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Pure momentum

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Pure momentum[*]

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Abstract

Momentum trading strategies exploit return persistence, but conventional past-year cumulative-return measures generate a noisy signal that attenuates performance. We propose a *pure momentum* strategy that identifies trends directly from daily returns. Our method reduces volatility, tail risk, and transaction costs while enhancing profitability. Performance is primarily driven by long positions in winners, supporting theories postulating overconfidence. The bad news instead appears to be incorporated more slowly. In particular, we show that omitting the most recent month is unnecessary to identify winners.

**Keywords: Momentum, drift test, reversals**

1 Introduction

Momentum is one of the most widely studied and implemented trading strategies in financial economics. Its effectiveness relies on the tendency for past trends in asset returns to persist into the future. Since the seminal contribution of Jegadeesh and Titman (1993), momentum is measured using the cumulative past returns of individual stocks over a formation period of roughly 12 months. The cross-sectional strategy is then executed by buying stocks with the highest past returns ("winners") and selling those with the lowest past returns ("losers").

This paper begins with a simple observation: large past returns are often a noisy indicator of the true underlying trend. Substantial price movements may reflect sudden jumps due to new information quickly absorbed by the market, or periods of elevated volatility driven by uncertainty about the asset's value. Neither scenario is inherently predictive, and there is little economic rationale for expecting the sign of such returns to persist. We refer to these instances as "illusory momentum." Stocks exhibiting illusory momentum also carry higher risk, so including them in momentum portfolios is likely to lower risk-adjusted performance.

Moreover, when a genuine trend is present, one that could potentially generate profitable persistence, the observed total return may be too small to include the stock in the top and bottom quantiles of momentum portfolios. In fact, existing economic theories (e.g., Da et al., 2014) suggest that smaller returns are more likely to persist, since they can more easily slip under the radar of analysts and traders. We refer to these cases as "hidden" momentum.

Figure 1 presents four examples from market data. Panels A and B display stocks with clear trends, positive in Panel A and negative in Panel B, that continued in the near future. Yet, these trends may generate relatively small returns compared to more volatile stocks over the same period, leading to hidden momentum. Such patterns are precisely those that a profitable momentum strategy is designed to exploit. Panel C, in contrast, shows a large positive return that quickly reversed. This return was driven by a price jump, likely reflecting the rapid incorporation of new information into prices. In such cases, the adjustment is almost immediate, leaving little scope for further predictability. Panel D also illustrates a sharp reversal, this time following a large negative return. Here, the pattern seems to be driven by high volatility rather than by a negative trend. While high volatility can produce large returns in either direction, it offers little persistence or predictability, and it also increases portfolio risk since volatility itself is highly persistent. Events like
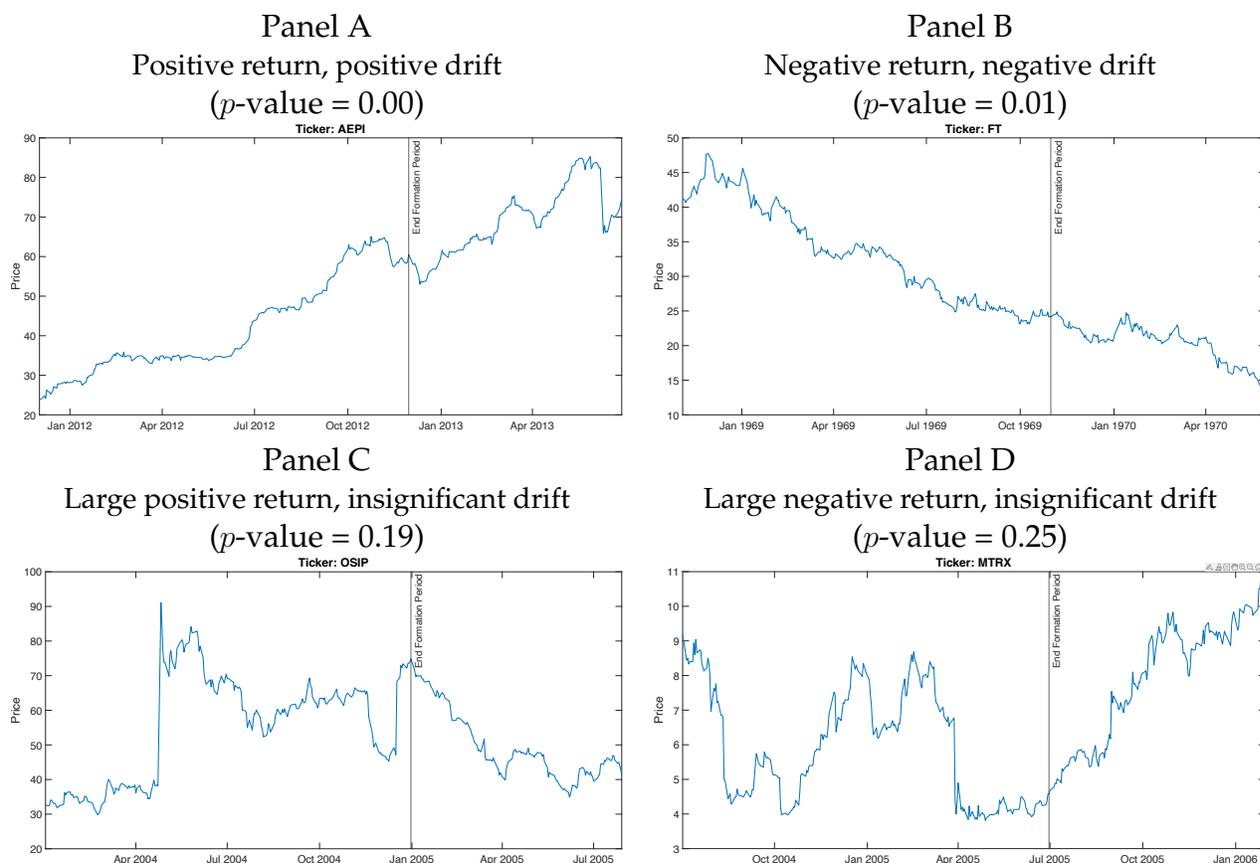
Figure 1: Examples of large total returns with and without drift. Panel A and B show two price patterns with clear trends, while Panel C and D display price changes that are mainly driven by a sudden jump or volatility in the formation period. The formation period is 12 months to 1 month prior to the formation date. The reported p-values are for one-sided test for the presence of significant negative/positive drift, as discussed in Section 2.

those shown in Panels C and D represent the illusory signals that a successful momentum strategy ought to avoid.

This paper proposes a strategy designed to reduce exposure to illusory momentum while increasing exposure to hidden momentum. The approach builds on the econometric framework for drift testing developed by Renò and Shi (2025), and the methodology is intuitive and reflects the discussion above. The core idea is to decompose the return over the formation period into the sum of daily returns. To eliminate the influence of jumps (which, as argued, are assumed to carry little predictive content) we apply the truncation method of Mancini (2009), which consists in eliminating daily returns whose absolute value is too large with respect to the stock's volatility. We then use the remaining daily returns to construct a test statistic, relying on wild bootstrap techniques (see e.g., Davidson and Flachaire, 2008) to generate p-values for both positive and negative drift. The main

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feature of wild bootstrap is to be robust to heteroskedasticity, thereby addressing volatility dynamics, the second source of illusory momentum discussed earlier. The resulting p-values are used to identify what we refer to as *pure momentum*, that is a refined measure of trend strength, stripped of distortions from jumps and volatility. We show empirically that portfolios based on pure momentum deliver substantially higher risk-adjusted returns than those based on traditional momentum, thus supporting our main claims. They are also less volatile and, importantly for traders, less expensive to trade.

Interestingly, the main economic narratives behind momentum profitability suggest the presence of non-negligible trends, as well as greater profitability when the trend is relatively small. The first narrative centers on investor overconfidence. Daniel et al. (1998) propose a behavioral theory in which momentum arises from investors' overconfidence in the precision of their private information and their tendency to overreact to public news that confirms their private signals. Hillert et al. (2014) show that stronger media coverage amplifies momentum, which they interpret as consistent with the theory of Daniel et al. (1998). Similarly, Lee and Swaminathan (2000) find that the past trading volume, reflecting the degree of investor overconfidence, affects both the magnitude and the persistence of momentum. These studies imply the presence of persistent trends, with an emphasis on public information and media coverage. The second main narrative concerns the slow diffusion of information. Hong and Stein (1999) argue that momentum arises from market inattention to news, resulting from the gradual diffusion of information among boundedly rational news-watchers. Hong et al. (2000) provide empirical evidence that momentum profitability is primarily driven by the short side of the portfolio, due to the sluggish adjustment to bad news. Using information from option market, Chen and Lu (2017) empirically show that momentum profits are stronger for stocks with slow information diffusion speed. Da et al. (2014) extend this idea by proposing the Frog-In-the-Pan (FIP) hypothesis, according to which investors with limited attention respond less to a series of frequent, gradual changes than to infrequent, dramatic ones. Huang (2022) finds that momentum strategies are more profitable when the return differential between past winners and losers during the formation period is small. Finally, recent work on emerging and non-U.S. developed markets by Goyal et al. (2025) provides strong support for the FIP hypothesis and argues that the slow diffusion of news best explains momentum formation. In all these cases, the gradual incorporation of information leads to the persistent continuation of small returns. Duffie (2010) also discusses the dynamics of asset prices driven by the slow movement of investment capital toward trading opportuni-

ties. Vayanos and Woolley (2013) propose that certain shocks impact the realized fund performance, triggering gradual fund flows from investors who infer the efficiency of managers from past fund performance. The reaction of fund managers to these flows induces gradual price movements, which in turn generate momentum. Although these studies describe different underlying mechanisms for momentum, all point to systematic and gradual price changes. Such price movements should be effectively reflected by the presence of drift. Risk and liquidity have also been linked to momentum profitability. For example, Sadka (2006) finds that liquidity risk accounts for a substantial portion of momentum profits when using high-frequency data, while Harvey and Siddique (2000) show that systematic skewness commands a significant risk premium due to the heavy tails in standard momentum returns.

The existing literature naturally lends itself to testable implications using market data, once equipped with the testing strategy we propose, one that eliminates illusory momentum and uncovers hidden momentum masked by small cumulated returns. Indeed, if overconfidence is the primary driver of momentum, then momentum should be more pronounced for stocks with high trading volumes, as the degree of overconfidence should be reflected in trading activity (Lee and Swaminathan, 2000; Goyal et al., 2025). In contrast, if the slow diffusion of information is the prevailing mechanism, it should be more prevalent among stocks with frictions that impede information flow, namely, high idiosyncratic volatility, small market capitalization, low trading volume, high transaction costs, and illiquidity, characteristics typically associated with limited media and analyst coverage. Interestingly, our findings support both mechanisms, but in distinct ways. Pure winners, i.e. winners that are detected by our test, tend to be large, liquid, low-volatility stocks with high trading volumes and low transaction costs, consistent with the overconfidence hypothesis. Pure losers, on the other hand, are typically smaller, more volatile, less liquid, and more costly to trade, features consistent with the slow diffusion of bad news (Hong et al., 2000).

Our study also contributes to the literature on improving the performance of momentum portfolios. Blitz et al. (2011) propose ranking stocks based on the residuals from the Fama–French three-factor model to isolate the impact of time-varying factor exposures. Moskowitz and Grinblatt (1999) form industry momentum by buying stocks in the three industries with the best performance and selling stocks in the three industries with the worst performance in the previous six months. Novy-Marx (2012) show that momentum profits are primarily driven by stock performance between twelve and seven months

prior to portfolio formation. However, Goyal and Wahal (2015) find that the same pattern does not emerge uniformly in international samples. Daniel and Moskowitz (2016) highlight that momentum can experience dramatic losses during periods of market rebounds following sharp market declines and high volatility. To improve momentum performance, they develop a dynamic weighting strategy based on predicted returns and variances. While they rely on traditional methods to select the stock composition of momentum portfolios, they enhance the strategy by leveraging the inverse of the past realized volatility. Barroso and Santa-Clara (2015) and Moreira and Muir (2017) also suggest that constant-volatility scaling improves momentum performance and can help mitigate crashes. However, Barroso and Detzel (2021) show that the volatility-scaling strategy substantially increases monthly turnover, and the strategy's profitability virtually disappears once transaction costs are accounted for. Our empirical analysis shows that pure momentum can mitigate these effects. Our paper is related to "low-risk puzzle", which challenges the principle that higher risk is compensated for higher expected returns. Studies such as Baker et al. (2011), Ang et al. (2006), and Frazzini and Pedersen (2014) demonstrate that stocks with low volatility consistently outperform those with high volatility, a statement we extend to pure winners.

In addition to momentum, short-term reversal is another well-known return-based strategy. It involves the reversal of the trend observed in the previous month and was first documented by Jegadeesh (1990) and Lehmann (1990). In this paper, we also examine stock price drift over the past month and explore its relationship with the performance of short-term reversal. Consistent with Avramov et al. (2006), the gross profits of the strategy are primarily concentrated in losers, and the profits of traditional short-term reversal strategies do not withstand transaction costs, with both long and short positions delivering negative cost-adjusted returns. In contrast, we show that the pure losers can still generate a notable average profit after accounting for transaction costs, but only if we use value-weighting and/or we exclude penny stocks. This suggests that traditional reversals tend to include very illiquid stocks when buying losers, as also noted by Avramov et al. (2006). Our strategy instead highlights a reversal premium for liquid stocks. Moreover, we show that pure winners do not exhibit a reversal. This may be related to the co-existence of short-term reversal and short-term momentum, as put forward recently by Medhat and Schmeling (2022). They find that short-term reversal tends to occur in low turnover deciles, while short-term momentum is observed in high turnover deciles. Our analysis also shows that the classic rule of skipping the most recent month for select-

ing momentum stocks is unnecessary for winners, while it still preserves some value for losers.

The rest of the paper is structured as follows. Section 2 summarizes the data and outlines the drift test of Renò and Shi (2025). Section 3 presents preliminary evidence of trend significance according to our test, linking it to volume, volatility, liquidity and firm size. Section 4 studies the profitability of pure momentum, comparing it to traditional momentum. Section 5 studies pure momentum portfolio in distress times. In Section 6, we discuss the empirical performance of pure reversals. Section 7 contains several robustness checks. Section 8 concludes. The paper is followed by three appendices. Appendix A explains our methodology for accounting for transaction costs. Appendix B details the analysis of pure reversals. Appendix D explores the robustness to an alternative drift test, also proposed by Renò and Shi (2025), which does not need to use truncation.

2 Data and methodology

Our sample covers all common stocks (with CRSP sharecode of 10 or 11) listed on NYSE, Amex, or Nasdaq (with exchange code of 1, 2, or 3) in the CRSP daily returns file. Following Fama and French (1996) and Daniel and Moskowitz (2016), we apply standard filters to the stock universe.[1] When forming portfolios, we require a stock to have a valid price before our formation period starts, a valid price and market capitalization on the portfolio formation date, and a valid return at the end of the formation period. By construction, the filters remove from consideration any stocks that were delisted during the formation period. We also require stocks to have at least 70% available values and at least 40% non-zero values in the formation period to ensure reliable estimation. These filters leave us with $23,086$ stocks, with an average of $3,835$ stocks per month.

If a stock is delisted during the holding period, its delisting return is incorporated as of the delisting date, when available in CRSP. For missing return of delisting and the delisting is performance-related (e.g. bankruptcy) with delisting code of 500 or 520 to 584, we set the delisting return to -30% for stocks listed in NYSE and AMEX following Shumway (1997), and set it to -55% for Nasdaq stocks as suggested by Shumway and Warther (1999). The portfolios are formed at the end of each month starting from July 1963 to December 2022. We use the 1-month T-bill return from Kenneth French's website

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[1]Also see the data description on Kenneth French's website (`https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_10_port_form_pr_12_2.html`).

as the risk-free rate. The Fama-French five factors proposed by Fama and French (2015) and the momentum factor are also obtained from the same source.

Assume you choose a formation period, which we conventionally set to $[0, T]$. For example, denoting by t the time in which the new portfolio is formed, this can be (expressed in months) $[t-12, t-1]$ for momentum, or $[t-1, t]$ for reversals. To measure traditional momentum, you only need to observe prices at the beginning and end of the formation period, and compute either the percentage or logarithmic return.

Our aim is to test whether the observed return has been generated by a genuine trend. To this purpose, we proceed formally as in Renò and Shi (2025), to which the reader is referred for the technical assumptions. We assume that the logarithmic price X_t in the interval $[0, T]$ is generated, during the formation period, by the classical Itō semimartingale:

$$X_t - X_0 = \int_0^t \mu_s \, ds + \int_0^t \sigma_s \, dW_s + J_t,$$

where μ_t and σ_t are stochastic processes, W_t is a Brownian motion, and J_t is a compensated jump process. Our aim is to test the null hypothesis $\int_0^T \mu_t dt = 0$, corresponding to the absence of an average trend in the sample, against the alternative $\int_0^T \mu_t dt \neq 0$. The case $\int_0^T \mu_t dt = 0$ corresponds to a situation in which the return over the formation period is entirely due to volatility (the component $\int_0^t \sigma_s dW_s$) and/or to jumps (the component dJ_t). The economic assumption underlying this test is that only the component μ_t is predictive of returns after time T, while the volatility and jump components contain no predictability.

To proceed with the test, we need to reconstruct the distribution of the total return $R_T = X_T - X_0$ under the null hypothesis. To this end, we employ a *wild bootstrap* (see, e.g., Huang et al., 2020); however, we must first eliminate jumps for the bootstrap to be valid. We do this using the classical truncation technique of Mancini (2009). We use n intra-period log-price observations during the formation period (e.g., daily prices), denoted by $X_0, X_{T/n}, X_{2T/n}, \ldots, X_T$. The test statistic is:

$$\tilde{R}_{T,n} = \sum_{i=1}^{n} (X_{iT/n} - X_{(i-1)T/n}) \mathbf{1}_{\{|X_{iT/n} - X_{(i-1)T/n}| < \theta_n\}},$$

where $\mathbf{1}_{\{.\}}$ is the indicator function and θ_n is a threshold. We set $\theta_n = 3 \cdot \left(\frac{MAD_n}{\Phi^{-1}\left(\frac{3}{4}\right)} \right)$, where

MAD_n is the median absolute deviation, defined as

$$MAD_n = \text{median}\left(|r_i - \text{median}(r_i)|\right),$$

where $r_i = X_{iT/n} - X_{(i-1)T/n}$, and $\Phi^{-1}(\cdot)$ is the inverse of the standard normal CDF. Operationally, this means that all daily returns whose absolute value exceeds three standard deviations, as estimated by $\left(\frac{MAD_n}{\Phi^{-1}\left(\frac{3}{4}\right)}\right)$, are truncated.[2]

From the above definition it follows that

$$\tilde{R}_{T,n} = R_T + \sum_{i=1}^{n}(X_{iT/n} - X_{(i-1)T/n})\mathbf{1}_{\{|X_{iT/n}-X_{(i-1)T/n}|\geq\theta_n\}},$$

which shows that the difference between $\tilde{R}_{T,n}$ and the original return R_T is due to large intra-period variations. As $\theta_n \to 0$ at a suitable rate, one can show that these large variations are generated by the jump component dJ_t only. Thus, $\tilde{R}_{T,n}$ is an estimator of the continuous part of the return only.

To estimate the distribution of $\tilde{R}_{T,n}$ under the null, we generate B wild-bootstrap replications of the continuous return as follows:

$$\tilde{R}_{T,n}^{*,j} = \sum_{i=1}^{n}(X_{iT/n} - X_{(i-1)T/n})\eta_{i,n}^{j}\mathbf{1}_{\{|X_{iT/n}-X_{(i-1)T/n}|<\theta_n\}}, \quad j = 1, \ldots, B$$

where $\eta_{i,n}^{j}$ are $B \times n$ independent random Bernoulli variates taking values ± 1 with probability 50%. Renò and Shi (2025) show that random flipping of the sign of the intra-period truncated returns $X_{iT/n} - X_{(i-1)T/n}$ reproduces the distribution of the test statistic $\tilde{R}_{T,n}$ when $\int_0^T \mu_t dt = 0$. Notice that there is no need to flip the sign of the return inside the indicator function because of the absolute value.

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[2]The theory for the proposed testing procedure to deliver the correct asymptotic distribution (Renò and Shi, 2025) requires $\theta_n \to 0$ at rate $\left(\frac{T}{n}\right)^{\omega}$, with $\omega < 0.5$. In practical applications, where n is fixed, the threshold is typically chosen as a multiple of the standard deviation of the continuous returns. Our threshold selection relies on the fact that $MAD_n/\Phi^{-1}\left(\frac{3}{4}\right)$ is a consistent estimator of the standard deviation under the assumption of Gaussianity. We set the threshold as three times this quantity. The median absolute deviation (MAD) is preferred over the sample variance due to its greater robustness to outliers, which makes it a more reliable estimator of continuous volatility in the presence of jumps. Section C in the Appendix studies the robustness of our results with respect to the choice of threshold. Section D studies robustness to an alternative drift test which dispenses with the threshold altogether.

From the bootstrapped returns, we can estimate the p-values using:

$$p^{\star}_{B,n,T} = \frac{1}{B} \sum_{j=1}^{B} \mathbf{1}_{\left\{ \tilde{R}^{*,j}_{T,n} \leq \tilde{R}_{T,n} \right\}}. \tag{1}$$

This p-value approximates the true p-value for the one-sided test $\int_0^T \mu_t dt > 0$, that is under the alternative that the cumulated drift over the period is negative. To obtain the $p-$value under the alternative that the accumulated drift over the period is positive, it is sufficient to use $1 - p^{\star}_{B,n,T}$ since the bootstrapped truncated return distribution is symmetric.

We conclude this Section by noticing that $p^{\star}_{B,n,T}$ can be used directly for portfolio sorting. Indeed, a small $p^{\star}_{B,n,T}$ indicates a high probability of rejecting the null of a positive drift, while an high $p^{\star}_{B,n,T}$ indicates a high probability of rejecting the null of a negative drift. For example, in the four examples in Figure 1, we have $p^{\star}_{B,n,T} = 1$ for Panel A (significant positive drift), $p^{\star}_{B,n,T} = 0.01$ for Panel B (significant negative drift), and $p^{\star}_{B,n,T} = 0.14$ and 0.8 for Panel C and D (no signal at the 10% significance level).

3   When is momentum significant?

Traditional momentum is based on the return in a given formation period. Following the standard literature, e.g., Fama and French (1996), Daniel and Moskowitz (2016), and Goyal et al. (2025), we use as the formation period at the end of month t the return from month $t-12$ to month $t-1$. Conventionally, the last month is skipped to avoid contamination from short-term reversal, whose analysis is assessed separately in Section 6 (and our analysis will show that we do not need to skip the last month when detecting winners). The identification of significant momentum is based on the wild-bootstrap test described in Section 2, using daily data in the formation period (on average, $n = 230$ daily returns) to compute $p^{\star}_{B,n,T}$ with $B = 1000$.

We start by considering p-values pooled across all formation periods and stocks satisfying the quality cuts described in Section 2, with 5% significance level. On average, 15.28% of positive returns reveal a significant trend, and 14.20% of negative returns reveal a negative trend. Next, we evaluate the percentage of significant momentum conditional on some key variables. We proceed as follows. For a given variable computed in the formation period, we slice it into 20 quantiles, and in each quantile we compute the average percentage of significantly positive and negative momentum (based on $p^{\star}_{B,n,T}$ and
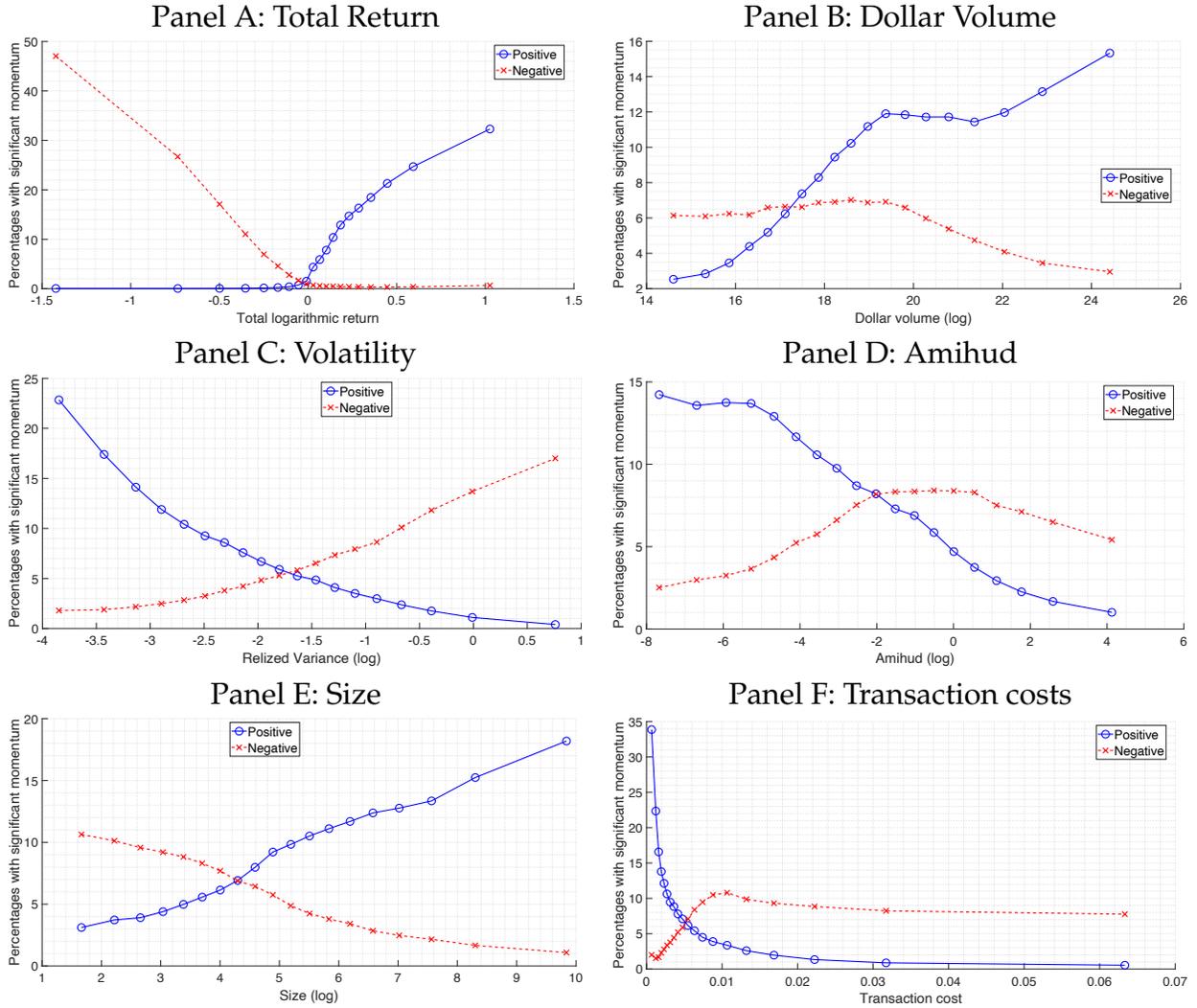
Figure 2: Average percentage of significantly positive and negative momentum, by 20 quantiles of total return, dollar volume, volatility, Amihud measure, size and transaction costs. We consider all (overlapping) 11-months formation periods in our sample and we report, for each of the 20 quantiles of the variable under consideration, the average percentage of significantly positive and negative momentum (based on $p_{B,n,T}^{\star}$ and $1 - p_{B,n,T}^{\star}$ respectively). Panel A shows the total historical return in the formation period. Panel B is for the total dollar volume traded. Panel C is for the (logarithmic) sum of squared daily returns in the formation period (that is, realized variance). Panel D is for the (logarithmic) Amihud measure in the formation period, that is absolute value of the formation period return divided by the total dollar volume. Panel E is for the (logarithmic) average size of the stock (average ME). Panel F is for transaction costs, estimated as the average, over the formation period, of the effective bid-ask spread as estimated by Hasbrouck (2009). The formation periods spans from July 1963 to December 2022.

$1 - p_{B,n,T}^{\star}$ respectively). Results are reported in Figure 2.

Panel A reports the percentage of rejections as a function of the total return in the formation period. The rejection rate increases with return size. However, in the extreme positive and negative return ventiles, only 32.30% and 47.05% of cases, respectively, are significant. This implies that more than half of stocks with the largest returns are not significant according to our simple test, suggesting that their large returns are illusory

as it may be driven by volatility and/or jumps rather than by a true trend, potentially limiting their predictability. On the other hand, Panel A of Figure 2 shows that significant trends can still be detected in less extreme returns, even for stocks that would not typically be included in a traditional momentum portfolio.

Panels B, D, and F examine different liquidity measures. Panel B analyzes total dollar volume during the formation period. Panel D focuses on the Amihud (2002) illiquidity measure, defined as the absolute value of the return divided by the total dollar volume over the formation period, multiplied by 10^6. Panel F analyzes the effective bid-ask spread measure proposed by Hasbrouck (2009), which we use as an estimate of transaction costs for individual stocks as reported in the last month of the formation period. The three panels convey a consistent pattern. Positive momentum is more likely to be significant for stocks with high volume, low illiquidity, and low transaction costs. In contrast, negative momentum tends to be significant at the opposite end of the liquidity spectrum, where volume is low, illiquidity is high, and transaction costs are elevated.

Panel C analyzes volatility, measured as the sum of daily squared returns over the formation period. Significant positive momentum is more likely to occur in low-volatility periods, whereas negative momentum is more significant during high-volatility periods. A similar pattern emerges in Panel E with respect to stock capitalization. Positive momentum is more prevalent among highly capitalized stocks, while negative momentum is more likely for stocks with low capitalization.

The descriptive analysis in this section thus uncovers new stylized facts about momentum: the distinct trading environments in which positive and negative trends emerge. In the introduction, we discussed two economic theories that can generate trends: overconfidence and slow diffusion of information. Positive trends are more likely to arise when volatility is low, liquidity is high, and stocks are highly capitalized. This pattern aligns more closely with the overconfidence hypothesis, as the degree of investor overconfidence is captured by trading volume, which can be employed as a proxy for overconfidence (Lee and Swaminathan, 2000; Goyal et al., 2025). In contrast, negative trends are more likely to occur when volatility is high, liquidity is low, and stocks have low capitalization. This is more consistent with the idea that information diffusion is slower for smaller stocks, which receive less media and analyst coverage. Additionally, negative trends are often associated with market crashes. This is evident in Figure 3, which reports the percentage of stocks with significant trends at the 5% and 10% significance levels. The frequency of positive trends is low during recessions and higher during expansions, whereas negative
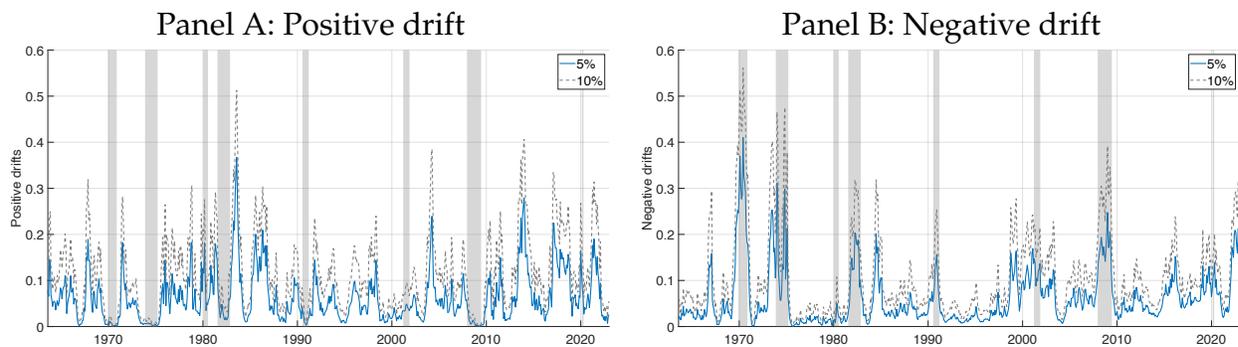
Figure 3: The number of stocks with drift significant at 5% **and** 10% **for momentum**. The numbers are standardized by the total number of stocks on the portfolio formation date from July 1963 to December 2022. The detection period is 12 months to 1 month prior to the formation date. The shaded areas represent the US recession periods reported by the National Bureau of Economic Research (NBER).

trends peak during recessions. Notably, this effect is not purely mechanical, as our trend test accounts for volatility, which tends to be particularly high during recessions.

In summary, our testing methodology offers a statistically rigorous analysis of both positive and negative trends, highlighting important economic differences between them. These differences may help explain predictability, an idea we test in the next section.

4 Is pure momentum trading profitable?

Yes. To demonstrate this, we implement the classic long–short strategy in two exercises designed to highlight the importance of trend detection. Throughout the analysis, Sharpe and Sortino ratios are annualized and computed relative to the 1-month T-bill rate.

4.1 Portfolios based on sorting

In the first exercise, we sort stocks into five quintiles based on their cumulative past returns during the formation period, labeled as *Losers*, *2*, *3*, *4*, and *Winners*. The *Winners* (*Losers*) quintile includes stocks whose returns fall within the top (bottom) 20% of cumulative historical returns during the formation period at each portfolio formation date.

Within each quintile, the stocks are then equally divided into five sub-quintiles based on the p-value of the presence of negative drift, labeled *Low*, *2*, *3*, *4*, and *High*, resulting in 5×5 portfolios. We recall that low p-values indicate the significance of negative trends, while high p-values indicate the significance of positive trends. Thus, sorting by the p-value of the presence of negative drift ensures that stocks with significantly negative drift

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are included in the *Low* quintile, while stocks with significantly positive drift are included in the *High* quintile. In this exercise, portfolios are equally weighted.

We find that distilling traditional momentum using our test to select significant trends is highly profitable. Panel A of Table 1 shows the average holding return of each of the 5×5 portfolios in the month $[t, t+1]$, with the signal for creating the portfolios being computed during the formation period $[t-11, t-1]$. Panel A indicates that the average return is highest for the High-Winners (HW) portfolio, and lowest for the Low-Losers (LL) portfolio. The corresponding long-short strategy would have yielded an annualized excess return of 19.20% over the risk-free rate, considerably higher than the 15.48% yielded by the traditional momentum long-short strategy, and significantly so, according to a standard t-test.

Panel B reports portfolio volatilities. In the 5×5 portfolios, annualized volatility ranges from 15.62% to 36.47%. Among the winners, the HW portfolio has the lowest volatility, while the LL portfolio shows the highest, consistent with the evidence in Section 3, which documents more frequent detections of negative drift under high volatility. Consequently, the long–short strategy (long HW, short LL) exhibits a volatility of 30.29%, considerably higher than that of the traditional long–short momentum portfolio (W–L(5)) based on five quintiles, whose volatility is 21.41%. This difference is statistically significant under a standard F-test for equality of variances. Part of this gap, however, may reflect a diversification effect. By construction, the traditional momentum portfolio includes five times as many stocks as the HW–LL portfolio. When we construct a traditional momentum portfolio using 25 quantiles—so that the long–short position involves the same number of stocks as the HW–LL strategy—its volatility rises to 35.04%, which is significantly higher than that of the HW–LL portfolio according to the F-test.

Panel C shows Sharpe ratios and confirms the evidence from Panel A on portfolio returns, even after controlling for volatility. The HW portfolio has the highest Sharpe ratio, while the LL portfolio has the lowest. The Sharpe ratio of the HW-LL portfolio is 0.63, significantly higher than 0.44 of the traditional momentum portfolio with 25 quantiles according to the test statistics of Barillas et al. (2020). The difference between the Sharpe ratio of HW-LL and that of the traditional momentum based on 5 quintiles is also significant, even though this portfolio contains five times more stocks and is thus better diversified.

Figure 4 shows the performance over longer holding horizons for the HW–LL portfolio and the traditional long–short momentum strategies formed with 5 and 25 quantiles, denoted as W–L(5) and W–L(25). The performance metrics show a clear maturity pattern

Table 1: Drift Significance and Momentum

This table reports annualized average 1-month portfolio excess holding returns (%) over risk-free rate, portfolio volatility, and associated Sharpe ratio. Portfolios are initially sorted into five quintiles based on cumulative past returns, labeled as *Losers*, *2*, *3*, *4*, and *Winners*. Within each quintile, the stocks are then equally divided into five quintiles on the *p*-value of the presence of negative drift, labeled as *Low*, *2*, *3*, *4*, and *High*, leading to 5×5 portfolios. Note that the significance is concentrated in Low-Losers and High-Winners portfolios. The *HW-LL* is the portfolio of buying High-Winners and selling Low-Losers. Portfolio *W–L(5)* buys the winner quintile and sells the loser quintile. Portfolio *W–L(25)* buys the top 20% of stocks within the winner quintile and sells the bottom 20% within the loser quintile to match *HW-LL* portfolio in the number of stocks. The return on W-L portfolio is the long-short return in excess of risk-free rate. In parentheses, we report the *p*-values for the differences between Portfolio *HW-LL* portfolio and Portfolios *W-L(5)* and *W-L(25)*. We use a paired t-test with Newey–West standard errors (12 lags) to compare returns, a two-sample F-test to assess equality of variances and Barillas et al. (2020)'s test to compare the maximum squared Sharpe ratios. The portfolios are formed from July 1963 to December 2022.

Panel A: Annualized 1-month Holding Returns in Excess of Risk-free Rate								
	Low	2	3	4	High	W - L(25)	W - L(5)	HW - LL
Losers	-6.16	-0.03	2.63	5.24	7.91	-2.53	1.92	
2	5.26	6.02	8.67	9.31	7.79		7.41	
3	7.68	10.04	10.96	9.96	9.66		9.66	
4	11.04	12.51	13.71	12.47	11.85		12.32	
Winners	10.48	16.48	16.52	16.52	17.38	17.29	15.48	
W-L						15.48	9.21	19.20
						(0.04)	(0.00)	
Panel B: Annualized Portfolio Volatility								
	Low	2	3	4	High	W - L (25)	W - L (5)	HW - LL
Losers	36.47	32.35	30.94	30.42	29.17	44.43	31.08	
2	22.25	21.81	21.78	21.66	21.00		21.23	
3	20.05	19.30	18.14	17.96	17.50		18.04	
4	21.23	19.68	18.35	17.43	15.62		17.84	
Winners	26.12	23.73	22.31	21.64	21.32	28.62	22.33	
W-L						35.04	21.41	30.29
						(0.00)	(0.00)	
Panel C: Annualized Sharpe Ratio								
	Low	2	3	4	High	W - L (25)	W - L (5)	HW - LL
Losers	-0.17	0.00	0.09	0.17	0.27	-0.06	0.06	
2	0.24	0.28	0.40	0.43	0.37		0.35	
3	0.38	0.52	0.60	0.55	0.55		0.54	
4	0.52	0.64	0.75	0.72	0.76		0.69	
Winners	0.40	0.69	0.74	0.76	0.82	0.60	0.69	
W-L						0.44	0.43	0.63
						(0.04)	(0.04)	

across all three strategies: expected returns decline as the investment horizon increases, while volatility rises and the Sharpe ratio falls after reaching their respective minimum (for volatility) and maximum (for the Sharpe ratio) at a two-month holding period. Although the traditional momentum strategy (W–L(5)) has lower volatility than HW–LL, the latter consistently delivers stronger risk-adjusted performance at all maturities. This advantage holds for expected return, volatility, and Sharpe ratio when momentum portfolios are constructed with the same number of stocks (W–L(25)).

Momentum portfolios based on sorting at longer holding horizons
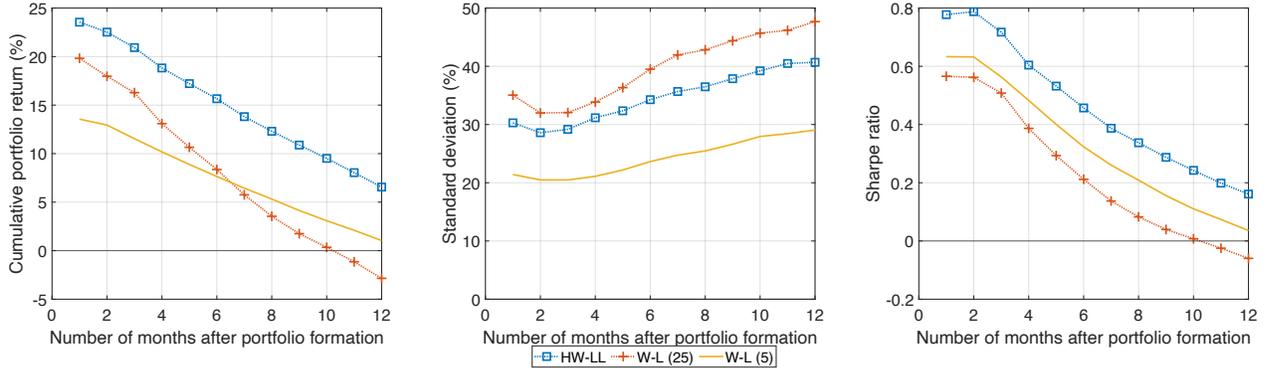
Figure 4: Cumulative buy-and-hold annualized long-short portfolio returns, volatility and Sharpe ratios from 1 month to 12 months. The figures compare portfolio performance over holding horizons up to 12 months. The portfolios are formed as explained in Section 4.1. Portfolio HW-LL is constructed by buying High-Winner and selling Low-Winner whose returns are mainly driven by drift. Portfolio W–L(5) buys the winner quintile and sells the loser quintile. Portfolio W–L(25) buys the top 20% of stocks within the winner quintile and sells the bottom 20% within the loser quintile to match HW–LL portfolio in the number of stocks. The detection period is 12 months to 1 month prior to the formation date. The portfolios are formed from July 1963 to December 2022.

4.2 Portfolios based on signal

The previous subsection showed that sorting based on significant momentum yields economically sizable and statistically significant profits. However, double-sorting does not guarantee that all stocks in the HW-LL portfolio display significant trends, so that they could still display illusory momentum. In this section, we form "pure momentum" portfolios based solely on the trend signal, that is, on $p^\star_{B,n,T}$. The pure losers are defined as stocks with $p^\star_{B,n,T} \leq \alpha$, while the pure winners are stocks with $p^\star_{B,n,T} \geq 1 - \alpha$. As discussed in Section 2, this is equivalent to using a one-sided test for the detection of positive/negative drift. In our analysis, we use significance levels ranging from 1% to 10%. We require at least 10 stocks to be included in the winner/loser portfolio to trade. If the test detects fewer stocks, we invest in the risk-free rate.

To make a meaningful comparison, we also form "traditional" winners and losers portfolios for each significance level α by selecting stocks based on the ranking of their cumulative past returns, while ensuring an equal number of stocks (when there are at least 10) in the long and short positions for both strategies. This signal-based comparison thus controls for diversification effects. In this Section, portfolios are equally weighted, rebalanced at the end of each month, and use the same formation period described in Section 2.

Figure 5 presents a 3×3 matrix of performance plots, with rows reporting average excess return (top), volatility (middle), and Sharpe ratio (bottom), and columns repre-
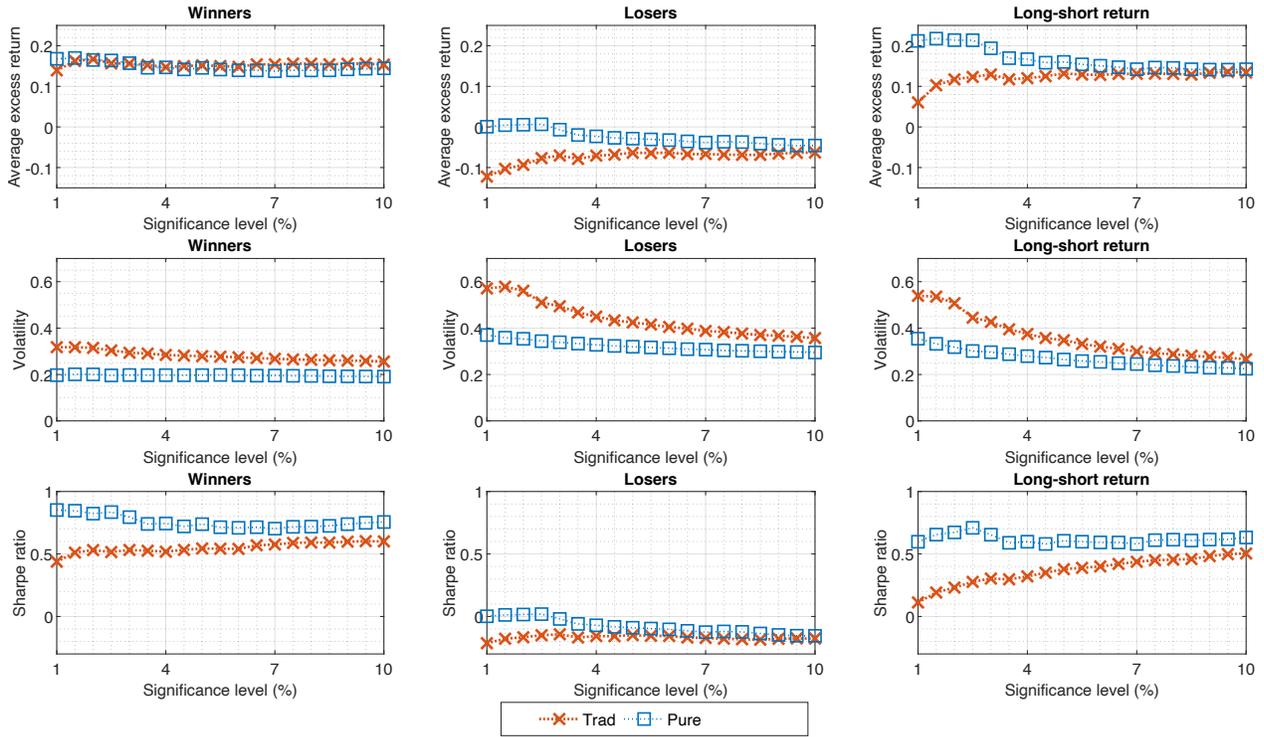
Figure 5: Annualized excess return, volatility and Sharpe ratio for winners, losers and long-short momentum portfolio. This figure reports the annualized equal-weighted average of 1-month holding period excess returns over the risk-free rate, as well as the corresponding standard deviation and Sharpe ratio of the returns on a *long* position in past winners, a *short* position in past losers, and the *long-short* portfolio with significance levels from 1% to 10% (one-sided tests). The pure momentum is constructed using stocks with significant trends at a specified significance level and traditional momentum is formed with the same number of stocks in the long and short positions, but chosen based on the ranking of their cumulative past returns. The portfolios are formed from July 1963 to December 2022.

senting portfolios of buying winners (left), selling losers (middle), and the corresponding long–short strategy (right). The figure shows that pure momentum portfolios exhibit better risk-adjusted performance than traditional momentum portfolios, with most of the profitability stemming from the winners. Regarding average realized returns, as shown in the top row of Figure 5, pure winners deliver roughly the same returns as traditional winners, while pure losers generate higher returns than traditional losers at low significance levels. Consequently, the long–short pure strategy attains higher average realized returns at lower significance thresholds. We also note that the expected return is mostly driven by winners for both the pure and the traditional strategy. However, the main advantage of the pure momentum strategies is the drastic reduction in volatility, both for winners and losers. The volatility reduction is more effective for lower α, that is, for more significant trends. Moreover, in agreement with the evidence in Section 3, traditional winners have a much lower volatility than traditional losers. Pure winners have lower volatility than

Momentum portfolios based on signal at longer holding horizons, gross
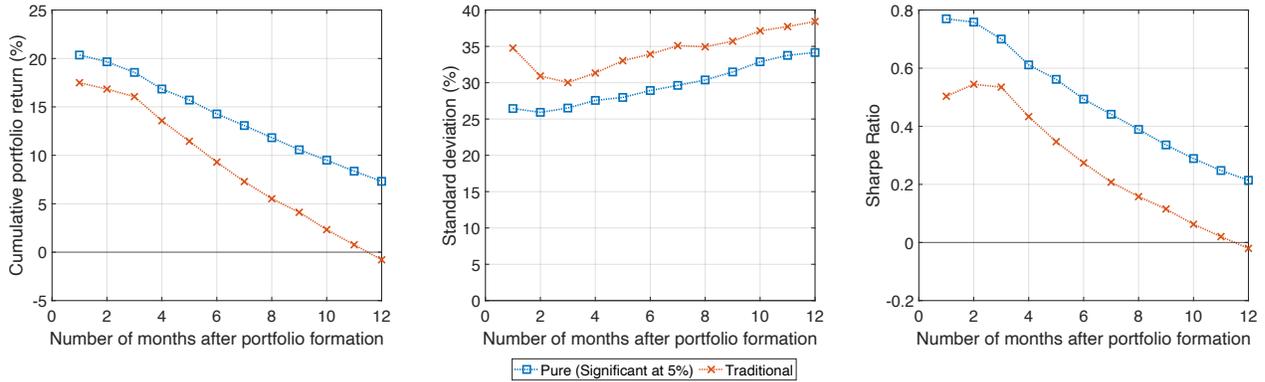
Figure 6: Cumulative buy-and-hold portfolio average returns, volatility and Sharpe ratios from 1 month to 12 months for pure and traditional momentum. This figure shows the annualized cumulative buy-and-hold returns, standard deviation and Sharpe ratio for pure and traditional momentum strategies formed with significance levels of 5% that are held from 1 month to 12 months. The portfolios are formed from July 1963 to December 2022.

pure losers too, but the gap is less pronounced.

Therefore, as presented in the bottom row, the Sharpe ratio of winners is considerably higher than the Sharpe ratio of losers (which is close to zero). At the 1% significance level, the Sharpe ratio of the pure winner portfolio is 0.85, 93% higher than the Sharpe ratio of traditional winners (0.44). This difference is statistically significant.[3] Selling losers does not appear to be profitable, and the difference between the Sharpe ratio of pure and traditional portfolios is never significant. However, when the two strategies are combined in a long-short portfolio, the difference between pure and traditional strategies is even larger. At 1%, the Sharpe ratio of pure long-short is 0.60, that of traditional long-short is 0.11. The difference attenuates as α increases, underlining the importance of testing for profitability.

The performance of the pure momentum portfolio (as well as that of the traditional momentum portfolio) declines as the holding period increases, as shown in Figure 6. We observe that the average portfolio return decreases, portfolio risk increases, and the Sharpe ratio declines. However, pure momentum maintains an advantage over traditional momentum at all holding horizons.

Importantly, pure momentum is more robust than traditional momentum to tail risk, as shown in Figure 7. Pure long-short strategies exhibit substantially lower negative skewness and kurtosis than their traditional counterparts, especially for low values of the sig-

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[3]We test the improvement in the Sharpe ratios using the technique of Barillas et al. (2020). The test is significant at the 1% level when $\alpha \leq 3\%$, and at the 5% level for all other cases, except for the portfolio formed with $\alpha = 7\%$, which is significant at the 10% level.

Tail measures for momentum portfolios, gross
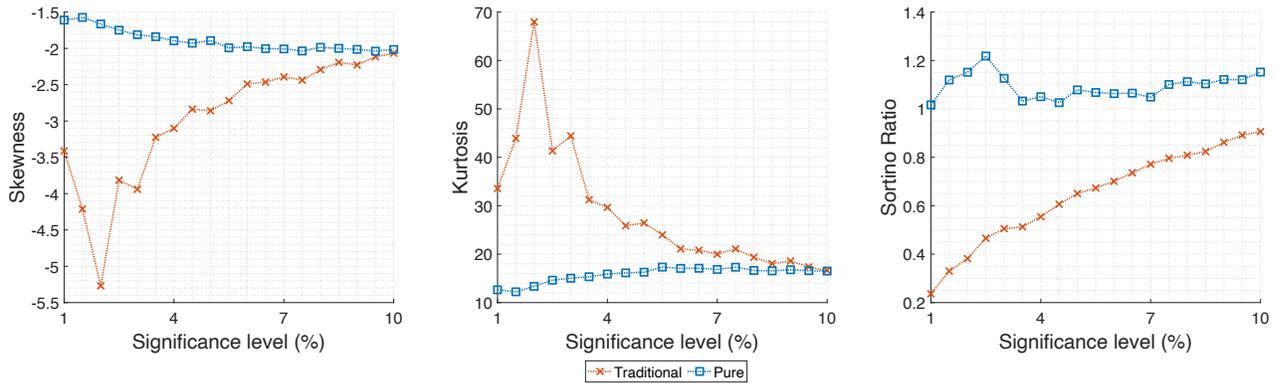
Figure 7: Skewness, kurtosis and Sortino ratio comparisons between pure and traditional momentum. The threshold used to compute the Sortino ratio is 0. The comparisons use 1-month holding period returns for pure and traditional momentum portfolios formed with significance levels from 1% to 10%. The portfolios are formed from July 1963 to December 2022.

nificance level α. As a result, the higher profitability in terms of the Sortino ratio (which accounts for tail risk) is even more pronounced than that of the Sharpe ratio. This can be interpreted as the robustness of our trend detection method to tail-risk events like jumps, which can instead contaminate the traditional momentum portfolio with little future compensation.

The superior performance of pure momentum becomes even more pronounced after accounting for transaction costs. To estimate the transaction costs at the portfolio level, we adopt the procedure of DeMiguel et al. (2009) which aggregates the change in portfolio weight multiplied by the one-way transaction cost for all stocks within the portfolio, see Appendix A. Despite the slightly higher (but practically negligible) average portfolio turnover associated with the pure momentum strategy, as reported in Figure 8, Panel A, rebalancing costs remain consistently lower for both pure winners and pure losers, as shown in Panel B of the same figure. Notably, pure winners are particularly cheap to trade.

Figure 9 replicates Figure 5, but incorporates transaction costs. The first key result is that transaction costs, in our sample, severely erode the performance of traditional momentum. Once trading costs are accounted for, the Sharpe ratio of the traditional long–short strategy turns negative, largely due to the poor performance of traditional losers. This finding is consistent with Lesmond et al. (2004), who show that the gross profits of standard momentum are primarily driven by frequent trading in illiquid stocks with high transaction costs that are especially pronounced when shorting traditional losers. By contrast, pure momentum portfolios continue to generate positive average returns, with

Panel A: Portfolio turnover   Panel B: Portfolio rebalancing costs
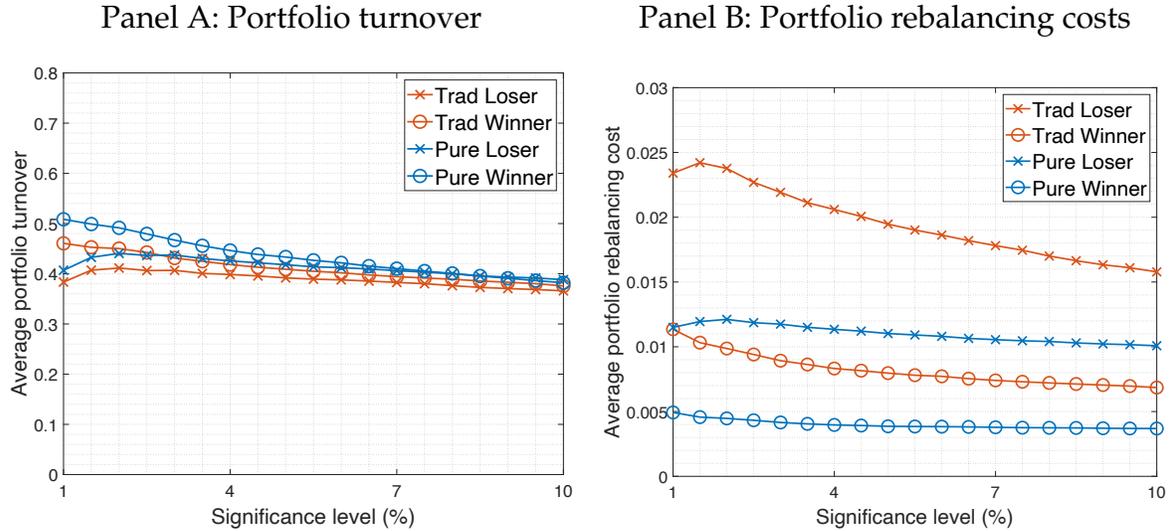
Figure 8: Portfolio turnover and rebalancing costs of momentum strategies. The graphs compare the average monthly portfolio turnover and rebalancing costs between pure and traditional momentum strategies for both winner and loser portfolios. We use the effective bid-ask spread measure proposed by Hasbrouck (2009) as our estimate of transactions cost for individual stocks.

performance still driven by buying pure winners. The net Sharpe ratio from buying pure winners at $\alpha = 1\%$ is 0.55, larger than the gross Sharpe ratio of traditional winners. In comparison, the net Sharpe ratio of traditional winners falls to 0.01, with the difference relative to pure winners statistically significant (p-value $= 3.6\%$). On the short side, selling pure losers is no longer profitable after transaction costs, though it remains less unprofitable than shorting traditional losers.

The resilience of pure winners to trading costs can be explained by the fact that the proposed test tends rejects more for stocks with larger market capitalization, higher liquidity, and lower volatility. Indeed, winners are sensibly less expensive than losers, and pure winners are sensibly less expensive than traditional winners (see again Panel B of Figure 8). Given the benefit of pure momentum strategies in terms of volatility reduction is unchanged, the difference in portfolio performance reflects the impact of cost netting. After accounting for transaction costs, the traditional momentum portfolio yields negative returns, whereas the pure momentum portfolio remains profitable. We conclude that, net of transaction costs, it makes sense only to buy the pure winners, since selling the pure losers still implies an increase in volatility and a negative return for the portfolio.

Finally, we perform a classic exercise and examine if the performance of pure momentum can be explained by well-known risk factors, and in particular by the Carhart (1997)'s momentum factor (UMD). We regress the time-series returns of the pure momentum long-short strategy on a six-factor model, which includes the five Fama-French factors
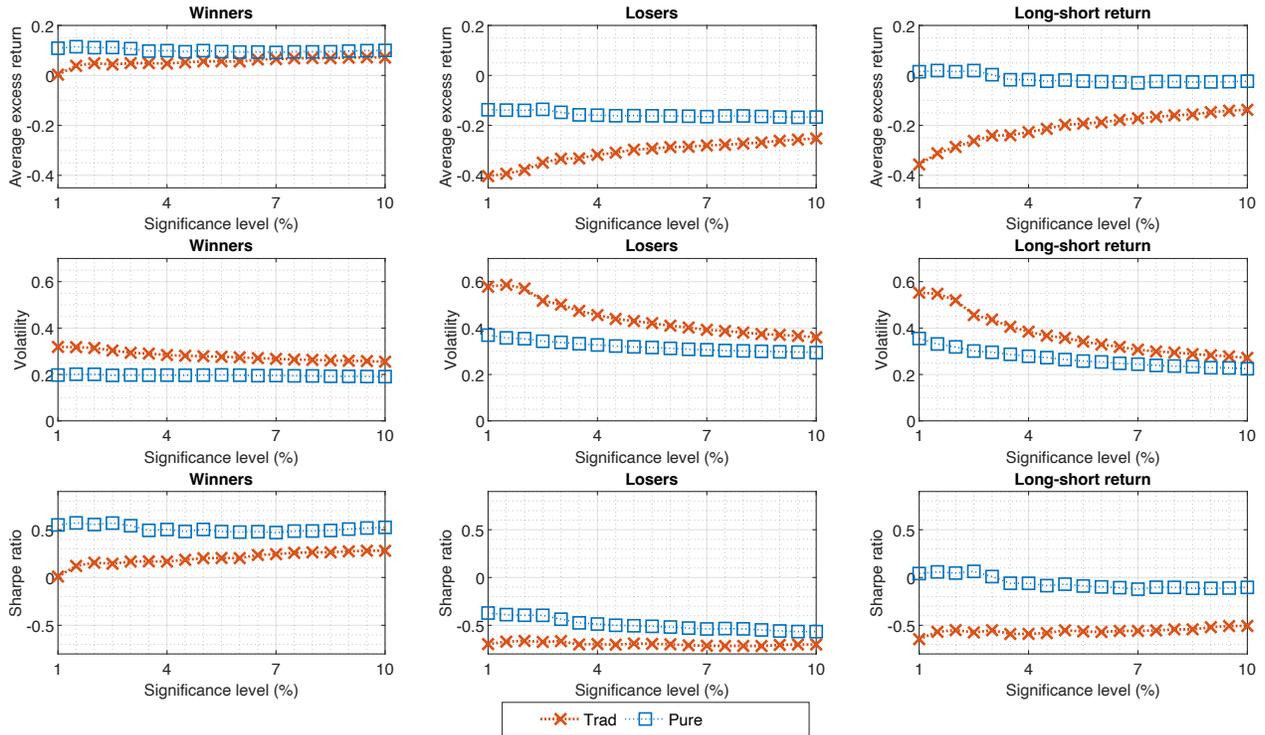
Figure 9: Annualized net excess return, volatility and Sharpe ratio for winners, losers and long-short momentum portfolio. This figure reports the annualized net-of-cost, equal-weighted average excess return over the risk-free rate, as well as the corresponding standard deviation and Sharpe ratio of the returns on a *long* position in past winners, a *short* position in past losers, and the *long-short* portfolios with significance levels from 1% to 10%. The pure momentum is constructed using stocks with significant trends at a specified significance level and traditional momentum is formed with the same number of stocks in the long and short positions, but chosen based on the ranking of their cumulative past returns. We use the effective bid-ask spread measure proposed by Hasbrouck (2009) as our estimate of transactions cost for individual stocks. The portfolios are formed from July 1963 to December 2022.

(MKT, SMB, HML, RMW, CMA) and the UMD factor. Figure 10 shows the estimated intercepts from the model as a function of the significance level α used to construct portfolios. If pure momentum can be explained by commonly accepted risk factors (including momentum, the UMD factor) the estimated intercept should be statistically indistinguishable from zero. Instead, the pure momentum strategy exhibits a positive intercept that is statistically significant, except for the portfolio formed at the 1% significance level, indicating that the pure strategy captures additional pricing information.

Overall, the findings of our exercises show that the detection of a significant trend is a better predictor of future returns than the cumulative past return. This effect is stronger for positive trends than negative trends. This predictability can be exploited in profitable strategies, which are even more lucrative after controlling for transaction costs and tail risk.
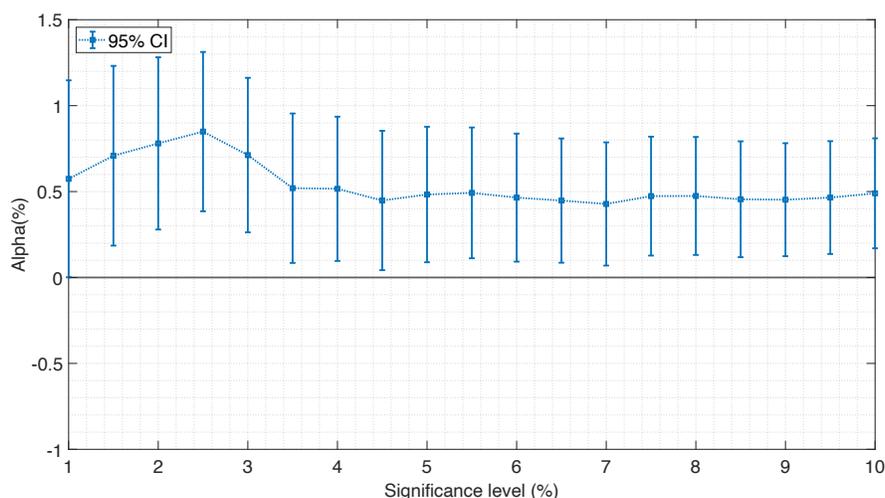
Figure 10: Risk-adjusted returns. The figure shows estimated abnormal returns (alphas) from time series regressions of returns of pure momentum portfolios constructed with significance levels from 1% to 10% on Fama-French five-factor model and their momentum factor. The portfolios are formed from July 1963 to December 2022.
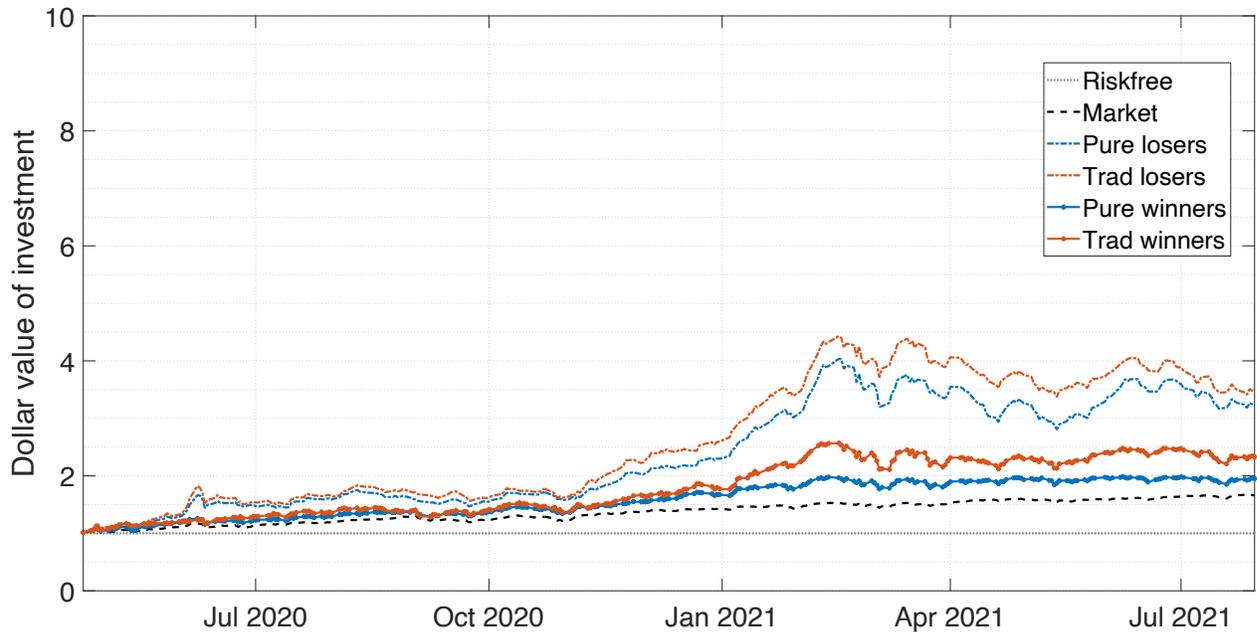
5 Pure momentum crashes?

Daniel and Moskowitz (2016) document pronounced momentum crashes caused by significant rebounds in the returns on loser portfolios. They observe that the loser portfolio generates more than twice the profits of the winner portfolio and that the winner portfolio underperforms the market during crash periods. Does it also hold for the pure momentum portfolio?

We use the pure momentum and traditional momentum portfolio at 10%, formed as explained in Section 4.1. We focus on two crash periods in our sample: the first following the 2009 financial crisis, and the second during the 2020 stock market crash triggered by the Covid-19 pandemic. We find that selecting stocks using the pure momentum test helps mitigating the impact of momentum crashes, although it remains challenging to eliminate them entirely. Figure 11, Panel A, compares the cumulative gains of pure and traditional portfolios from 9 March 2009 to 28 March 2013. It is the same period as used in Panel A of Figure 2 of Daniel and Moskowitz (2016), to which Panel A of Figure 11 can be directly compared. Investing with the traditional strategy can result in significantly larger losses compared to the pure strategy. Panel A shows that traditional losers experienced a dramatic rebound during the period, with losses at least 40% higher compared to the losses of pure losers. If we cumulate losses up to the end of the period, pure loser portfolio would have lost roughly a 40% of traditional loser portfolio (3.55 vs 5.39). Meanwhile,
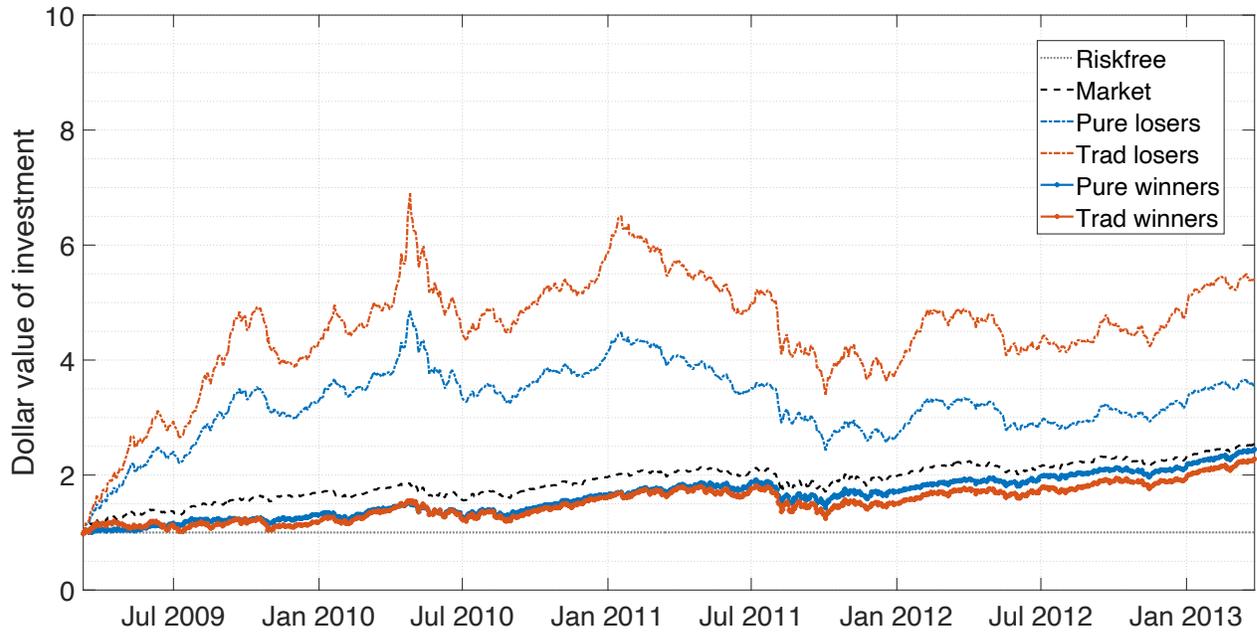
Figure 11: Momentum crashes. The plots show cumulative daily gains from investments to six portfolios: risk-free asset, the stock market return provided by Kenneth French, (3) the pure and traditional losers and winners constructed as explained in Section 4.1 over the period from 9 March 2009 to 28 March 2013 and from 24 April 2020 to 30 July 2021 with a significance level of 10%.

pure winners outperform traditional winners.

Similar patterns can be observed in the recent stock market crash in 2020 as shown in Figure 11, Panel B, although this crash is less severe than the preceding one. The period runs now from 24 April 2020 to 30 July 2021. We also observe that the market rebounds following the COVID crash leaded to massive losses when shorting losers. However, selecting pure momentum stocks would have mitigated the losses in this case too.

6 Short-term reversals

Jegadeesh (1990) firstly documents that buying the past-month losers and selling past-month winners deliver a significantly positive return, indicating a reversal of the past-month trend. This leads researchers to change the formation period for momentum to $[t-12, t-1]$ skipping the last month. In this section, we explore the profitability of pure reversal portfolios.

We proceed as follows. Identification of significant reversal is still based on the wild-bootstrap test described in Section 2, using daily data in the formation period $[t-1, t]$ (on average, $n = 20.63$ daily returns). We note that, compared to pure momentum formation, we use approximately one tenth of the returns to test significance of reversals. The p-values $p_{B,n,T}^{\star,R}$ are computed again with $B = 1000$, with the same interpretation as above (high $p_{B,n,T}^{\star,R}$ indicating significant positive trend and thus pure winners, and low $p_{B,n,T}^{\star,R}$ indicating negative trends and thus pure losers).

Figure 12 shows that we can still detect a large number of pure reversals, but to a much lesser extent than in the case of pure momentum. On average, when using a significance level of 5%, we detect a significant positive trend in 8.66% of the instances, and a significant negative trend in 9.04% of the instances. The loss in power can be attributed to the fact that we are using fewer daily returns.

Figure 13 shows the performance of strategies, based on the signal in the last month, which sell pure winners, buy pure losers, and the corresponding long-short strategy, for different significance levels α. The traditional portfolio is formed as described in Section 4.2. Figure 13 is for equally weighted portfolios and rebalanced at the end of each month. The corresponding figure after netting transaction costs is shown in Figure 22 in Appendix B.

Regarding losers, Figure 13 shows that although traditional losers generate higher expected returns than pure losers, they also come with higher volatility. As a result, the two

Panel A: Positive drift

Panel B: Negative drift
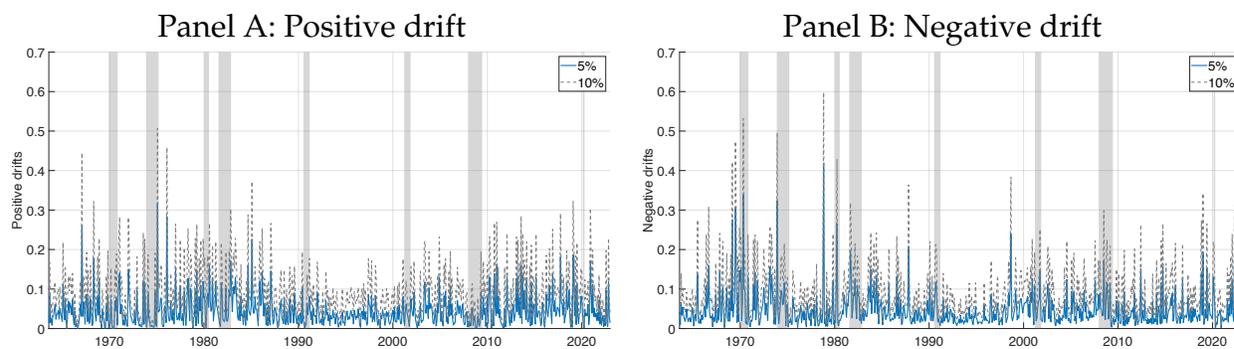
Figure 12: The number of stocks with trends significant at 5% **and** 10% **for short-term reversal.** The numbers are standardized by the total number of stocks at the portfolio formation date from July 1963 to December 2022. The detection period is the last month as of the formation date. The shaded areas represent the US recession periods reported by the National Bureau of Economic Research (NBER).

Short-term reversals, based on signal, gross
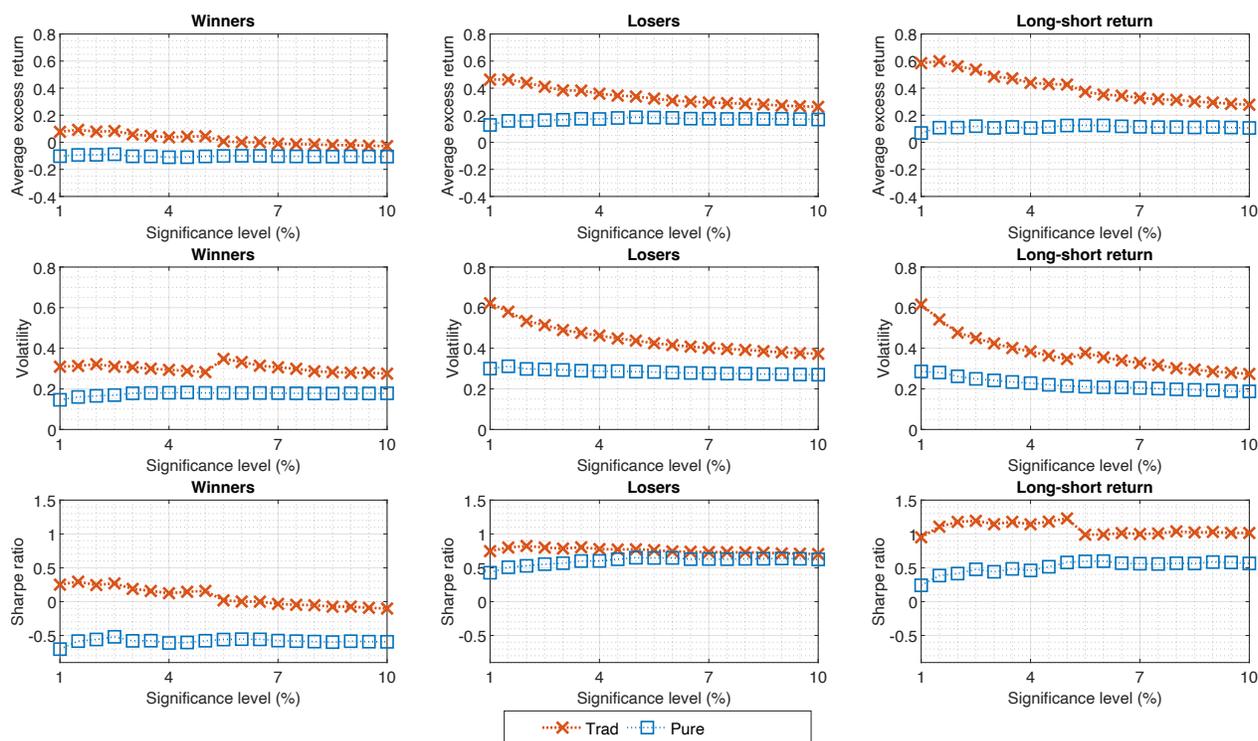
Figure 13: Annualized excess return, volatility and Sharpe ratio for past-month winners, losers and long-short short-term reversal portfolio. This figure reports the annualized equal-weighted average of 1-month holding returns in excess of risk-free rate, as well as standard deviations, and Sharpe ratios of the returns on a *short* position in past winners, a *long* position in past losers, and the long-short portfolios formed at significance levels ranging from 1% to 10%. The pure reversal strategy is constructed using stocks with significant trends at a specified significance level and traditional short-term reversal is formed with the same number of stocks in the long and short positions, but chosen based on the ranking of their cumulative returns in the past month. The portfolios are formed from July 1963 to December 2022.

strategies deliver similar Sharpe ratios, with traditional losers retaining a slight advantage.

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Panel A: Portfolio turnover   Panel B: Portfolio rebalancing costs
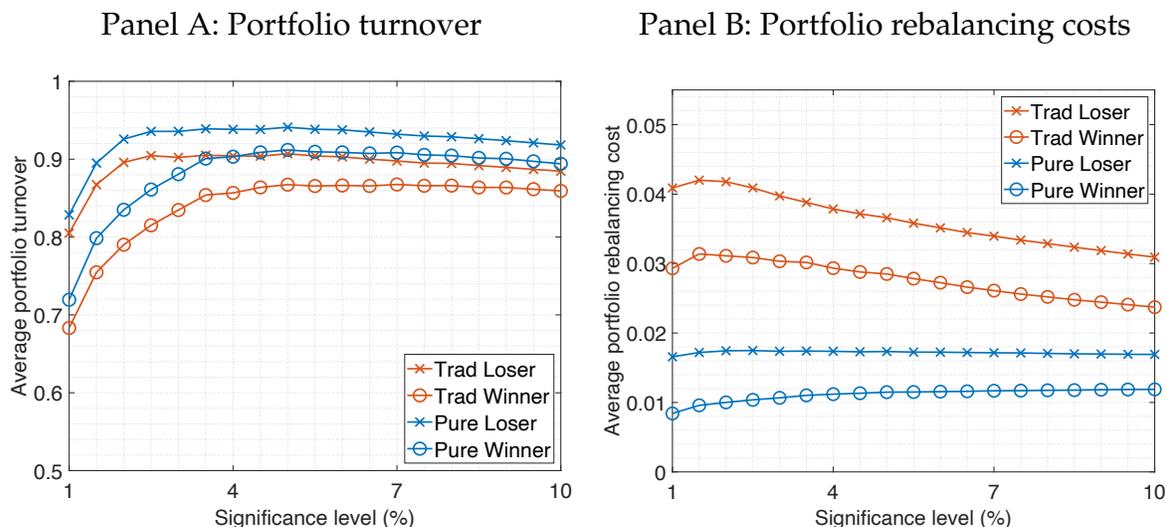
Figure 14: Portfolio turnover and rebalancing costs of short-term reversal strategies. The graphs compare the average monthly portfolio turnover and rebalancing costs between pure and traditional short-term reversal strategies for both winner and loser portfolios. We use the effective bid-ask spread measure proposed by Hasbrouck (2009) as our estimate of transactions cost for individual stocks.

For winners, the pattern differs markedly. While shorting traditional winners yields modest profitability, shorting pure winners leads to financial losses (even if with lower volatility). Regarding long-short portfolios, most of the profitability of the two strategies comes from buying losers, in agreement with the results of Avramov et al. (2006). In this case, the traditional reversal long-short strategy performs better than pure momentum, this being due to the negative performance of buying pure winners.

We further note that, as shown in Panel A of Figure 14, both portfolios are characterized by extreme turnover. Panel B of the same Figure shows instead that transaction costs are much lower for pure reversal portfolios than for traditional portfolios, with the gap increasing with more significant signal. Thus, even for reversals, pure strategies are more cost-effective (as also shown in 22 in Appendix B).

The underperformance of buying pure last-month losers strongly depends on equal weighting. Figure 15 shows the performance of buying losers when we use value-weighting instead. With value-weighting, buying pure losers is more profitable than buying traditional losers, with profitability remaining positive after netting transaction costs, something that does not hold for traditional losers. Similarly, as shown in Figure 25 in Appendix B, buying pure losers is more profitable than buying traditional losers if we exclude penny stocks. These findings suggests that profitability of traditional reversals mostly hinges on reversals of low-value, low-price stocks. The profitability of pure momentum portfolios is instead robust to value weighting and the exclusion of penny stocks,
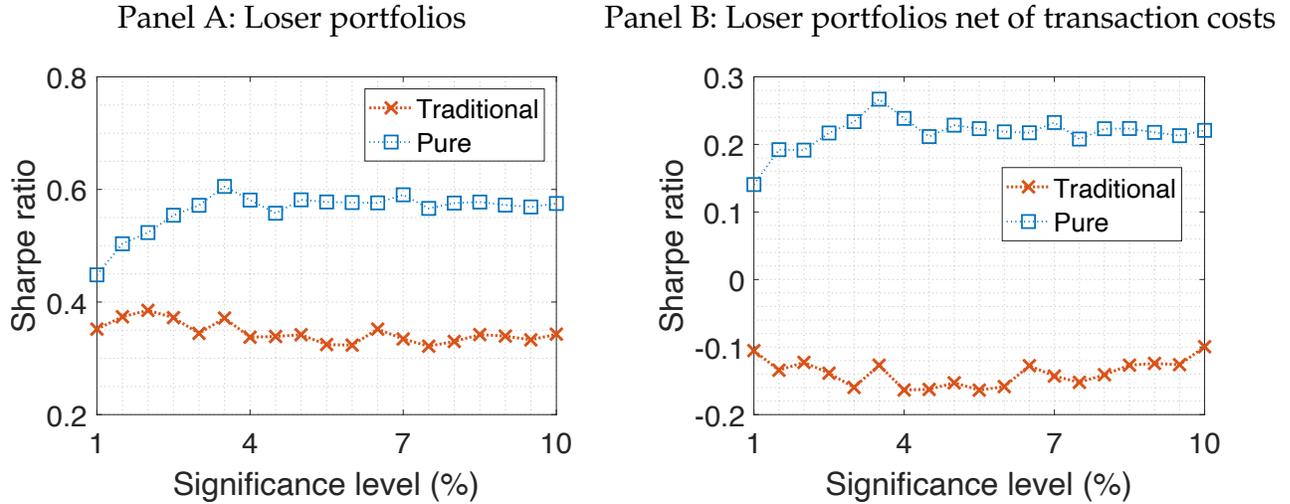
Panel A: Loser portfolios   Panel B: Loser portfolios net of transaction costs

Figure 15: Gross and net Sharpe ratios of value-weighted short-term reversal loser portfolios. This figure reports the annualized Sharpe ratios for value-weighted loser portfolios formed using significance levels from 1% to 10%. To prevent a single large-cap stock from dominating portfolio performance, we set a maximum weight cap of 10%. The portfolios are formed from July 1963 to December 2022. The estimated transactions cost for individual stocks is the effective bid-ask spread measure proposed by Hasbrouck (2009).

as shown in Section 7.2.

The underperformance associated with selling pure last-month winners is not mitigated by value-weighting. Our results indicate that it is actually profitable to buy last-month pure winners; that is, momentum signal extends to the last month (for winners) and there is no need to skip it. Reinforcing this point, Figure 21 in Appendix B shows that winners in the last month exhibit characteristics similar to those in the $[t-12, t-1]$ period: high trading volume, low volatility, low illiquidity and transaction costs, and large size. This suggests again that the signal in the previous month is more likely to persist than to reverse when subjected to statistical testing.

Figure 16 compares pure winners and traditional winners based on the $[t-12, t-1]$ formation period (11 months) and the $[t-12, t]$ formation period (12 months) in which the last month is included. The figure shows that there is no significant evidence, once we control for the significance level, of the superiority of the 11-month window, as shown by the test of Barillas et al. (2020), in line with the above findings.

In summary, for reversals we find that buying pure losers outperforms buying traditional losers, but only in value-weighted portfolios, and this advantage holds even after accounting for transaction costs. For last-month pure winners, by contrast, we show that they can serve as an additional signal reinforcing the trend over the past year, rather than as a basis for selling them based on last-month performance. Overall, our approach of testing for the significance of the last-month signal can be adapted to design profitable

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Panel A: Pure winners   **Panel B: Traditional winners**
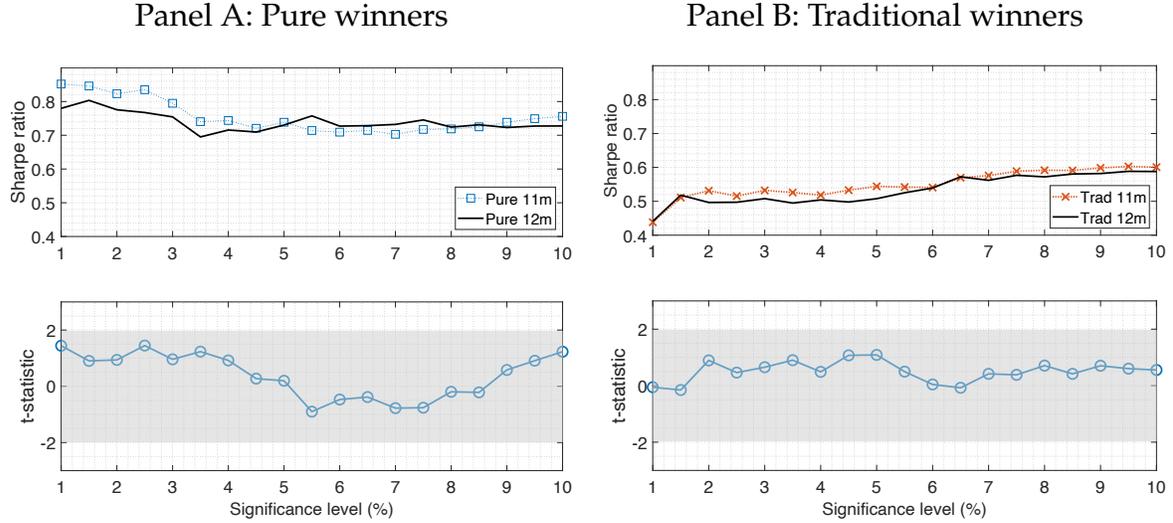
Figure 16: Sharpe ratios of pure and traditional momentum winners formed with 11-month and 12-month periods. This figure reports annualized Sharpe ratios for past pure winners (Panel A) and past traditional winners (panel B). Each panel compares performance using the $[t-12, t-1]$ formation period (11 months) with the $[t-12, t]$ formation period (12 months). The graphs below show the test statistics of Barillas et al. (2020) to compare the difference in Sharpe ratio between 11-month winners and 12-month winners, with the grey area being the two-sided critical region at 95%. The portfolios are formed from July 1963 to December 2022.

strategies, even though the reversal signal relies on far fewer observations than the momentum signal.

7 Robustness

7.1 Robustness to firm size

The results in Table 1 remain robust in both small- and large-cap stocks. Small-cap (large-cap) stocks are defined as those whose market capitalization at the formation date is below (above) contemporaneous NYSE median market capitalization. Table 2 shows the results using the portfolio sorting method described above in the two size groups separately.

We observe that momentum tends to be stronger for small-cap stocks than for large-cap stocks, aligned with the findings of Fama and French (2008). The realized return of the HW–LL portfolio remains significantly higher than that of the W–L(25) portfolio for small-cap stocks, with the improvement even stronger than in the unconditioned case. However, it is significantly smaller for large-cap stocks. Volatility of the HW-LL portfolio is smaller than that of the W-L(25) portfolio in both cases. As a result, the Sharpe ratio of the HW-LL portfolio is significantly higher than that of the W-L(25) for small-cap stocks (0.71 vs 0.41), but lower for large-cap stocks (0.36 vs 0.46) but the difference is not significant.

The W-L(5) portfolio in the small-cap stock group produces an annualized return of 10.02% while the portfolio in the large-cap stock group delivers an annualized return of 4.00%, both are statistically significant from zero. However, forming a momentum portfolio by distilling stocks with significant trends still greatly improves performance for both groups. The return on HW-LL portfolio in the small-cap stock group is significantly increased by 11.57% and the portfolio return is enhanced by 4.80% in the large-cap stock group. The improvement in Sharpe ratio for small-cap stocks is also significant at the 5% significance level and significant at the 10% level for large-cap stocks.

7.2 Robustness to value-weighting method and exclusion of penny stocks

The analysis presented in Section 4.2 is based on equal-weighted portfolio returns. As shown in Figure 17, we show that the superiority of pure winners relative to traditional winners persists when using value-weighted returns of portfolios constructed using significance levels below 5%, and this holds for both gross and net performance.

Moreover, to address concerns that including penny stocks may disproportionately affect the performance comparison, we exclude stocks with prices below $5 on the portfolio formation date when constructing portfolios. Figure 18 compares gross and net Sharpe ratios of pure and traditional winners, using both equal-weighted and value-weighted portfolio returns. Panels A and C show that the Sharpe ratios of pure winners are consistently higher than those of traditional winners based on equal-weighted returns. Panels B and D show that, for value-weighted returns, the Sharpe ratios of pure winners also consistently exceed those of traditional winners when portfolios are constructed using lower significance levels.

7.3 Robustness to sample period

We also examine whether the findings from the previous sections change when the earlier sample period is included. Figures 19 and 20 show that our results remain robust in both gross and net performance comparisons using portfolios formed from January 1928 to December 2022.

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Table 2: Drift Significance and Momentum in Small-cap and Large-cap Firms

At the end of each month, stocks are divided to two size groups (Small and Large) using NYSE median market capitalization. Stocks in each size group are sorted into five quintiles based on cumulative past returns, labeled as *Losers, 2, 3, 4,* and *Winners.* Within each quintile, the stocks are then equally divided into five quintiles on *p*-value of the presence of negative drift, labeled as *Low, 2, 3, 4,* and *High.* Note that the significance is concentrated in Low-Losers and High-Winners portfolios. The *HW-LL* is the portfolio of buying High-Winners and selling Low-Losers. The portfolio *W - L(5)* is formed by buying *Winners* quintile and selling *Losers* quintile. The portfolio *W - L(25)* is formed by buying top 20% of stocks in winner quintile and selling bottom 20% of stocks in loser quintile, so the numbers of stocks included in portfolios HW-LL and W-L(25) are identical. In parentheses, we report the *p*-values for the differences between Portfolio *HW-LL* portfolio and Portfolios *W - L(5)* and *W - L(25).* We use Newey-West t-statistics with 12 lags to compare returns, a two-sample F-test to assess equality of variances and Barillas et al. (2020)'s test to compare the maximum squared Sharpe ratios. The portfolios are formed from July 1963 to December 2022.

Panel A: Annualized 1-month holding returns in excess of risk-free rate

	Small								Large							
	Low	2	3	4	High	W - L (25)	W - L (5)	HW - LL	Low	2	3	4	High	W - L (25)	W - L (5)	HW - LL
Losers	-6.81	-0.11	1.69	5.20	9.07	-2.44	1.81		1.43	2.78	5.26	4.30	6.05	-1.76	3.97	
2	4.13	6.35	8.82	10.02	8.92		7.65		6.36	6.39	7.45	8.09	8.23		7.30	
3	6.47	10.36	12.53	12.36	10.78		10.51		7.15	6.57	7.34	7.82	8.75		7.53	
4	10.60	14.39	14.40	14.87	14.51		13.76		7.03	8.53	8.12	8.82	9.39		8.39	
Winners	10.18	16.69	17.06	17.81	19.11	16.84	16.17		8.96	11.17	12.62	14.18	14.58	16.14	12.31	
W-L						14.93	10.02	21.57						13.55	4.00	8.80
						(0.01)	(0.00)							(0.01)	(0.00)	

Panel B: Portfolio volatility

	Small								Large							
	Low	2	3	4	High	W - L (25)	W - L (5)	HW - LL	Low	2	3	4	High	W - L (25)	W - L (5)	HW - LL
Losers	38.31	35.07	33.23	33.25	31.72	46.93	33.35		26.17	23.37	22.84	22.07	21.36	30.26	22.35	
2	24.35	23.79	24.35	24.25	23.57		23.46		18.55	17.97	17.60	17.47	17.24		17.12	
3	21.37	20.99	20.91	20.37	19.11		19.96		17.61	16.69	16.26	15.54	15.57		15.70	
4	22.40	21.10	19.79	19.47	17.97		19.46		18.21	17.30	16.69	15.76	15.43		15.98	
Winners	28.01	25.16	23.43	23.01	22.70	29.41	23.59		22.09	21.82	21.24	21.16	21.53	28.66	20.75	
W-L						36.28	21.91	30.32						29.39	18.65	24.53
						(0.00)	(0.00)							(0.00)	(0.00)	

Panel C: Annualized Sharpe ratio

	Small								Large							
	Low	2	3	4	High	W - L (25)	W - L (5)	HW - LL	Low	2	3	4	High	W - L (25)	W - L (5)	HW - LL
Losers	-0.18	0.00	0.05	0.16	0.29	-0.05	0.05		0.05	0.12	0.23	0.19	0.28	-0.06	0.18	
2	0.17	0.27	0.36	0.41	0.38		0.33		0.34	0.36	0.42	0.46	0.48		0.43	
3	0.30	0.49	0.60	0.61	0.56		0.53		0.41	0.39	0.45	0.50	0.56		0.48	
4	0.47	0.68	0.73	0.76	0.81		0.71		0.39	0.49	0.49	0.56	0.61		0.52	
Winners	0.36	0.66	0.73	0.77	0.84	0.57	0.69		0.41	0.51	0.59	0.67	0.68	0.56	0.59	
W-L						0.41	0.46	0.71						0.46	0.21	0.36
						(0.03)	(0.02)							(0.13)	(0.07)	

29

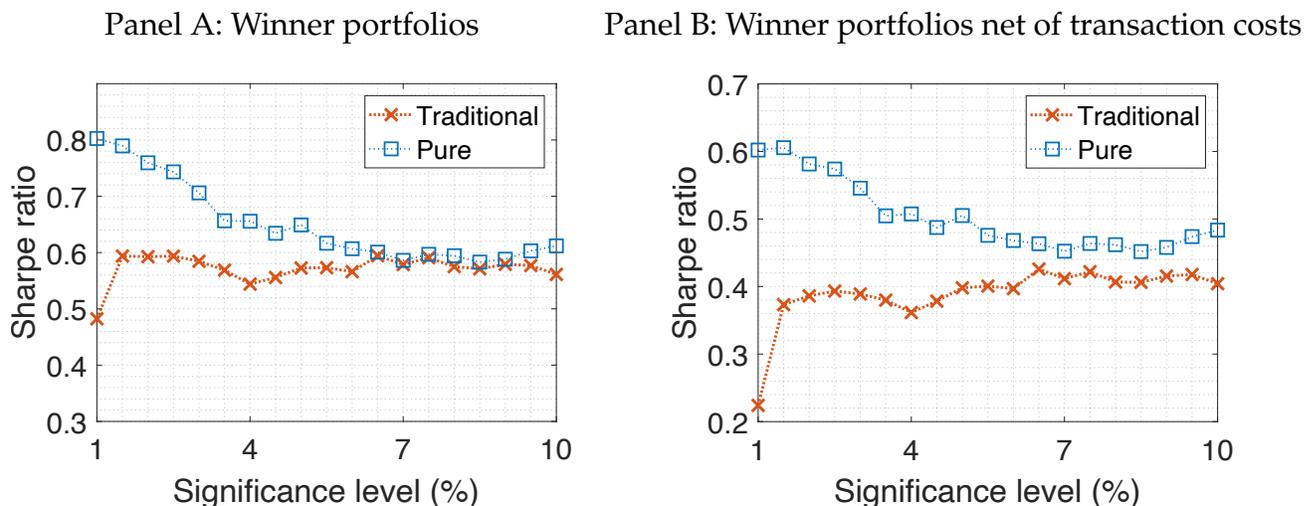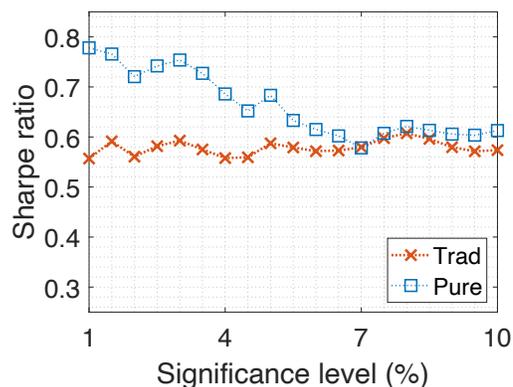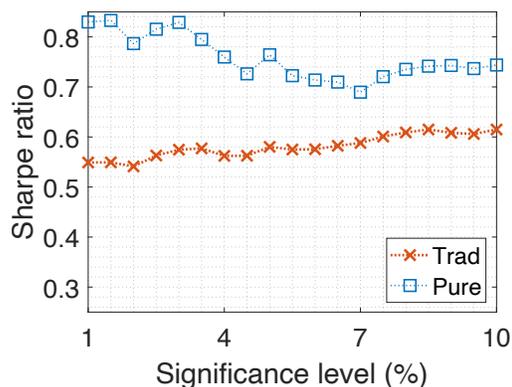| Panel A: Winner portfolios	Panel B: Winner portfolios net of transaction costs

Figure 17: Gross and net Sharpe ratios of value-weighted momentum winner portfolios. This figure reports the annualized Sharpe ratios for value-weighted winner portfolios formed using significance levels from 1% to 10%. To prevent a single large-cap stock from dominating portfolio performance, we set a maximum weight cap of 10%. The portfolios are formed from July 1963 to December 2022. The estimated transactions cost for individual stocks is the effective bid-ask spread measure proposed by Hasbrouck (2009).

8 Conclusion

We propose a pure momentum strategy that identifies genuine price trends in daily returns by filtering out the confounding effects of jumps and volatility. The resulting strategy achieves highly significant returns with lower risk, consistently outperforming traditional momentum approaches. Its performance remains robust both in-sample and out-of-sample, and across different asset universes and holding horizons. The performance of the pure momentum strategy is especially strong for winner portfolios, during crisis periods, and over short holding horizons of one to two months. It also shows remarkable resilience to transaction costs and superior tail-risk performance. Overall, the evidence supports the view that pure momentum captures behavioral biases or market frictions that are orthogonal to traditional risk-based explanations.

A natural extension of our analysis is to examine the performance of pure momentum strategies across different asset classes, including bonds, currencies, and commodities, and in international equity markets that exhibit varying degrees of market frictions. We leave this investigation for future research.
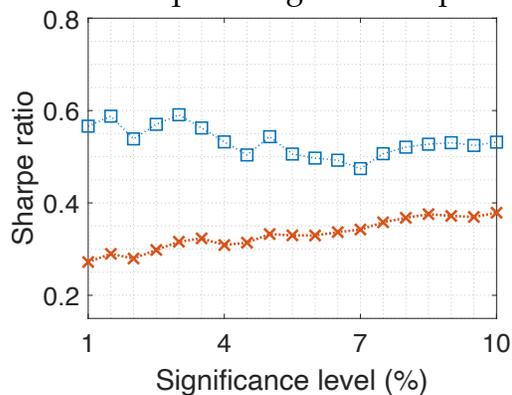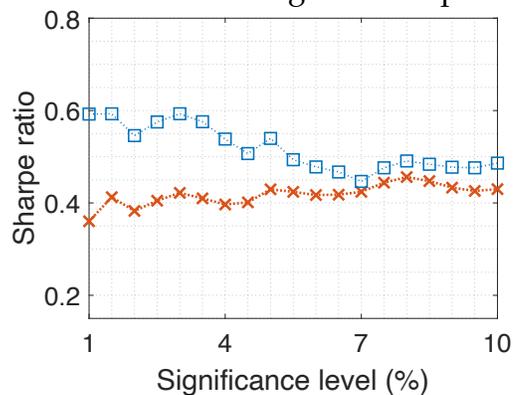
Figure 18: Gross and net Sharpe ratios of momentum winner portfolios excluding penny stocks. This figure reports the annualized Sharpe ratios for the winner portfolios formed with equal weights and value weights using significance levels from 1% to 10%. For value-weighted returns, to prevent a single large-cap stock from dominating portfolio performance, we set a maximum weight cap of 10%. The estimated transactions cost for individual stocks is the effective bid-ask spread measure proposed by Hasbrouck (2009). Stocks priced below $5 on the formation date are excluded from portfolio formation. The portfolios are formed from July 1963 to December 2022.

References

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets 5*(1), 31–56.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2006). The cross-section of volatility and expected returns. *Journal of Finance 61*(1), 259–299.

Avramov, D., T. Chordia, and A. Goyal (2006). Liquidity and autocorrelations in individual stock returns. *Journal of Finance 61*(5), 2365–2394.

Baker, M., B. Bradley, and J. Wurgler (2011). Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly. *Financial Analysts Journal 67*(1), 40–54.

Momentum portfolios performance, based on signal, gross, 1928-2022
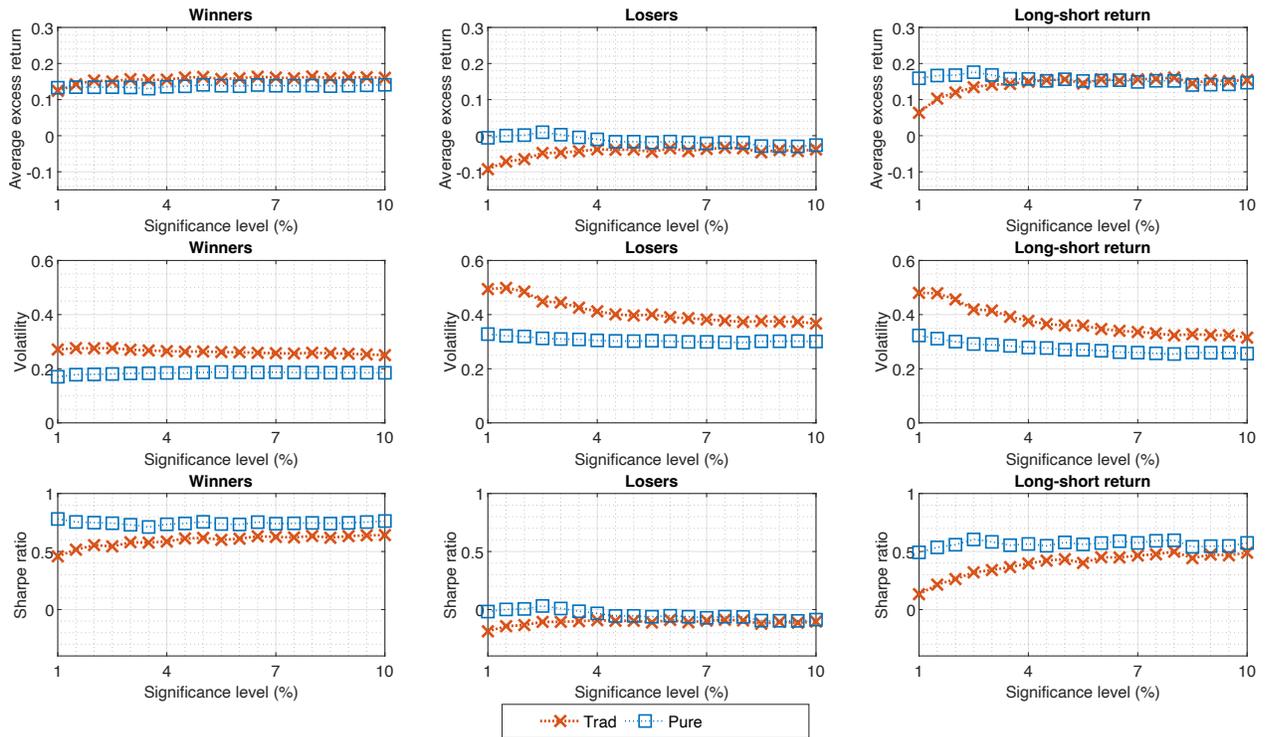
Figure 19: Annualized excess return, volatility and Sharpe ratio for winners, losers and long-short momentum portfolio formed from January 1928 to December 2022. This figure reports the annualized equal-weighted excess returns over risk-free rate as well as the standard deviations and Sharpe ratios for a *long* position in past winners, a *short* position in past losers, and the *long-short* portfolios formed with significance levels from 1% to 10%. The pure momentum is constructed using stocks with significant trends at a specified significance level and traditional momentum is formed with the same number of stocks in the long and short positions, but chosen based on the ranking of their cumulative past returns. The portfolios are formed from January 1928 to December 2022.

Barillas, F., R. Kan, C. Robotti, and J. Shanken (2020). Model comparison with sharpe ratios. *Journal of Financial and Quantitative Analysis 55*(6), 1840–1874.

Barroso, P. and A. Detzel (2021). Do limits to arbitrage explain the benefits of volatility-managed portfolios? *Journal of Financial Economics 140*(3), 744–767.

Barroso, P. and P. Santa-Clara (2015). Momentum has its moments. *Journal of Financial Economics 116*(1), 111–120.

Blitz, D., J. Huij, and M. Martens (2011). Residual momentum. *Journal of Empirical Finance 18*(3), 506–521.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance 52*(1), 57–82.

Chen, Z. and A. Lu (2017). Slow diffusion of information and price momentum in stocks: Evidence from options markets. *Journal of Banking & Finance 75*, 98–108.
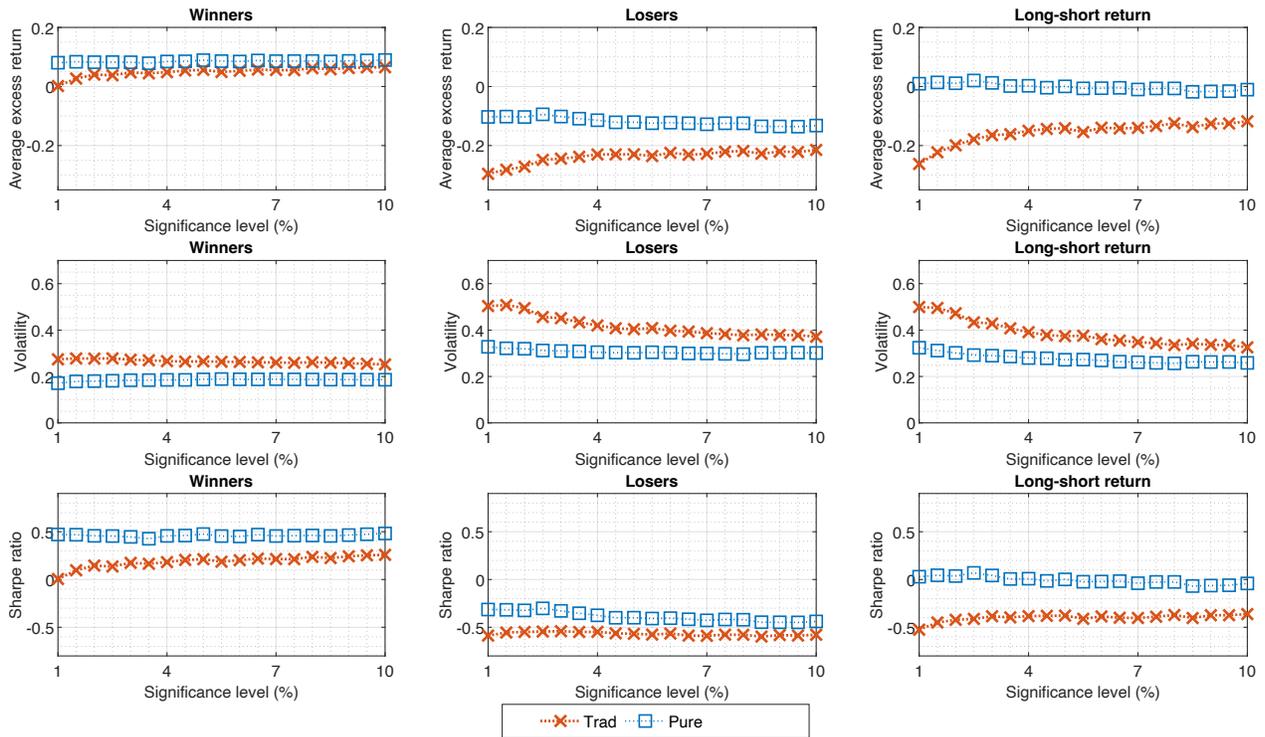
Figure 20: Annualized net excess return, volatility and Sharpe ratio for winners, losers and long-short momentum portfolio formed from January 1928 to December 2022. This figure reports the annualized net-of-cost equal-weighted excess returns over risk-free rate as well as the standard deviations and Sharpe ratios for a *long* position in past winners, a *short* position in past losers, and the *long-short* portfolios formed with significance levels from 1% to 10%. The pure momentum is constructed using stocks with significant trends at a specified significance level and traditional momentum is formed with the same number of stocks in the long and short positions, but chosen based on the ranking of their cumulative past returns. The portfolios are formed from January 1928 to December 2022. The estimated transactions cost for individual stocks is the effective bid-ask spread measure proposed by Hasbrouck (2009).

Da, Z., U. G. Gurun, and M. Warachka (2014). Frog in the pan: Continuous information and momentum. *Review of Financial Studies* 27(7), 2171–2218.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam (1998). Investor psychology and security market under-and overreactions. *Journal of Finance* 53(6), 1839–1885.

Daniel, K. and T. J. Moskowitz (2016). Momentum crashes. *Journal of Financial Economics* 122(2), 221–247.

Davidson, R. and E. Flachaire (2008). The wild bootstrap, tamed at last. *Journal of Econometrics* 146(1), 162–169.

DeMiguel, V., L. Garlappi, and R. Uppal (2009). Optimal versus naive diversification: How inefficient is the 1/n portfolio strategy? *Review of Financial Studies* 22(5), 1915–1953.

Detzel, A., R. Novy-Marx, and M. Velikov (2023). Model comparison with transaction

costs. *Journal of Finance 78*(3), 1743–1775.

Duffie, D. (2010). Presidential address: Asset price dynamics with slow-moving capital. *Journal of Finance 65*(4), 1237–1267.

Fama, E. F. and K. R. French (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance 51*(1), 55–84.

Fama, E. F. and K. R. French (2008). Dissecting anomalies. *Journal of Finance 63*(4), 1653–1678.

Fama, E. F. and K. R. French (2015). A five-factor asset pricing model. *Journal of Financial Economics 116*(1), 1–22.

Frazzini, A. and L. H. Pedersen (2014). Betting against beta. *Journal of Financial Economics 111*(1), 1–25.

Goyal, A., N. Jegadeesh, and A. Subrahmanyam (2025). Empirical determinants of momentum: A perspective using international data. *Review of Finance 29*(1), 241–273.

Goyal, A. and S. Wahal (2015). Is momentum an echo? *Journal of Financial and Quantitative Analysis 50*(6), 1237–1267.

Harvey, C. R. and A. Siddique (2000). Conditional skewness in asset pricing tests. *Journal of Finance 55*(3), 1263–1295.

Hasbrouck, J. (2009). Trading costs and returns for us equities: Estimating effective costs from daily data. *Journal of Finance 64*(3), 1445–1477.

Hillert, A., H. Jacobs, and S. Müller (2014). Media makes momentum. *Review of Financial Studies 27*(12), 3467–3501.

Hong, H., T. Lim, and J. C. Stein (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *Journal of Finance 55*(1), 265–295.

Hong, H. and J. C. Stein (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance 54*(6), 2143–2184.

Huang, D., J. Li, L. Wang, and G. Zhou (2020). Time series momentum: Is it there? *Journal of Financial Economics 135*(3), 774–794.

Huang, S. (2022). The momentum gap and return predictability. *Review of Financial Studies 35*(7), 3303–3336.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *Journal of Finance 45*(3), 881–898.

Jegadeesh, N. and S. Titman (1993). Returns to buying winners and selling losers: Impli-

cations for stock market efficiency. *Journal of Finance 48*(1), 65–91.

Lee, C. M. and B. Swaminathan (2000). Price momentum and trading volume. *Journal of Finance 55*(5), 2017–2069.

Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *Quarterly Journal of Economics 105*(1), 1–28.

Lesmond, D. A., M. J. Schill, and C. Zhou (2004). The illusory nature of momentum profits. *Journal of Financial Economics 71*(2), 349–380.

Mancini, C. (2009). Non-parametric threshold estimation for models with stochastic diffusion coefficient and jumps. *Scandinavian Journal of Statistics 36*(2), 270–296.

Medhat, M. and M. Schmeling (2022). Short-term momentum. *Review of Financial Studies 35*(3), 1480–1526.

Moreira, A. and T. Muir (2017). Volatility-managed portfolios. *Journal of Finance 72*(4), 1611–1644.

Moskowitz, T. J. and M. Grinblatt (1999). Do industries explain momentum? *Journal of Finance 54*(4), 1249–1290.

Novy-Marx, R. (2012). Is momentum really momentum? *Journal of Financial Economics 103*(3), 429–453.

Novy-Marx, R. and M. Velikov (2016). A taxonomy of anomalies and their trading costs. *Review of Financial Studies 29*(1), 104–147.

Renò, R. and S. Shi (2025). Drift sign. Working Paper.

Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics 80*(2), 309–349.

Shumway, T. (1997). The delisting bias in crsp data. *Journal of Finance 52*(1), 327–340.

Shumway, T. and V. A. Warther (1999). The delisting bias in crsp's nasdaq data and its implications for the size effect. *Journal of Finance 54*(6), 2361–2379.

Vayanos, D. and P. Woolley (2013). An institutional theory of momentum and reversal. *Review of Financial Studies 26*(5), 1087–1145.

A Transaction cost calculations

We use the effective bid-ask spread measure proposed by Hasbrouck (2009) as our estimate of transaction costs for individual stocks. The estimation is conducted using Gibbs sampling on daily closing prices, allowing for a longer historical sample compared to alternative approaches based on high-frequency transaction data. Hasbrouck (2009) also show that the estimate is highly correlated with the transaction-level estimate. The Gibbs method requires relatively long sequences of daily returns for reliable estimation. Therefore, there are a notable amount of missing observations in the early periods. The missing transaction cost observations are approximated with estimated trading costs from the most similar stocks with available cost estimates. This similarity is determined based on Euclidean distance in size and idiosyncratic volatility rank space in line with Novy-Marx and Velikov (2016).

To estimate the transaction cost at the portfolio level, we adopt the procedure of DeMiguel et al. (2009) which aggregates the change in portfolio weight multiplied by the one-way transaction cost for all stocks within the portfolio, see also Novy-Marx and Velikov (2016) and Detzel et al. (2023). Denote R_t^i as the return on stock i, $\omega_{i,t}$ as the desired weight of stock i in the portfolio, $c_{i,t}$ as the relative round-trip transaction cost of stock i at time t, and N is total number of stocks in the portfolio. The portfolio turnover (TO_t) is calculated as

$$TO_t = \frac{1}{2} \sum_{i=1}^{N} |\omega_{i,t} - \widetilde{\omega}_{i,t}|,$$

where $\widetilde{\omega}_{i,t}$ is the portfolio weight before rebalancing at time t

$$\widetilde{\omega}_{i,t} = \frac{\omega_{i,t-1}(1 + R_t^i)}{\sum_{N}^{i=1} \omega_{i,t-1}(1 + R_t^i)},$$

and portfolio rebalancing cost is

$$TC_t = \sum_{i=1}^{N} \frac{c_{i,t}}{2} |\omega_{i,t} - \widetilde{\omega}_{i,t}|.$$

The portfolio return net of cost is then computed as

$$R_t^{net} = \sum_{i=1}^{N} \omega_{i,t} R_t^i - TC_t.$$

B   Short term reversals: detailed analysis

This section shows results when detecting significant reversals in the $[t-1, t]$ formation period. The first figures are computed as for the $[t-12, t-1]$ formation period in the main text, and in particular Figure 21 parallels Figure 2, and Figure 22 parallels Figure 9. Instead, Figures 23, 24, 25 and 26 compare the gross/net performance of pure reversal strategy versus traditional reversal after excluding penny stocks, with equal weighting in Figures 23 and 24, and value weighting in Figures 25 and 26.
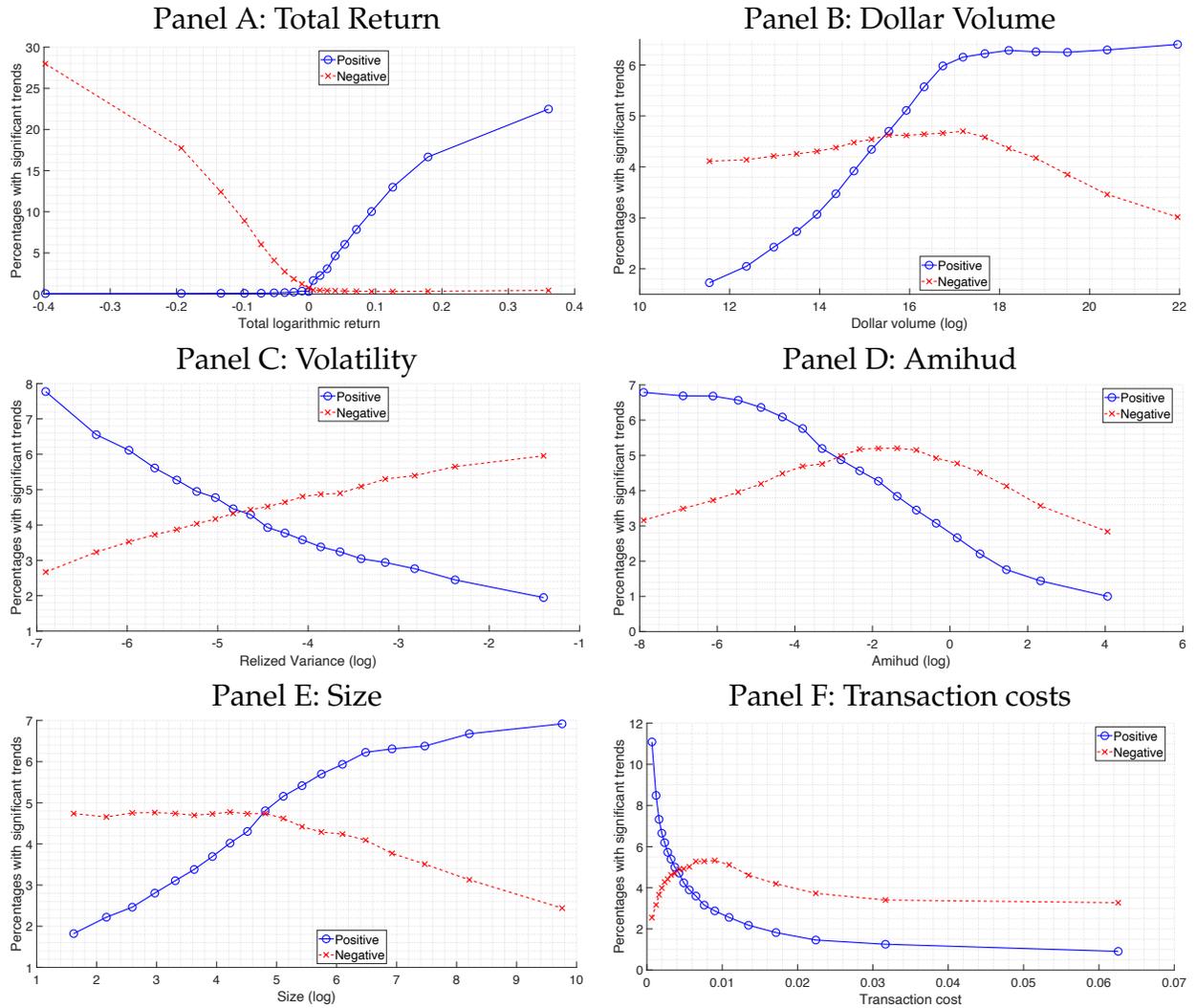
Figure 21: Average percentage of significantly positive and negative 1-month drift, by 20 quantiles of total return, dollar volume, volatility, Amihud measure, size and transaction costs. We consider all (not overlapping) 1-month formation periods in our sample and we report, for each of the 20 quantiles of the variable under consideration, the average percentage of significantly positive and negative momentum (based on $p^{\star}_{B,n,T}$ and $1 - p^{\star}_{B,n,T}$ respectively). Panel A shows the total return in the formation period. Panel B is for the total dollar volume traded. Panel C is for the (logarithmic) sum of squared daily returns in the formation period (that is, realized variance). Panel D is for the (logarithmic) Amihud measure in the formation period, that is absolute value of the formation period return divided by the total dollar volume. Panel E is for the (logarithmic) average size of the stock (average ME). Panel F is for transaction costs, estimated as the average, over the formation period, of the effective bid-ask spread as estimated by Hasbrouck (2009). The formation periods spans from July 1963 to December 2022.

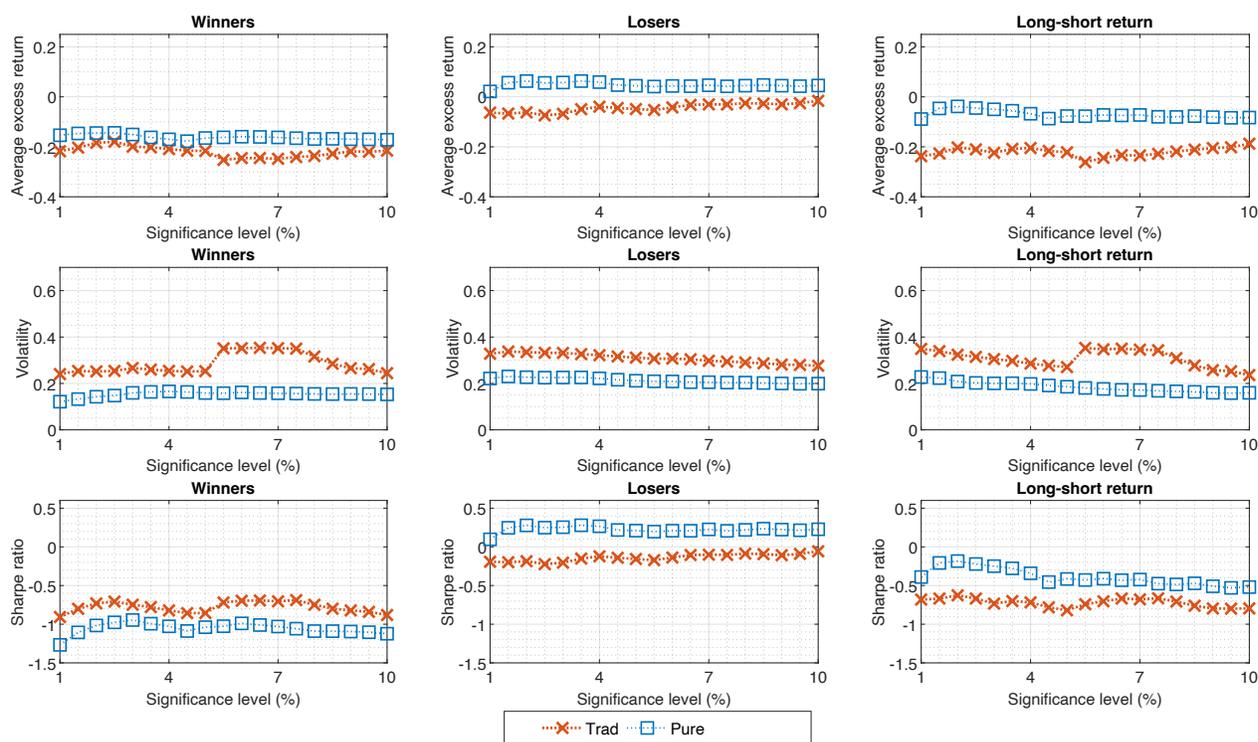**Figure 22: Net performance for winners, losers and long-short short-term reversal portfolio.** This figure reports the annualized net-of-cost equal-weighted average excess return over risk-free rate, as well as standard deviations, and Sharpe ratios for a short position in past winners, a long position in past losers, and the long-short portfolios across p-values ranging from 1% to 10%. The pure short-term reversal portfolio is constructed using stocks with significant trends at a specified significance level and traditional short-term reversal is formed with the same number of stocks in the long and short positions, but chosen based on the ranking of their cumulative returns in the past month. We use the effective bid-ask spread measure proposed by Hasbrouck (2009) as our estimate of transactions cost for individual stocks. The portfolios are formed from July 1963 to December 2022.

Figure 23: Gross performance for winners, losers and long-short short-term reversal portfolio excluding penny stocks. This figure reports the annualized equal-weighted average excess return over risk-free rate, as well as standard deviations, and Sharpe ratios for a short position in past winners, a long position in past losers, and the long-short portfolios across p-values ranging from 1% to 10%. The pure short-term reversal portfolio is constructed using stocks with significant trends at a specified significance level and traditional short-term reversal is formed with the same number of stocks in the long and short positions, but chosen based on the ranking of their cumulative returns in the past month. Stocks priced below $5 on the formation date are excluded from portfolio formation.

Short-term reversal portfolios performance, based on signal, net, excluding penny stocks
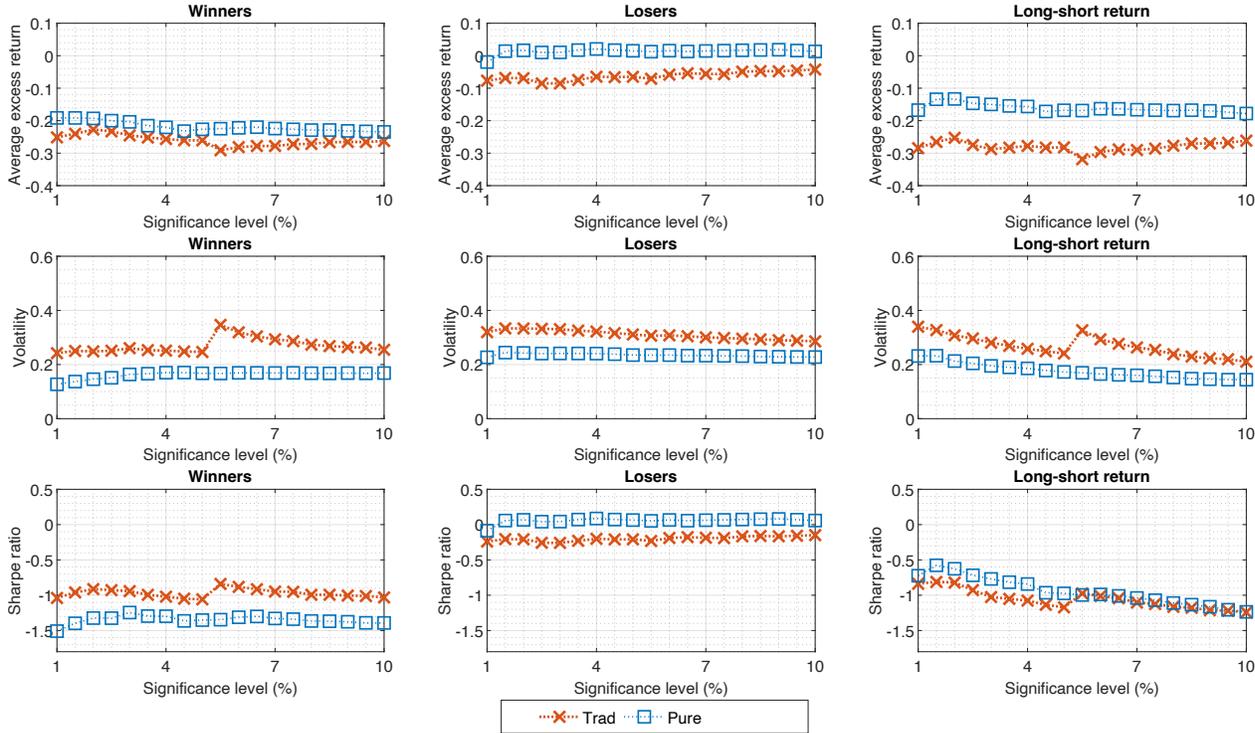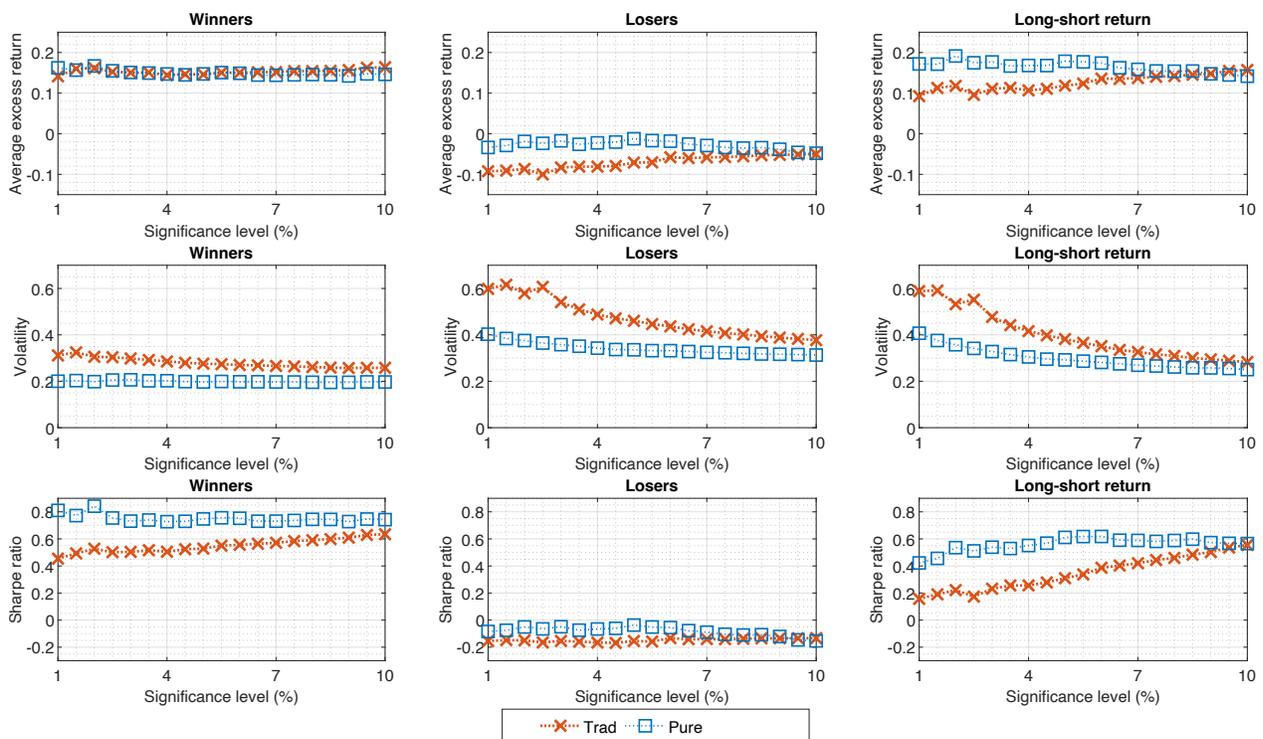

Figure 24: Net performance for winners, losers and long-short short-term reversal portfolio excluding penny stocks. This figure reports the annualized net-of-cost equal-weighted average excess return over risk-free rate, as well as standard deviations, and Sharpe ratios for a short position in past winners, a long position in past losers, and the long-short portfolios across p-values ranging from 1% to 10%. The pure short-term reversal is constructed using stocks with significant trends at a specified significance level and traditional short-term reversal is formed with the same number of stocks in the long and short positions, but chosen based on the ranking of their cumulative returns in the past month. We use the effective bid-ask spread measure proposed by Hasbrouck (2009) as our estimate of transactions cost for individual stocks. The portfolios are formed from July 1963 to December 2022. Stocks priced below $5 on the formation date are excluded from portfolio formation.

Short-term reversal portfolios performance, based on signal, gross, excluding penny stocks, value-weighting
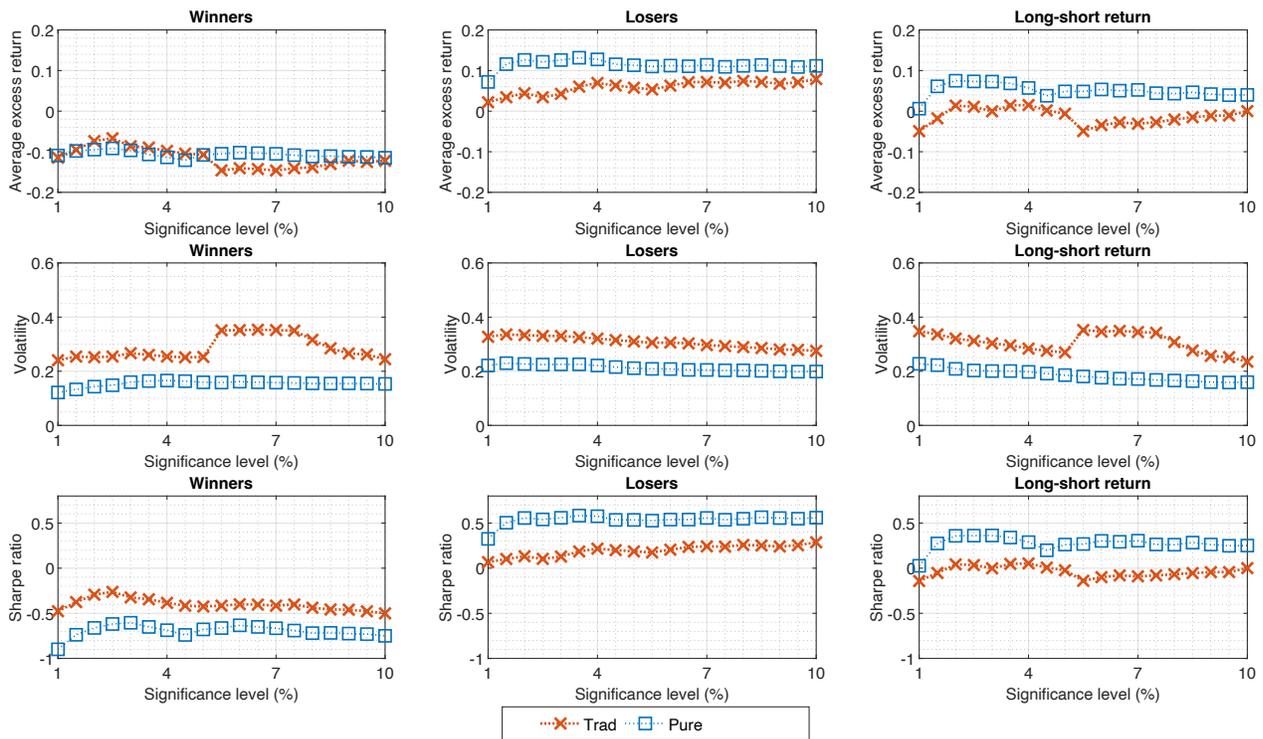
Figure 25: Gross performance for winners, losers and long-short short-term reversal portfolio excluding penny stocks. This figure reports the annualized value-weighted average excess return over risk-free rate, as well as standard deviations, and Sharpe ratios for a short position in past winners, a long position in past losers, and the long-short portfolios across p-values ranging from 1% to 10%. The pure short-term reversal is constructed using stocks with significant trends at a specified significance level and traditional short-term reversal is formed with the same number of stocks in the long and short positions, but chosen based on the ranking of their cumulative returns in the past month. The portfolios are formed from July 1963 to December 2022. Stocks priced below $5 on the formation date are excluded from portfolio formation.

Short-term reversal portfolios performance, based on signal, net, excluding penny stocks, value-weighting

Figure 26: Net performance for winners, losers and long-short short-term reversal portfolio excluding penny stocks. This figure reports the annualized net-of-cost value-weighted average excess return over risk-free rate, as well as standard deviations, and Sharpe ratios for a short position in past winners, a long position in past losers, and the long-short portfolios across p-values ranging from 1% to 10%. The pure short-term reversal is constructed using stocks with significant trends at a specified significance level and traditional short-term reversal is formed with the same number of stocks in the long and short positions, but chosen based on the ranking of their cumulative returns in the past month. We use the effective bid-ask spread measure proposed by Hasbrouck (2009) as our estimate of transactions cost for individual stocks. The portfolios are formed from July 1963 to December 2022. Stocks priced below \$5 on the formation date are excluded from portfolio formation.

C   Robustness to the threshold

This section evaluates the robustness of our results to an alternative truncation threshold, defined as four standard deviations of the mean absolute deviation, for both momentum and short-term reversal strategies. The main findings for the momentum strategy remain robust under this threshold across gross and net performance (Figures 27 - 28), equal- and value-weighted portfolio formation (Figure 29), and the exclusion of penny stocks (Figure 30). For the short-term reversal strategy, the results are also similar in gross and net performance (Figures 31 - 32), under equal- and value-weighted portfolio formation (Figure 33), and after excluding penny stocks (Figure 34).

C.1   Momentum portfolios

Momentum portfolios performance, based on signal, gross, larger threshold

Figure 27: Gross performance for winners, losers and long-short momentum portfolio with four mean absolute deviations as the truncation threshold. This figure reports the annualized equal-weighted one-month holding-period average excess returns over the risk-free rate, as well as the corresponding standard deviations and Sharpe ratios, for a *long* position in past winners, a *short* position in past losers, and the *long–short* portfolio with significance levels from 1% to 10% (one-sided tests). The pure momentum is constructed using stocks with significant trends at a specified significance level and traditional momentum is formed with the same number of stocks in the long and short positions, but chosen based on the ranking of their cumulative returns. The sample period is July 1963 to December 2022. The threshold to truncate jump is set at four times the mean absolute deviation.

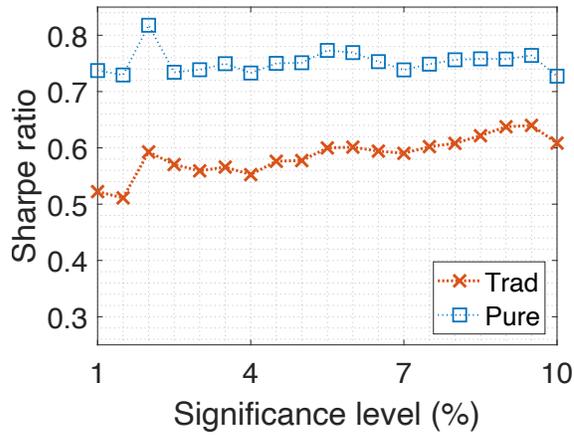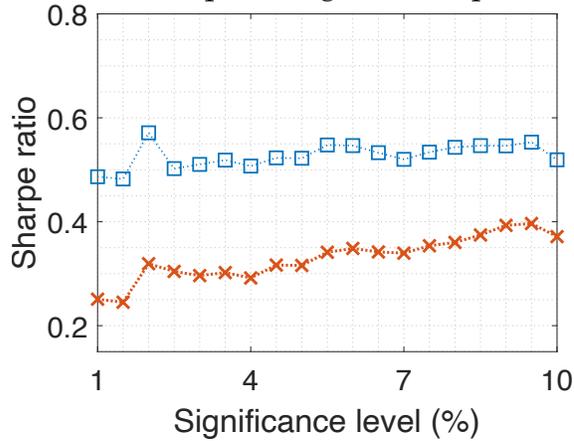# Momentum portfolios performance, based on signal, net, larger threshold
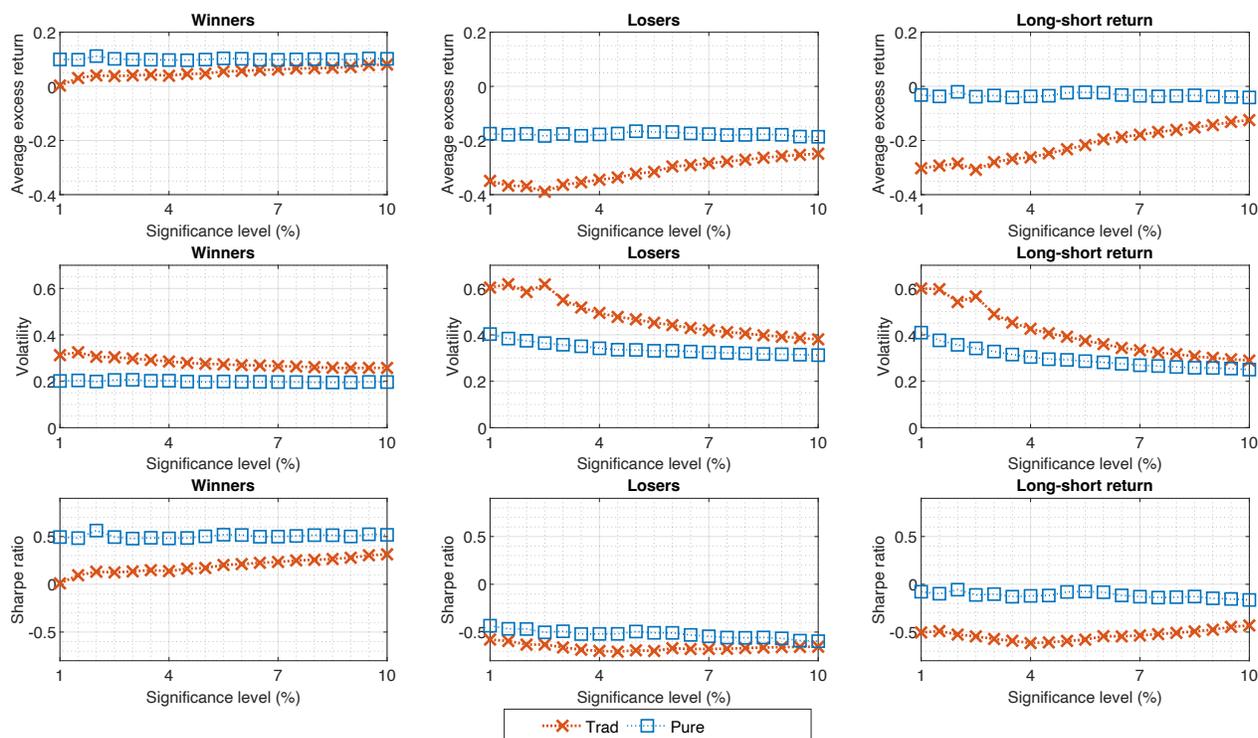
Figure 28: Net performance for winners, losers and long-short momentum portfolio with four mean absolute deviations as the truncation threshold. This figure reports the annualized equal-weighted one-month holding-period average excess returns over the risk-free rate, as well as the corresponding standard deviations and Sharpe ratios, for a *long* position in past winners, a *short* position in past losers, and the *long–short* portfolio with significance levels from 1% to 10% (one-sided tests). The pure momentum is constructed using stocks with significant trends at a specified significance level and traditional momentum is formed with the same number of stocks in the long and short positions, but chosen based on the ranking of their cumulative returns. We use the effective bid-ask spread measure proposed by Hasbrouck (2009) as our estimate of transactions cost for individual stocks. The sample period is July 1963 to December 2022. The threshold to truncate jumps is set at four times the mean absolute deviation.
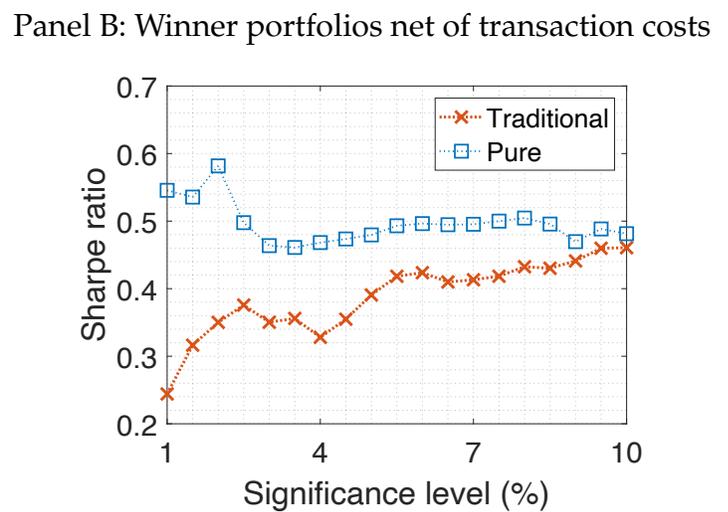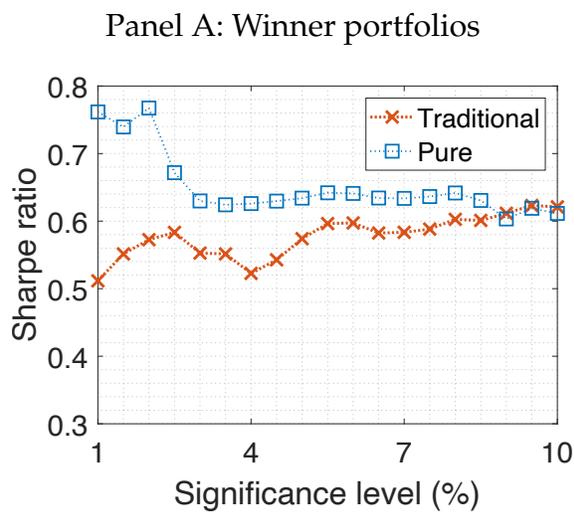
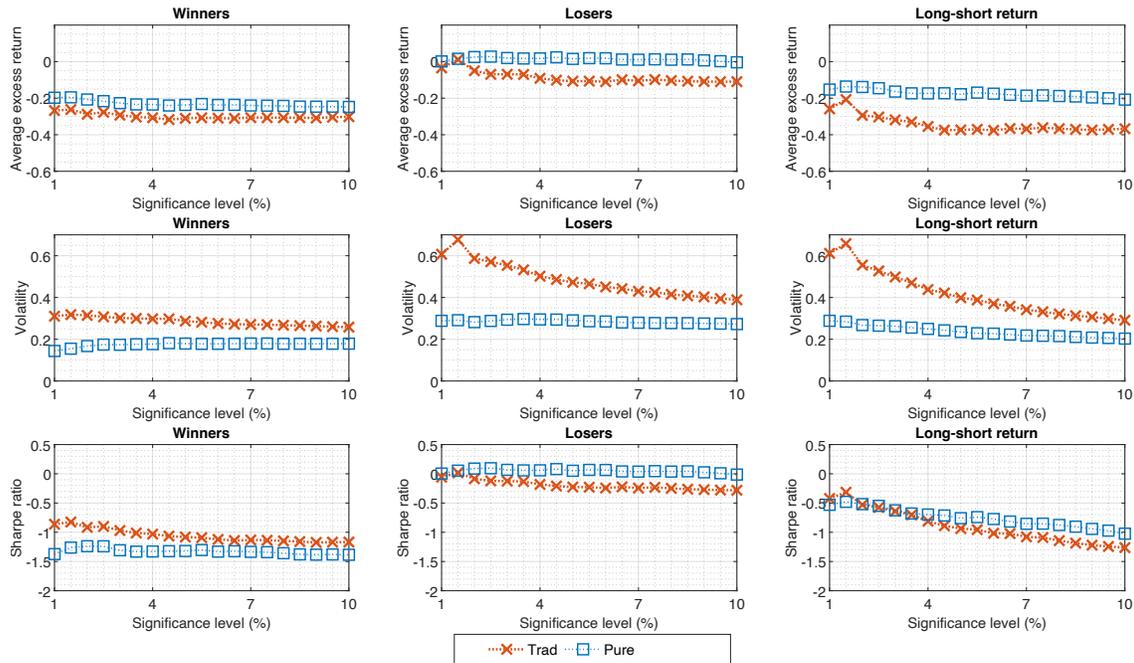**Figure 29: Gross and net Sharpe ratios of value-weighted momentum winner portfolios with four mean absolute deviations as the truncation threshold.** This figure reports the annualized Sharpe ratios for value-weighted winner portfolios formed using significance levels from 1% to 10%. To prevent a single large-cap stock from dominating portfolio performance, we set a maximum weight cap of 10%. The portfolios are formed from July 1963 to December 2022. The estimated transactions cost for individual stocks is the effective bid-ask spread measure proposed by Hasbrouck (2009). The threshold to truncate jumps is set at four times the mean absolute deviation.

Figure 30: Gross and net Sharpe ratios of momentum winner portfolios excluding penny stocks with four mean absolute deviations as the truncation threshold. This figure reports the annualized Sharpe ratios for the winner portfolios formed with equal weights and value weights using significance levels from 1% to 10%. For value-weighted returns, to prevent a single large-cap stock from dominating portfolio performance, we set a maximum weight cap of 10%. The estimated transactions cost for individual stocks is the effective bid-ask spread measure proposed by Hasbrouck (2009). Stocks priced below $5 on the formation date are excluded from portfolio formation. The portfolios are formed from July 1963 to December 2022. The threshold to truncate jumps is set at four times the mean absolute deviation.

C.2 Short-term reversal portfolios

Short-term reversal portfolios performance, based on signal, gross, larger threshold
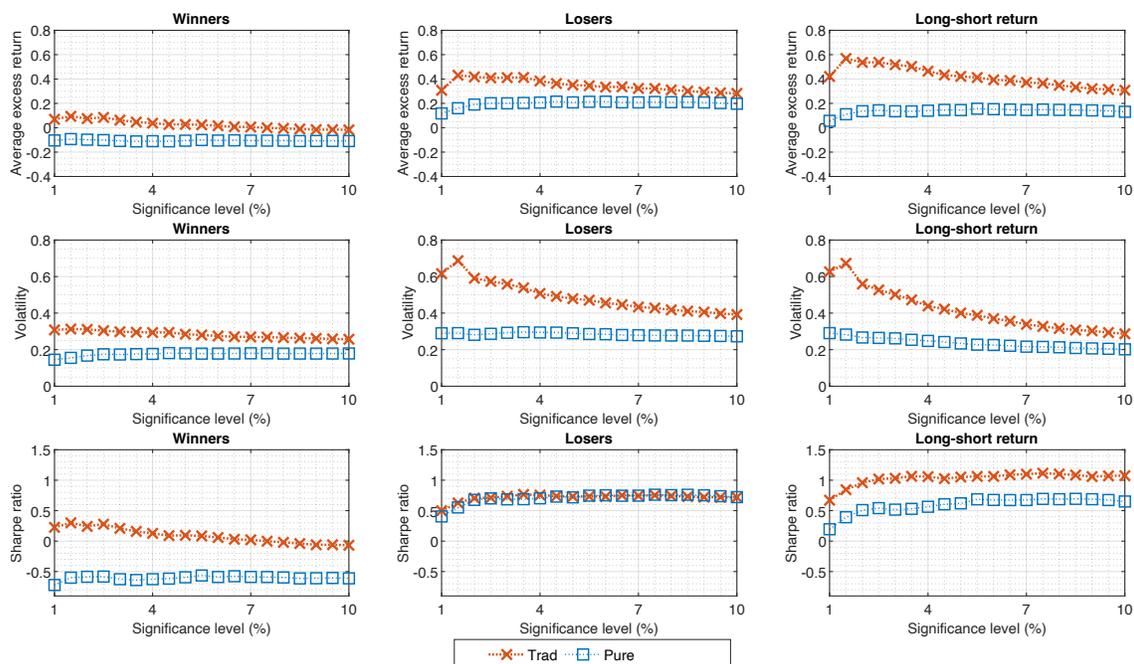
Figure 31: Gross performance for past-month winners, losers and long-short short-term reversal portfolios with four mean absolute deviations as the truncation threshold. This figure reports the annualized equal-weighted average of 1-month holding returns in excess of risk-free rate, as well as standard deviations, and Sharpe ratios of the returns on a *short* position in past winners, a *long* position in past losers, and the long-short portfolio across significance levels ranging from 1% to 10%. The pure short-term reversal is constructed using stocks with significant trends at a specified significance level and traditional short-term reversal is formed with the same number of stocks in the long and short positions, but chosen based on the ranking of their cumulative returns in the past month. The portfolios are formed from July 1963 to December 2022. The threshold to truncate jumps is set at four times the mean absolute deviation.

Short-term reversal portfolios performance, based on signal, net, larger threshold
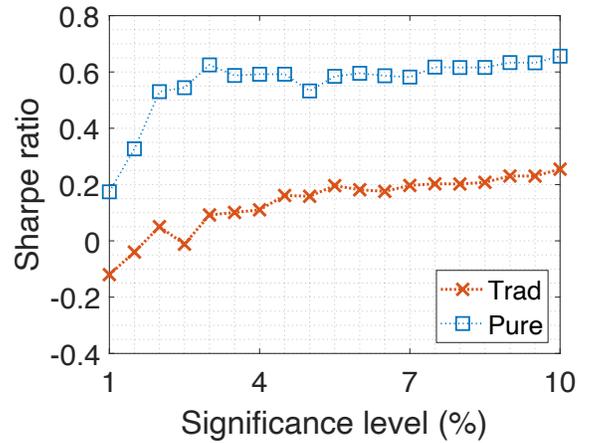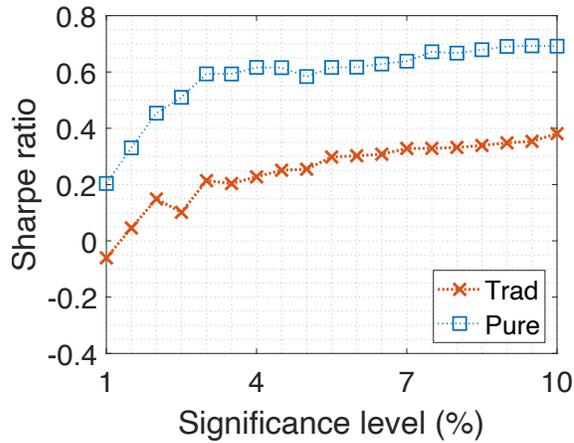

Figure 32: Net performance for winners, losers and long-short short-term reversal portfolios with four mean absolute deviations as the truncation threshold. This figure reports the annualized net-of-cost equal-weighted average excess return over risk-free rate, as well as standard deviations, and Sharpe ratios of the returns on a *short* position in past winners, a *long* position in past losers, and the long-short portfolio across various *p*-values ranging from 1% to 10%. The pure short-term reversal is constructed using stocks with significant trends at a specified significance level and traditional short-term reversal is formed with the same number of stocks in the long and short positions, but chosen based on the ranking of their cumulative returns in the past month. The portfolios are formed from July 1963 to December 2022. The threshold to truncate jumps is set at four times the mean absolute deviation.
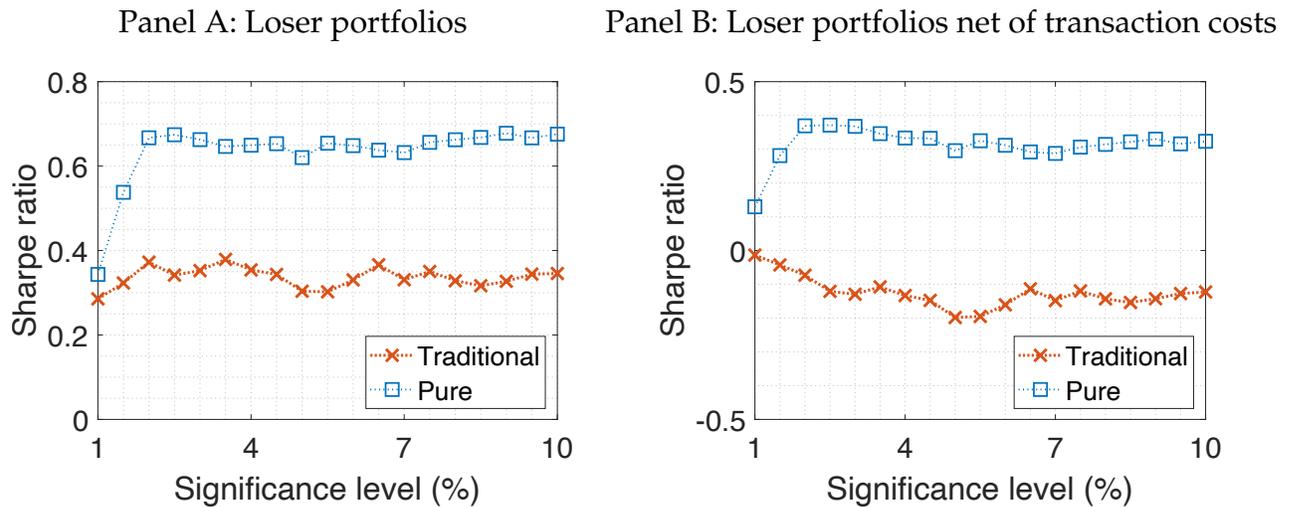
Figure 33: Gross and net Sharpe ratios of value-weighted short-term reversal loser portfolios with four mean absolute deviations as the truncation threshold. This figure reports the annualized Sharpe ratios for value-weighted loser portfolios formed using significance levels from 1% to 10%. To prevent a single large-cap stock from dominating portfolio performance, we set a maximum weight cap of 10%. The portfolios are formed from July 1963 to December 2022. The estimated transactions cost for individual stocks is the effective bid-ask spread measure proposed by Hasbrouck (2009). The threshold to truncate jumps is set at four times the mean absolute deviation.
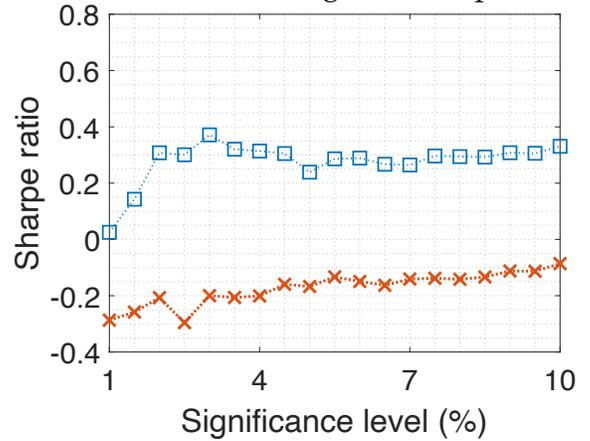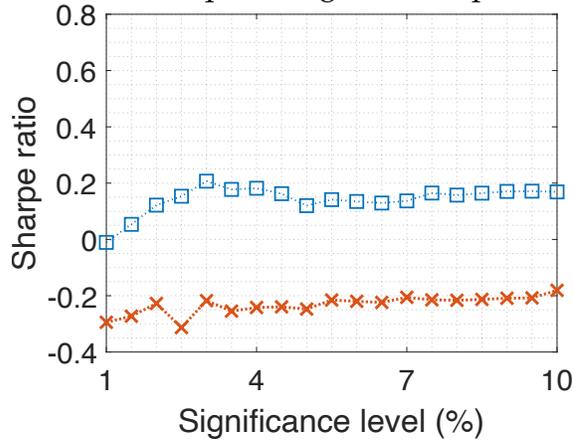
Figure 34: Gross and net Sharpe ratios of short-term reversal loser portfolios excluding penny stocks with four mean absolute deviations as the truncation threshold. This figure reports the annualized Sharpe ratios for the loser portfolios formed with equal weights and value weights using significance levels from 1% to 10%. For value-weighted returns, to prevent a single large-cap stock from dominating portfolio performance, we set a maximum weight cap of 10%. The estimated transactions cost for individual stocks is the effective bid-ask spread measure proposed by Hasbrouck (2009). Stocks priced below $5 on the formation date are excluded from portfolio formation. The portfolios are formed from July 1963 to December 2022. The threshold to truncate jumps is set at four times the mean absolute deviation.

D Testing without thresholding

Renò and Shi (2025) propose a second drift test, dubbed RHSACD, which does not need the specification of a threshold to eliminate jumps, and is instead based on the autocovariance of a suitable functional of daily returns. The test is constructed as follows. Define $p(x) = \max\{x, 0\}$ and $n(x) = \min\{x, 0\}$, respectively. The realized positive and negative half-power autocovariances are defined as:

$$\widehat{P} = \sum_{i=1}^{\lfloor T/\Delta_n \rfloor} p(\Delta_i X)^{1/2} p\left(\Delta_{i-1} X\right)^{1/2}, \quad \widehat{N} = \sum_{i=1}^{\lfloor T/\Delta_n \rfloor} \left[-n(\Delta_i X)\right]^{1/2} \left[-n(\Delta_{i-1} X)\right]^{1/2},$$

where $\Delta_i X = X_{iT/n} - X_{(i-1)T/n}$ denotes daily returns. The RHSACD test statistic is defined as:

$$\text{RHSACD} = \sqrt{2}\left(\widehat{P} - \widehat{N}\right).$$

The estimates of the p-values are conducted using wild bootstrap of daily returns $\Delta_i X$. The null and the alternative are the same as for the test in Section 2, so the p-values have the same interpretation. Asymptotic validity of wild bootstrap is proved in Renò and Shi (2025).

We implement this alternative test as a robustness check. Figure 35 shows the number of detections at 5% and 10% critical region. Figure 36 show the performance of portfolios based on the RHSACD signal. The results are virtually unchanged.
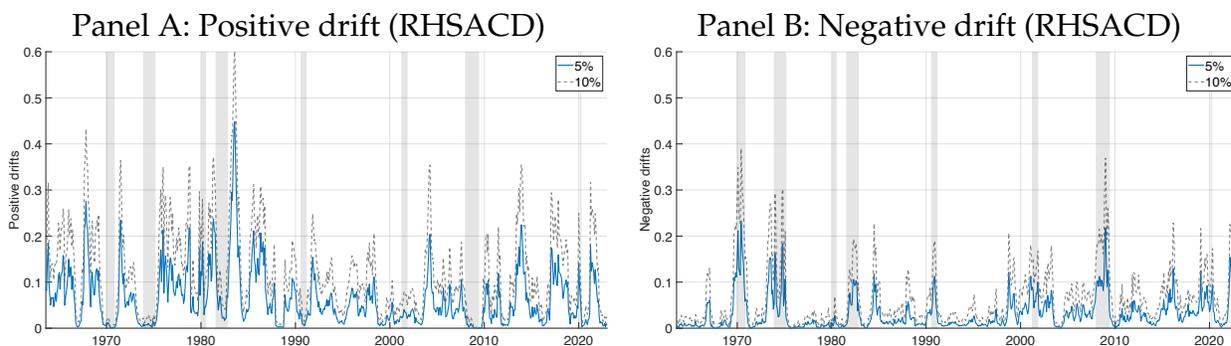
Figure 35: The number of stocks with drift significant at 5% and 10% for momentum detected with RHSACD test. The number of stocks with drift significant at 5% and 10% using RHSACD test proposed by Renò and Shi (2025), standardized by the total number of stocks on the portfolio formation date from July 1963 to December 2022. The detection period is 12 months to 1 month prior to the formation date. The shaded areas represent the US recession periods reported by the National Bureau of Economic Research (NBER).
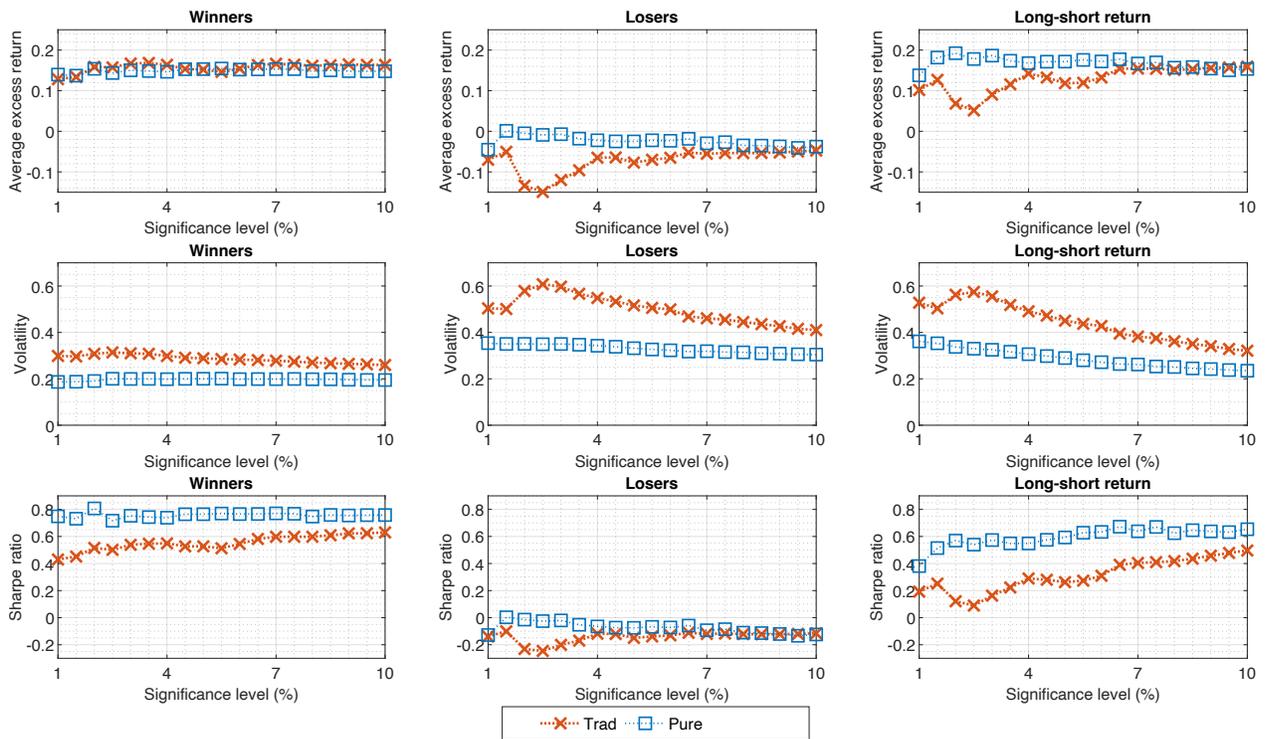
Figure 36: Annualized excess return, volatility and Sharpe ratio for winners, losers and long-short momentum portfolio detected using RHSACD test. This figure reports the annualized equal-weighted average 1-month holding returns in excess of risk-free rate, as well as standard deviation, and Sharpe ratios of the returns on a long position in past winners, a short position in past losers, and the long-short portfolio across p-values ranging from 1% to 10% using RHSACD test proposed by Renò and Shi (2025). The pure momentum is constructed using stocks with significant trends at a specified significance level and traditional momentum is formed with the same number of stocks in the long and short positions, but chosen based on the ranking of their cumulative returns. The portfolios are formed from July 1963 to December 2022.