls, Table A2 to the momentum sorts conditional on maximum drawdown, Table A3 to the fundamentals and investment characteristics, Table A4 to the behavioral and lottery signals, and Table A5 to the uncertainty and liquidity proxies. All other aspects of the portfolio construction, the sample, and the inference are identical to those of the corresponding tables in the main text.

The value-weighted premia are uniformly smaller than their equal-weighted counterparts, as expected once the smaller stocks receive proportionally less weight, but the qualitative conclusions of the main text survive. Across the 190 conditional cells reported in Panel A of Tables A1, A3, A4, and A5, the value-weighted maximum drawdown spread is positive in 187 and is individually significant at the 5% level in 88; the three negative estimates, in the second $MOM12$ quintile, the second CGO quintile, and the third MAX quintile, are all economically negligible and statistically indistinguishable from zero. The eight-factor alphas display the same pattern. The loss of individual significance in roughly half of the cells is unsurprising given that each conditional portfolio holds a fifth of a single control quintile and that value weighting concentrates the exposure in a small number of large stocks; the sign consistency across the cells is the more informative feature. Table A2 continues to show that the momentum spread within the high maximum drawdown group vanishes once the portfolios are held for twelve months, falling from 0.92% per month under monthly rebalancing to an insignificant 0.05%.

Two qualifications deserve emphasis. First, the concentration of the premium in the least liquid stocks documented in Section 3.5 is fully preserved under value weighting:

the $ILLIQ$ gradient in Table A5 runs from an insignificant 0.31% per month in the most liquid quintile to 1.74% per month (t-statistic=8.07) in the least liquid quintile of the sample excluding micro-cap stocks, and from 0.31% to 1.28% per month among large-cap stocks. Second, the $IVOL$ gradient is preserved in direction but weakens materially in magnitude and precision. In the sample excluding micro-cap stocks the top $IVOL$ quintile spread falls from 1.00% per month under equal weighting to 0.40% per month (t-statistic=1.63) under value weighting, with an eight-factor alpha of 0.28% per month that is indistinguishable from zero; among large-cap stocks the top quintile spread of 0.75% per month (t-statistic=3.07) and its alpha of 0.63% per month (t-statistic=2.63) remain significant. The holding cost channel therefore operates most visibly among the equal-weighted portfolios and among the large-cap stocks, and the value-weighted evidence within the broader universe should be read as directionally supportive rather than conclusive.

Table A1: Double Sort Portfolios on MDD and Return-based Controls (VW).

This table is the value-weighted analog of Table 6. It reports value-weighted average monthly returns (Panel A) and eight-factor model alphas (Panel B) for portfolios double-sorted on MDD and a return-based control variable. At each month-end t, NYSE/Amex/Nasdaq common stocks are sorted into quintiles (Q1–Q5) based on the control variable, and within each quintile stocks are further sorted into quintiles based on MDD, measured over months $t-24$ to $t-12$. Portfolio returns are weighted by the market capitalization of the month preceding the return measurement. For each control variable quintile, the table reports the return spread between the highest and lowest MDD quintiles ($H-L$). "Ex-micro" excludes stocks in the bottom 20% of NYSE market capitalization; "Large Cap" includes stocks above the NYSE median. t-statistics (in parentheses) are computed using Newey–West (1987) heteroskedasticity- and autocorrelation-robust standard errors. Control variables include *MOM12*, *LTR*, and *STR*. The sample period is July 1968–December 2024.

	Ex-micro					Large Cap				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Panel A. Average Returns										
$MOM12$	0.59	-0.09	0.39	0.12	1.00	0.54	0.03	0.26	0.23	0.99
	(2.29)	(-0.43)	(1.98)	(0.63)	(3.93)	(2.28)	(0.15)	(1.38)	(1.17)	(4.41)
LTR	0.73	0.45	0.31	0.24	0.35	0.95	0.59	0.32	0.29	0.49
	(3.12)	(2.09)	(1.37)	(1.15)	(1.62)	(3.96)	(2.69)	(1.59)	(1.40)	(2.12)
STR	0.32	0.19	0.40	0.48	0.74	0.33	0.42	0.39	0.51	0.86
	(1.24)	(0.86)	(1.86)	(2.44)	(2.99)	(1.32)	(2.05)	(1.79)	(2.71)	(3.65)
Panel B. Eight-factor model α										
$MOM12$	0.53	-0.23	0.31	0.14	0.85	0.45	-0.08	0.29	0.24	0.95
	(2.53)	(-1.42)	(1.68)	(0.89)	(3.81)	(2.13)	(-0.46)	(1.61)	(1.74)	(4.35)
LTR	0.70	0.53	0.30	0.28	0.51	0.92	0.57	0.30	0.38	0.72
	(3.71)	(2.88)	(1.62)	(1.58)	(2.72)	(5.15)	(3.20)	(1.61)	(2.33)	(3.55)
STR	0.11	0.10	0.32	0.45	0.70	0.28	0.34	0.28	0.51	0.91
	(0.55)	(0.55)	(1.62)	(2.60)	(3.41)	(1.37)	(2.06)	(1.39)	(2.69)	(4.40)

Table A2: Momentum Portfolios Conditional on Maximum Drawdown (VW).

This table is the value-weighted analog of Table 7. At each month-end t, stocks are first classified into "High" and "Low" MDD groups using the top and bottom quintile breakpoints of the maximum drawdown measured over months t–24 to t–12, and within each group stocks are further sorted into five portfolios based on momentum, defined as the cumulative return from $t-12$ to $t-1$. The table reports value-weighted average monthly excess returns for each momentum quintile, from the lowest (L) to the highest (H), together with the high-minus-low ($H-L$) momentum spread. Portfolio returns are weighted by the market capitalization of the month preceding the return measurement. The monthly rebalancing rows reform the portfolios every month; the 12-month holding period rows average the returns of the twelve overlapping portfolio vintages. Micro-cap stocks, whose market capitalization falls below the NYSE bottom 20% quantile, are excluded before sorting. The symbols *, **, and *** indicate significance of the $H-L$ return at the 10%, 5%, and 1% level, respectively, based on Newey–West heteroskedasticity- and autocorrelation-robust standard errors.

		Momentum					
	MDD	L	2	3	4	H	$H-L$
Panel A. Full sample (July 1968–December 2024)							
Monthly rebalancing	High	0.77	0.72	0.76	1.07	1.69	0.92***
	Low	0.34	0.48	0.33	0.57	0.95	0.61***
12-month holding period	High	1.01	0.86	0.88	0.89	1.06	0.05
	Low	0.56	0.51	0.54	0.60	0.70	0.14
Panel B. Before momentum crashes (July 1968–December 1999)							
Monthly rebalancing	High	0.60	0.57	0.62	1.03	1.68	1.08***
	Low	0.46	0.34	0.27	0.51	0.96	0.50*
12-month holding period	High	0.87	0.75	0.84	0.84	1.05	0.18
	Low	0.54	0.45	0.45	0.54	0.75	0.21

Table A3: Double Sort Portfolios on MDD and Fundamentals & Investment (VW).

This table is the value-weighted analog of Table 8. It reports value-weighted average monthly returns (Panel A) and eight-factor model alphas (Panel B) for portfolios double-sorted on MDD and a fundamental or investment-related characteristic. At each month-end t, NYSE/Amex/Nasdaq common stocks are sorted into quintiles (Q1–Q5) based on the characteristic, and within each quintile stocks are further sorted into quintiles based on MDD. Portfolio returns are weighted by the market capitalization of the month preceding the return measurement. For each characteristic quintile, the table reports the return spread between the highest and lowest MDD quintiles ($H-L$). "Ex-micro" excludes stocks in the bottom 20% of NYSE market capitalization; "Large Cap" includes stocks above the NYSE median. t-statistics (in parentheses) are computed using Newey–West (1987) robust standard errors. Fundamental and investment-related characteristics include *ACCRUAL*, *ATURN*, *BM*, *DE*, *GPROF*, *PS*, and *ROE*. The sample period is July 1968–December 2024.

	Ex-micro					Large Cap				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Panel A. Average Returns										
ACCRUAL	0.86	0.37	0.18	0.37	0.33	0.96	0.43	0.13	0.25	0.46
	(3.26)	(1.47)	(0.83)	(1.77)	(1.40)	(3.95)	(2.07)	(0.58)	(1.24)	(2.26)
ATURN	0.31	0.44	0.44	0.59	0.65	0.42	0.45	0.48	0.70	0.51
	(1.27)	(1.78)	(1.74)	(2.15)	(3.09)	(1.86)	(1.96)	(2.11)	(2.90)	(2.43)
BM	0.47	0.39	0.18	0.46	0.49	0.61	0.48	0.34	0.40	0.57
	(1.89)	(1.67)	(0.85)	(1.96)	(1.90)	(2.59)	(2.36)	(1.71)	(1.75)	(2.30)
DE	0.51	0.42	0.18	0.54	0.43	0.69	0.19	0.14	0.55	0.46
	(2.33)	(1.62)	(0.80)	(2.30)	(2.07)	(3.11)	(0.81)	(0.72)	(2.53)	(2.35)
GPROF	0.38	0.36	0.18	0.45	0.61	0.34	0.48	0.16	0.50	0.62
	(1.65)	(1.44)	(0.74)	(1.80)	(2.89)	(1.56)	(2.02)	(0.68)	(2.09)	(3.13)
PS	0.59	0.24	0.30	0.18	0.51	0.43	0.31	0.25	0.29	0.62
	(2.65)	(1.14)	(1.39)	(0.86)	(1.87)	(2.03)	(1.53)	(1.18)	(1.35)	(2.48)
ROE	0.76	0.30	0.57	0.38	0.45	0.93	0.30	0.57	0.43	0.61
	(2.72)	(1.33)	(2.42)	(2.00)	(2.04)	(3.27)	(1.30)	(2.75)	(2.28)	(2.70)
Panel B. Eight-factor model α										
ACCRUAL	0.66	0.28	0.22	0.36	0.26	0.91	0.31	0.16	0.20	0.50
	(2.68)	(1.30)	(1.25)	(2.00)	(1.14)	(3.81)	(1.92)	(0.90)	(1.11)	(2.57)
ATURN	0.08	0.39	0.54	0.66	0.40	0.10	0.40	0.53	0.93	0.40
	(0.44)	(1.67)	(2.27)	(3.15)	(2.47)	(0.53)	(1.96)	(2.26)	(4.68)	(2.33)
BM	0.58	0.50	0.10	0.28	0.34	0.85	0.51	0.35	0.23	0.43
	(2.84)	(2.87)	(0.60)	(1.41)	(1.49)	(4.50)	(2.93)	(1.98)	(1.09)	(1.93)
DE	0.57	0.73	0.02	0.25	0.12	0.74	0.55	0.03	0.30	0.17
	(2.69)	(3.16)	(0.10)	(1.33)	(0.67)	(2.82)	(2.59)	(0.17)	(1.49)	(1.01)
GPROF	0.34	0.16	0.25	0.65	0.54	0.09	0.34	0.25	0.73	0.59
	(1.66)	(0.79)	(1.26)	(3.05)	(2.80)	(0.51)	(1.60)	(1.23)	(3.40)	(3.22)
PS	0.35	0.15	0.11	-0.01	0.74	0.29	0.20	0.07	0.15	0.89
	(2.08)	(0.90)	(0.63)	(-0.08)	(3.15)	(1.92)	(1.24)	(0.37)	(0.79)	(4.36)
ROE	0.57	0.13	0.34	0.36	0.44	0.80	0.20	0.46	0.43	0.61
	(2.43)	(0.67)	(1.76)	(1.89)	(2.29)	(3.38)	(0.96)	(2.54)	(2.48)	(2.87)

Table A4: Double Sort Portfolios on MDD and Behavioral & Lottery Signals (VW).

This table is the value-weighted analog of Table 9. It reports value-weighted average monthly returns (Panel A) and eight-factor model alphas (Panel B) for portfolios double-sorted on MDD and a behavioral or lottery-related signal. At each month-end t, NYSE/Amex/Nasdaq common stocks are sorted into quintiles (Q1–Q5) based on the signal, and within each quintile stocks are further sorted into quintiles based on MDD. Portfolio returns are weighted by the market capitalization of the month preceding the return measurement. For each signal quintile, the table reports the return spread between the highest and lowest MDD quintiles ($H-L$). "Ex-micro" excludes stocks in the bottom 20% of NYSE market capitalization; "Large Cap" includes stocks above the NYSE median. t-statistics (in parentheses) are computed using Newey–West (1987) robust standard errors. Behavioral and lottery-related signals include *CGO*, *HIGH52W*, *ID*, *MAX*, and *RRATIO*. The sample period is July 1968–December 2024.

	Ex-micro					Large Cap				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Panel A. Average Returns										
CGO	0.66	-0.01	0.07	0.44	0.54	0.62	0.15	0.13	0.44	0.52
	(2.74)	(-0.04)	(0.32)	(2.08)	(2.66)	(2.83)	(0.70)	(0.62)	(2.08)	(2.55)
HIGH52W	0.50	0.05	0.24	0.62	0.51	0.46	0.15	0.17	0.61	0.63
	(1.90)	(0.25)	(1.13)	(2.57)	(2.56)	(1.79)	(0.73)	(0.85)	(2.86)	(3.32)
ID	0.48	0.43	0.56	0.35	0.35	0.45	0.42	0.67	0.57	0.47
	(1.76)	(1.95)	(2.60)	(1.50)	(1.48)	(1.69)	(1.98)	(3.28)	(2.57)	(2.11)
MAX	0.31	0.36	0.11	0.65	1.00	0.31	0.28	-0.01	0.85	1.03
	(1.80)	(1.88)	(0.53)	(2.87)	(3.85)	(1.88)	(1.53)	(-0.08)	(3.70)	(3.96)
RRATIO	0.74	0.29	0.30	0.27	0.61	0.68	0.41	0.40	0.40	0.63
	(3.51)	(1.34)	(1.30)	(1.13)	(2.41)	(3.39)	(2.03)	(1.78)	(1.77)	(2.59)
Panel B. Eight-factor model α										
CGO	0.51	-0.26	0.05	0.54	0.55	0.51	0.03	0.03	0.49	0.56
	(2.30)	(-1.23)	(0.27)	(2.62)	(3.10)	(2.52)	(0.16)	(0.18)	(2.50)	(2.88)
HIGH52W	0.39	-0.09	0.19	0.60	0.41	0.40	0.14	0.15	0.49	0.55
	(1.72)	(-0.54)	(1.15)	(2.46)	(2.34)	(1.75)	(0.82)	(0.77)	(2.40)	(3.12)
ID	0.66	0.33	0.46	0.29	0.30	0.69	0.33	0.50	0.62	0.56
	(2.97)	(1.89)	(2.67)	(1.79)	(1.64)	(2.94)	(1.66)	(2.92)	(3.10)	(2.84)
MAX	0.07	0.22	0.03	0.61	0.96	0.11	0.11	-0.06	0.77	0.99
	(0.51)	(1.33)	(0.19)	(2.90)	(4.20)	(0.72)	(0.62)	(-0.33)	(3.49)	(3.70)
RRATIO	0.66	0.18	0.23	0.23	0.65	0.67	0.33	0.29	0.41	0.82
	(3.54)	(0.97)	(1.18)	(1.15)	(2.93)	(3.58)	(1.79)	(1.53)	(2.15)	(3.42)

Table A5: Double Sort Portfolios on MDD and Uncertainty & Liquidity (VW).

This table is the value-weighted analog of Table 10. It reports value-weighted average monthly returns (Panel A) and eight-factor model alphas (Panel B) for portfolios double-sorted on MDD and an uncertainty or liquidity proxy. At each month-end t, NYSE/Amex/Nasdaq common stocks are sorted into quintiles (Q1–Q5) based on the proxy, and within each quintile stocks are further sorted into quintiles based on MDD. Portfolio returns are weighted by the market capitalization of the month preceding the return measurement. For each proxy quintile, the table reports the return spread between the highest and lowest MDD quintiles ($H-L$). "Ex-micro" excludes stocks in the bottom 20% of NYSE market capitalization; "Large Cap" includes stocks above the NYSE median. t-statistics (in parentheses) are computed using Newey–West (1987) robust standard errors. Uncertainty and liquidity proxies include *AVGTURN*, *ILLIQ*, *IVOL*, and β_{MKT}. The sample period is July 1968–December 2024.

	Ex-micro					Large Cap				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Panel A. Average Returns										
AVGTURN	0.12	0.35	0.33	0.23	0.70	0.13	0.12	0.36	0.14	1.00
	(0.67)	(1.92)	(1.73)	(1.12)	(2.65)	(0.81)	(0.76)	(2.04)	(0.65)	(3.75)
ILLIQ	0.31	0.12	0.13	0.70	1.74	0.31	0.16	0.42	0.85	1.28
	(1.57)	(0.59)	(0.60)	(3.07)	(8.07)	(1.52)	(0.85)	(2.06)	(4.15)	(6.94)
IVOL	0.06	0.18	0.18	0.42	0.40	0.15	0.05	0.28	0.30	0.75
	(0.40)	(1.12)	(1.01)	(1.98)	(1.63)	(0.96)	(0.32)	(1.55)	(1.54)	(3.07)
β_{MKT}	0.53	0.41	0.36	0.36	0.55	0.56	0.42	0.35	0.48	0.58
	(2.22)	(1.80)	(1.84)	(1.80)	(2.34)	(2.68)	(1.95)	(1.88)	(2.34)	(2.50)
Panel B. Eight-factor model α										
AVGTURN	-0.03	0.25	0.26	0.24	0.53	-0.06	0.07	0.26	0.17	0.87
	(-0.17)	(1.39)	(1.64)	(1.19)	(2.34)	(-0.44)	(0.46)	(1.66)	(0.74)	(3.27)
ILLIQ	0.35	0.05	0.07	0.62	1.61	0.38	0.12	0.27	0.82	1.17
	(2.03)	(0.33)	(0.54)	(3.77)	(8.36)	(2.08)	(0.77)	(1.65)	(4.79)	(6.78)
IVOL	-0.11	0.06	-0.01	0.28	0.28	-0.05	0.00	0.12	0.17	0.63
	(-0.79)	(0.38)	(-0.06)	(1.42)	(1.15)	(-0.38)	(0.02)	(0.61)	(0.93)	(2.63)
β_{MKT}	0.53	0.36	0.33	0.33	0.65	0.54	0.38	0.31	0.44	0.76
	(2.61)	(1.92)	(1.83)	(1.71)	(2.99)	(2.75)	(2.04)	(1.74)	(2.39)	(3.57)