Pure momentum
(Extended Abstract)

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March 8, 2024

Abstract

Momentum, one of the strongest and most comprehensively studied trading strategies, bets on the persistence of past trend. The trend is typically measured by the past cumulative returns of individual stocks and therefore the strategy is implemented by buying stocks with highest past returns and selling stocks with lowest past returns. However, the past cumulative return can be a noisy proxy for the past trend, especially for those stocks with high volatility. We apply a test to detect the presence of drift in the stock returns in the formation period eliminating the impact of volatility. We form our pure momentum portfolios based on the strength of the drift, which we argue is a more precise measure of trend. We find that our pure momentum strategies deliver significantly higher Sharpe ratio, higher Sortino ratio, lower volatility, less negative skewness, and lower kurtosis. Moreover, the strategy return is not fully spanned by the Fama-French five-factor model plus their momentum factor with abnormal returns significantly different from zero.

Keywords: Momentum, drift test, portofolio management

*Preliminary and incomplete version, prepared for conference submission. Do not quote without explicit permission of all the authors. Roberto Renò and Roméo Tédongap are from ESSEC Business School. Xinyi Zhang is from University of Warwick and CY Cergy Paris Univesity.

1 Motivation

Momentum is one of the most pervasive trading strategies with strong evidence of positive average returns. The success of the strategy implies the persistence of past trend in the future asset returns. Since Jegadeesh and Titman (1993), the trend is typically measured by the past cumulative returns of individual stocks and therefore, the strategy is implemented by buying stocks with highest past returns (winners) and selling stocks with lowest past returns (losers). However, the past returns may fail to accurately capture the trend since apart from a significant drift, high volatility can also drive a extremely high or low return. Figure 1 Panel A and B show two examples of the price patterns that are dominated by the drift, while Panel C and D display price changes that are mainly driven by volatility. All of them have high past cumulative return, but including the stocks with high volatility as showed in Panel C and D can potentially increase the uncertainty on the portfolio return. In this paper, we propose a pure momentum portfolio based on the strength of the drift in stock returns while mitigating of the impact of volatility.

We employ the test advocated by Kolokolov et al. (2023) for the presence of a non-negligible drift. The test is developed based on the difference between the standard realized variance estimator and their Block Uniformly Minimum Variance Unbiased (BUMVU) estimator. They point out that the classical realized variance estimator, calculated as the sum of squared returns is contaminated by the drift component and they propose the BUMVU estimator that is immune to the drift and minimizes the estimator variance. The difference as a result can be used to detect the presence of the drift. The $\alpha\%$ critical values are computed from wild permutation bootstrap.

Figure 2 presents the in-sample median return and Sharpe ratio of the significant stocks within the traditional momentum winner and loser deciles across significance levels. It is obvious that as significance strengthens, the median return and Sharpe ratio generally increase in both long and short positions. Note that the relationship between the average return or Sharpe ratio and the significance level is not strictly monotonic because of the trade-off between the signal strength and the portfolio diversification. The evidence motivates the paper to leverage the information for developing superior trading strategies and to construct an improved version of momentum factors.

Based on the preliminary findings, our objective is to formulate a strategy that maximizes signal extraction for momentum and short-term reversal approaches, while preserving portfolio diversification advantages, especially during periods of scarce signals. In the meanwhile, we aim to minimize turnover to mitigate transaction costs. In our pure momentum strategy, for each of the positions (long or short), we remove the noise in the portfolio by exclusively including the significant constitutes of traditional momentum, which apparently results in a smaller number of stocks compared to the conventional holdings, according to Figure 5 which will be discussed in Section 3. The reduced number of stocks in the portfolio could potentially diminish diversification benefits. To mitigate the effect, we incorporate the most significant stocks held in the previous month, excluding constituents that are considered strongly insignificant in the current period. Ideally, a sufficient number of stocks from the previous holdings can bridge the gap in the number of stocks, ensuring a comparable number of stocks between traditional momentum and our pure momentum portfolios. However, in certain periods, the number of previously held eligible stocks may be smaller than the discrepancy. In such cases, we include as many as possible according to their statistics[1] in either the winner or loser portfolio, even if this results in a lower number of stocks. The strategy is designed to capture as many signals as possible while simultaneously limit turnover.

We find that our noiseless momentum strategies deliver significantly higher Sharpe ratio, lower volatility, less negative skewness, lower kurtosis, higher Sortino ratio and smaller maximum drawdown. Moreover, the strategy return is not fully spanned by the Fama-French five-factor model plus their momentum factor with abnormal returns significantly different from zero.

Our paper is connected to the extensive body of research investigating momentum trading strategies since the pioneering work of Jegadeesh and Titman (1993). The strategy based on returns has consistently shown significant profitability, which cannot be fully spanned by widely accepted factor models. This phenomenon continues to pose a significant challenge in the field of asset pricing Cochrane (2011). A number of studies have been developed to to comprehend its origins. Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999) propose behavioral models suggesting that momentum profits stem from inherent biases in how investors process information. The other branch of studies argue that the abnormal profits of momentum is compensated for risk. Sadka (2006) find liquidity risk contributes a substantial proportion of momentum profits with high-frequency data. Lee and Swaminathan (2000) reveals that past trading volume affects both the magnitude and persistence of momentum. There are also some studies challenging the profitability of momentum strategy. Lesmond et al. (2004) argue that the momentum profits are driven by frequent trading in illiquid stocks with high trading

[1] We require test statistic BD is greater than 0 to exclude constituents that are considered strongly insignificant in the current period. We will discuss with more details in Section 3.

costs. After accounting for trading costs, the momentum profits disappear. However, our finding suggests that the momentum strategy remains profitable net of transaction cost while removing penny stocks[2].

Our study fundamentally contributes to the studies to improve the momentum portfolio. Blitz et al. (2011) propose to rank stocks on the residual from Fama-French three-factor model to isolate the impact of time-varying exposures to the factors. Moskowitz and Grinblatt (1999) form industry momentum by buying stocks in three industries with the best performance and selling stocks in the three industries with the worst performance in the prior six months. Novy-Marx (2012) shows that the strategy is even more profitable using firms' performance twelve to seven months prior to portfolio formation. In contrast, using the conventional portfolio formation period and data filters as suggested in Fama and French (1996) and Daniel and Moskowitz (2016), our momentum strategies are exclusively built on the strength of the drift after eliminating the impact of volatility. Our study also deviates from enhanced momentum strategies such as constant-volatility scaling approach proposed by Barroso and Santa-Clara (2015) and Moreira and Muir (2017). Daniel and Moskowitz (2016) show momentum can experience dramatic loss during the period of market rebounds following market plummeting and high market volatility. They also develop a dynamic weighting strategy based on the predicted return and variance. They rely on traditional method of selecting stock composition of momentum portfolio but leverage the momentum portfolio by the inverse of the past realized volatility of the strategy. Barroso and Detzel (2021) show that the volatility-scaling method largely enhances monthly turnover and the commensurate increases in transaction costs sweep away the profitability.

In additional to momentum, short-term reversal is another well-know return-based strategy and was first documented by Jegadeesh (1990) and Lehmann (1990). It has also been found consistent superior performance by the literature. Avramov et al. (2006) investigate the relationship between short-term reversal and illiquidity, noting that profits may not withstand transaction costs. They observe that profits are primarily concentrated in loser stocks, particularly at weekly frequencies, with higher turnover stocks displaying more pronounced reversals than low turnover stocks. Notably, they find substantially greater reversal in less liquid stocks compared to highly liquid ones, suggesting that high turnover and low liquidity stocks encounter more price pressure in the preceding week. Conversely, at the monthly frequency, the impact of turnover on autocorrelations reverses

[2]For more information, see section 3.

in comparison to the weekly frequency; low turnover stocks exhibit more reversals than high turnover stocks. Additionally, Medhat and Schmeling (2022) highlight that short-term reversal in low turnover deciles and short-term momentum in high turnover deciles. We also examine if our pure short-term reversal strategy can outperform the conventional return-based reversal strategy.

2 Testing for significant momentum

The test statistics is the one proposed in Kolokolov et al. (2023). For each integer $m \geq 2$, the test statistics can be written as,

$$BD_n^m = \frac{n}{n-m+1} \sum_{i=1}^{n-m+1} \frac{1}{m-1} \sum_{k=1}^{m-1} \frac{1}{m-k} \sum_{j=1}^{m-k} \Delta_{i+j-1} X \Delta_{i+j+k-1} X, \tag{1}$$

that is as a specific combination of the sample autocovariance of the returns.

Under $\mathcal{H}_0$ (momentum is zero), the test statistic converges in probability to zero and it is asymptotically mixed-normal, while BD_n^m diverges under $\mathcal{H}_1$ (momentum is different from zero), as proved in the quoted paper. We implement the test with $m = n - 1$.

To compute (one-sided) test p-values in small samples, we adopt a wild bootstrap procedure. Let $\eta_i^j{}_{1 \leq i \leq n, 1 \leq j \leq N}$ be an $N \times n$ matrix of independent and identically distributed random variables. For each integer $m \geq 2$, define the wild-bootstrap analogs of the test statistic BD_n^m:

$$BD_{n,j}^{\star,m} = \frac{n}{n-m+1} \sum_{i=1}^{n-m+1} \frac{1}{m-1} \sum_{k=1}^{m-1} \frac{1}{m-k} \sum_{u=1}^{m-k} \Delta_{i+u-1} \widetilde{X} \Delta_{i+u+k-1} \widetilde{X} \eta_{i+u-1}^j. \tag{2}$$

Intuitively, $BD_{n,j}^{\star,m}$ represent the test statistics BD_n^m computed using returns with randomly permuted signs. This sign permutation extirpates the observed autocorrelation of the returns generated by the presence of the non-negligible drift, preserving their stochastic volatility structure and being robust to the presence of zeros, as well as to the presence of jumps. Consequently, under both $\mathcal{H}_0$ and $\mathcal{H}_1$, the distribution of each test statistic $BD_{n,j}^{\star,m}$ is the same as of the original test statistics BD_n^m under $\mathcal{H}_0$. Thus, the wild-bootstrap p-value for $\mathcal{H}_0$ can be computed by the following algorithm:

1. Given the return data, compute the test statistic BD_n^m.

2. Generate N independent wild-bootstrap copies $BD_{n,j}^{\star,m}$, $j = 1, 2, \ldots, N$. [3]

3. Estimate the one-sided p-value as

$$p^\star = \frac{1}{N} \sum_{j=1}^{N} \mathbf{1}_{BD_{n,j}^{\star,m} \leq BD_n^m}. \tag{3}$$

We use a one-sided test since, under $\mathcal{H}_1$, the test statistics BD_n^m are positive, see Eq. (**??**). Indeed, the autocorrelation of a pure-drift process is always positive. The α% critical values can be computed as the corresponding sample α-quantiles of $BD_{n,1}^{\star,m}, BD_{n,2}^{\star,m}, \ldots, BD_{n,N}^{\star,m}$.

3 Data description and summary statistics

3.1 Data description

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 CRSP daily returns file. We include delisting return as of the delisting date if it is 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 sample spans the period from January 1965 to December 2022[4] and monthly returns are calculating by compounding daily returns in the month. We use 30-day T-bill daily return as risk-free rate, which is obtained from CRSP and is compounded in the same way as the daily stock returns.

Following Fama and French (1996)[5] and Daniel and Moskowitz (2016), we apply filters to the stock universe. We require a stock must have a valid price before formation period starts, a valid price and market capitalization on the portfolio formation date, and a valid return at the end of formation period. We also require a stock must have at least 70%

[3] We use $N = 1,000$ to implement the test.

[4] We have the data dated back to January 1927, but for the main analysis, we use the sample starting from January 1965 due to limited number of stocks before July 1963 as discussed in Jegadeesh and Titman (1993). In our test, the number of stocks with significant drift is not sufficient to form portfolios if we use data in the earlier period. Please see Figure 3. For our portfolio formation, we need prior 12-month returns to identify momentum signal, so 1965 is the first full calendar year that meets the requirement.

[5] Also see https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_10_port_form_pr_12_2.html

available values and at least 40% non-zero values in the formation period to ensure reliable estimation. Every stock must meet all of requirements to be included in a portfolio. To mitigate the impact of small and illiquidity stocks, we exclude stocks with price below $5 and market capitalization smaller than NYSE tenth percentile following Jegadeesh and Titman (2001). It leaves us in total 24604 stocks for the sample and on average 4261 stocks in each month. We form momentum portfolios at the end of each month based on returns from 11 months to 1 month prior to formation date. We skip the most recent month to prevent interference from another widely recognized anomaly, the short-term reversal, which we will assess separately.

3.2 Trading strategy and summary statistics

As the benchmark, traditional momentum is formed based on stock ranking of the past cumulative return in the formation period and allocate equal number of stocks to ten portfolios. The decile 10 represents the best-performing stocks (winners) and the decile 1 is the worst-performing stocks (losers). The equally-weighted holding return for each decile is calculated for 1 to 12 months. The self-financed portfolio is constructed by buying the winner decile and selling the loser decile.

We perform the wild permutation bootstrap described in the previous section to measure the strength of dirft in the stock returns using the corresponding formation periods for momentum and short-term reversal. Figure 5 shows the average percentage of significant drift in each decile of traditional momentum. The proportion shows a U-shaped pattern regardless of the significance levels, indicating that the signal is more frequently to be observed in the extreme deciles. We also notice that the significance is mostly concentrated in positive trends. At 5% level, approximately 30% of stocks in Decile 10 with highest past returns are associated with significant drift, as opposed to 5% in Decile 1. The similar pattern is also observed with significance level at 10%, 20%, and 50%. Moreover, the number of significant stocks exhibits robust cyclical patterns across time as shown in Figure 3, and the numbers of positive drift and negative drift tend to be negatively correlated regardless of the significance level. In particular, the number of "losers" sharply increases while the number of "winners" declines in the midst of economic recessions and stock market downturns, such as the dot-com bubble crisis and the Great Financial Crisis spanning from 2007 to 2009. In contrast, the number of "winners" soars when market rebounds following the previous plunge and the number of "losers" declined to very low level. For short-term reversal, similarly, the signal is more frequently to be observed in the extreme deciles, but there are more downward drifts for the reversal.

Based on the findings, our goal is to formulate a new strategy that maximizes signal extraction for momentum and short-term reversal approaches, while preserving portfolio diversification advantages, especially during periods of scarce signals. In the meanwhile, we aim to minimize turnover to mitigate transaction costs. Therefore, for each of the positions (long or short), we remove the noise in the portfolio by exclusively including the significant constitutes of traditional momentum, which apparently results in a smaller number of stocks compared to the conventional holdings, according to Figure 5. The reduced number of stocks in the portfolio could potentially diminish diversification benefits. To mitigate the effect, we incorporate the most significant stocks held in the previous month, ensuring their test statistic BD is greater than 0, thus excluding constituents that are considered strongly insignificant in the current period. Specifically, we rank the stocks based on the relative magnitude of their their test statistic BD and the bootstrapped critical value for a 20% significance level in the current period. Intuitively, the greater the significance of the stock, the higher the ratio will be. We incorporate the most significant stocks based on the disparity between the number required for the conventional momentum decile and the count of significant stocks. Ideally, a sufficient number of stocks from the previous holdings can bridge the gap, ensuring a comparable number of stocks between traditional momentum and our pure momentum portfolios. However, in certain periods, the number of previously held eligible stocks may be smaller than the gap. In such cases, we include as many as possible while ensuring their statistics are positive in either the winner or loser portfolio, even if this results in a lower number of stocks. The strategy is designed to capture as many signals as possible while simultaneously limit turnover. After the two steps, if there is still no significance in either top or bottom portfolio, we invest in the risk-free asset.

Table 1 displays the average number of stock constituents in both traditional momentum and our pure momentum portfolios at the significance level of 5%, 10%, 20%, and 50%. Meanwhile, Figure 7 illustrates the fluctuation of these numbers over time. In the loser portfolio, the number of stocks is significantly lower compared to the traditional loser decile. This discrepancy may stem from the fact that stocks experiencing declines are often linked with higher volatility, in contrast to those experiencing upward trends, leading to more stocks exhibiting drift. Furthermore, the counts of constituents in both winner and loser portfolios also follow cyclic patterns, with substantial decreases in the number of upward drift observed during stock market crashes, contrasting with spikes in the downward drift.

Table 1: The average number of stock constituents in the traditional momentum and pure momentum with p value of 5%, 10%, 20%, and 50%.

	Trad MOM	Pure MOM			
		p=0.05	p=0.1	p=0.2	p=0.5
Winner	203	124	152	172	191
Loser	203	13	25	47	106

We use the effective bid-ask spread measure proposed by Hasbrouck (2009) as our estimate of transactions costs. The estimation is conducted using Gibbs sampling, which offers a primary benefit by relying on daily closing prices, enabling a longer historical sample compared to the approaches based on high-frequency transaction data, which is available only as far back as 1983 at the earliest. Hasbrouck (2009) also show the estimate is highly correlated with the transaction-level estimate. The Gibbs estimation method requires relatively long sequences of reported daily returns. Consequently, there is 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).

4 Preliminary results

4.1 Univariate portfolios analysis

4.1.1 Momentum

Figure 8 compares the annualized equally-weighted return and Sharpe ratio of a long position in past winners, a short position in past losers, and the long-short portfolio as defined by both traditional momentum and our momentum strategies across various p values ranging from 5% to 50%. Hereafter we designate stocks included in the long position of our pure momentum strategy as "pure winners" and those included in the short position as "pure losers." Their conventional counterparts are referred to as "traditional winners" and " traditional losers." Without accounting for transaction costs, our pure momentum strategy delivers much higher average return on the long-short portfolio, and surprisingly, the gain is primarily from shorting the losers. A more striking finding is observed after incorporating transaction costs in Figure 9. Our strategy can generate higher return and higher Sharpe ratio in both long and short positions compared to traditional strategy when we select stocks with p value less than 10%. The findings are quite robust with value-weighted returns as shown in Figure 10 and the results net of transaction cost in Figure 11.

4.1.2 Short-term reversal

For short-term reversal based on the most recent month returns, our strategy consistently outperforms the conventional counterpart, both before and after accounting for transaction costs. Some noteworthy discoveries emerges with the reversal strategy. First of all, after excluding micro-cap stocks, in Figure 12, short selling the recent winners generates on average negative returns. Second, the long-short portfolio returns is less promising when comparing with results based on the universe without exclusion as shown in Figure 16. However, the remarkable performance diminishes once transaction costs are incorporated, regardless of whether micro-cap stocks are included or not. The finding seems to align with the conclusion of Avramov et al. (2006). Third, buying the recent losers on average delivers positive returns even net of transaction cost, and the performance is better with value-weighted portfolio, as shown in Figure 13 for equally-weighted return and 15 for value-weight return.

4.2 Bivariate momentum portfolio analysis

Table 2 presents the results from bivariate sorts of past returns from 11 months to 1 month before portfolio formation date and the signed value of (1 - p value) with the sign decided by the past return. In our test, lower the p value, more likely there exists a non-zero drift. After adding the sign to (1- p value), the more significant negative drifts are included in the bottom quintile and the significant positive drifts are in the top quintile in univariate sort. For the sorts conditional on past returns, the quintiles with lowest past returns (Cumret Q1) and highest past returns (Cumret Q5) generally have consistently negative or positive past returns. Therefore, in Cumret Q1, the significant drifts are concentrated in the SignedP Q1 and very insignificant ones are in the SignedP Q5. It is the opposed for the Cumret Q5 as shown in Panel C. We find significant spread in 1-month holding return between stocks with significant and insignificant drifts in the quintile with highest past returns, but no significance is found in other return quintile. It confirms our previous findings that the drifts are concentrated with high returns. We also observe a monotonic relationship between signed (1 - p value) and realized variance calculated as the sum of daily returns. The realized variance increases with p value in the Q1, Q4, and Q5 of cumulative return quintile. The average realized variance is close across signed value quintiles of Q2 and Q3. The Sharpe ratio is also higher in low p value quintile (SignedP Q5) than in high p value quintile (SignedP Q1) in the top two cumulative return quintiles.

Table 3 shows the results from bivariate sorts of past returns from 11 months to 1 month before portfolio formation date and realized variance. First of all, we do not find significant spread between high and low realized variance quintiles regardless of the past returns. The p value tends to be smaller for stocks with lower realized variance. Moreover, the dispersion between realized variance is large. The average realized variance in the RV Q5 is more than 10 times as high as the realized variance in RV Q1. The realized variance tends to be larger for extreme portfolios especially for "losers". The high volatility may also explain why the much less significance in found in lowest return portfolio.

4.3 Performance and market conditions

As discussed in Section 3, signals for both upward and downward drifts are subject to variation over time, and in certain periods, these signals can be scarce. For instance, upward signals in the stock universe are rarely found during the Great Financial Crisis from 2007 to 2009. Chordia and Shivakumar (2002) also shows different performance of momentum across different market states. In this section, we separate the performance to:

1. volatile state when both upward and downward signals are rare on the market;

2. market boom when the upward signal is strong while downward signal is weak;

3. market bust when upward is weak but downward is strong;

4. balanced period with reasonable number signals observed in both directions.

Table 2: Bivariate momentum portfolios of stocks sorted on past returns and signed (1 - p value)
Quintile portfolios are constructed every month by first sorting on past cumulative return from 11 months to 1 month before portfolio formation date and within each quintile then sorting on sign(cumret) * (1- p value). "Cumret Q1" is the portfolio with lowest past returns and "Cumret Q5" is the portfolio with highest past returns. Panel A, B, and C report average 1-month holding return (monthly), Sharpe ratio and associated standard deviation. The associated t statistics for return difference are also reported in Panel A. Panel D shows the signed p value and Panel E presents average realized variance.

Panel A: 1-month holding return (in percentage)

	SignedP Q1	SignedP Q2	SignedP Q3	SignedP Q4	SignedP Q5	High - Low	t-stat
Cumret Q1	0.65	0.75	0.90	0.80	0.52	-0.12	-0.89
Cumret Q2	0.97	1.02	0.93	0.97	0.96	-0.01	-0.13
Cumret Q3	1.08	1.17	1.15	1.17	1.19	0.11	1.37
Cumret Q4	1.35	1.37	1.40	1.42	1.34	-0.01	-0.08
Cumret Q5	1.50	1.66	1.65	1.59	1.78	0.28	2.48
High - Low	0.86	0.92	0.75	0.80	1.26		
t-stat	3.56	3.89	3.07	3.25	4.53		

Panel B: Sharpe ratio of 1-month holding return

	SignedP Q1	SignedP Q2	SignedP Q3	SignedP Q4	SignedP Q5
Cumret Q1	0.03	0.04	0.06	0.05	0.02
Cumret Q2	0.10	0.11	0.09	0.10	0.09
Cumret Q3	0.13	0.15	0.15	0.16	0.16
Cumret Q4	0.18	0.18	0.20	0.21	0.21
Cumret Q5	0.16	0.20	0.20	0.20	0.23

Panel C: 1-month holding return standard deviation (in percentage)

	SignedP Q1	SignedP Q2	SignedP Q3	SignedP Q4	SignedP Q5
Cumret Q1	9.07	8.97	9.12	9.11	9.49
Cumret Q2	5.92	6.11	6.11	6.28	6.46
Cumret Q3	5.34	5.27	5.20	5.19	5.10
Cumret Q4	5.60	5.50	5.28	4.94	4.55
Cumret Q5	6.98	6.62	6.42	6.26	6.24

Panel D: signed p value

	SignedP Q1	SignedP Q2	SignedP Q3	SignedP Q4	SignedP Q5
Cumret Q1	-0.17	-0.37	-0.53	-0.69	-0.90
Cumret Q2	-0.42	-0.65	-0.81	-0.98	0.80
Cumret Q3	-0.78	0.98	0.82	0.67	0.47
Cumret Q4	0.95	0.69	0.54	0.40	0.24
Cumret Q5	0.68	0.39	0.26	0.15	0.06

Panel E: realized variance

	SignedP Q1	SignedP Q2	SignedP Q3	SignedP Q4	SignedP Q5
Cumret Q1	0.60	0.66	0.71	0.77	0.78
Cumret Q2	0.34	0.33	0.32	0.33	0.34
Cumret Q3	0.25	0.25	0.24	0.23	0.24
Cumret Q4	0.28	0.27	0.25	0.22	0.18
Cumret Q5	0.55	0.51	0.43	0.38	0.33

Table 3: Bivariate momentum portfolios of stocks sorted on past returns and realized variance

Quintile portfolios are constructed every month by first sorting on past cumulative return from 11 months to 1 month before portfolio formation date and within each quintile then sorting on reazlied variance. "Cumret Q1" is the portfolio with lowest past returns and "Cumret Q5" is the portfolio with highest past returns. Panel A, B, and C report average 1-month holding return (monthly), Sharpe ratio and associated standard deviation. The associated t statistics for return difference are also reported in Panel A. Panel D shows the signed p value and Panel E presents average realized variance.

Panel A: 1-month holding return (in percentage)							
	RV Q1	RV Q2	RV Q3	RV Q4	RV Q5	High - Low	t-stat
Cumret_Q1	0.79	0.57	0.61	0.57	1.08	0.29	0.84
Cumret_Q2	0.99	1.00	0.92	0.94	0.99	0.00	-0.01
Cumret_Q3	1.09	1.09	1.17	1.21	1.20	0.11	0.51
Cumret_Q4	1.21	1.34	1.39	1.39	1.55	0.34	1.48
Cumret_Q5	1.52	1.71	1.80	1.84	1.32	-0.20	-0.84
High - Low	0.73	1.14	1.18	1.27	0.24		
t-stat	3.56	4.73	4.68	4.53	0.78		
Panel B: Sharpe ratio of 1-month holding return							
Cumret Q1	0.06	0.02	0.03	0.02	0.06		
Cumret Q2	0.14	0.12	0.09	0.08	0.07		
Cumret Q3	0.20	0.16	0.16	0.14	0.11		
Cumret Q4	0.24	0.22	0.20	0.17	0.15		
Cumret Q5	0.26	0.24	0.22	0.19	0.11		
Panel C: 1-month holding return standard deviation (in percentage)							
Cumret Q1	6.70	8.23	9.11	10.48	12.49		
Cumret Q2	4.60	5.51	6.25	6.93	8.54		
Cumret Q3	3.65	4.58	5.15	5.97	7.62		
Cumret Q4	3.48	4.43	5.06	5.92	7.86		
Cumret Q5	4.40	5.62	6.60	7.82	8.86		
Panel D: signed p value							
Cumret Q1	-0.47	-0.52	-0.54	-0.56	-0.59		
Cumret Q2	-0.79	-0.81	-0.82	-0.83	-0.82		
Cumret Q3	0.79	0.82	0.84	0.85	0.86		
Cumret Q4	0.46	0.54	0.58	0.61	0.64		
Cumret Q5	0.24	0.29	0.32	0.34	0.36		
Panel E: realized variance							
Cumret Q1	0.16	0.30	0.45	0.70	1.92		
Cumret Q2	0.07	0.13	0.20	0.32	0.95		
Cumret Q3	0.04	0.08	0.13	0.22	0.72		
Cumret Q4	0.04	0.08	0.13	0.22	0.72		
Cumret Q5	0.08	0.15	0.24	0.39	1.33		

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A Figures

Figure 1: Example stocks with high past returns but with and without significant drift
Panel A and B show two examples for the price patterns that are dominated by the drift, while Panel C and D display price changes that are mainly driven by volatility.

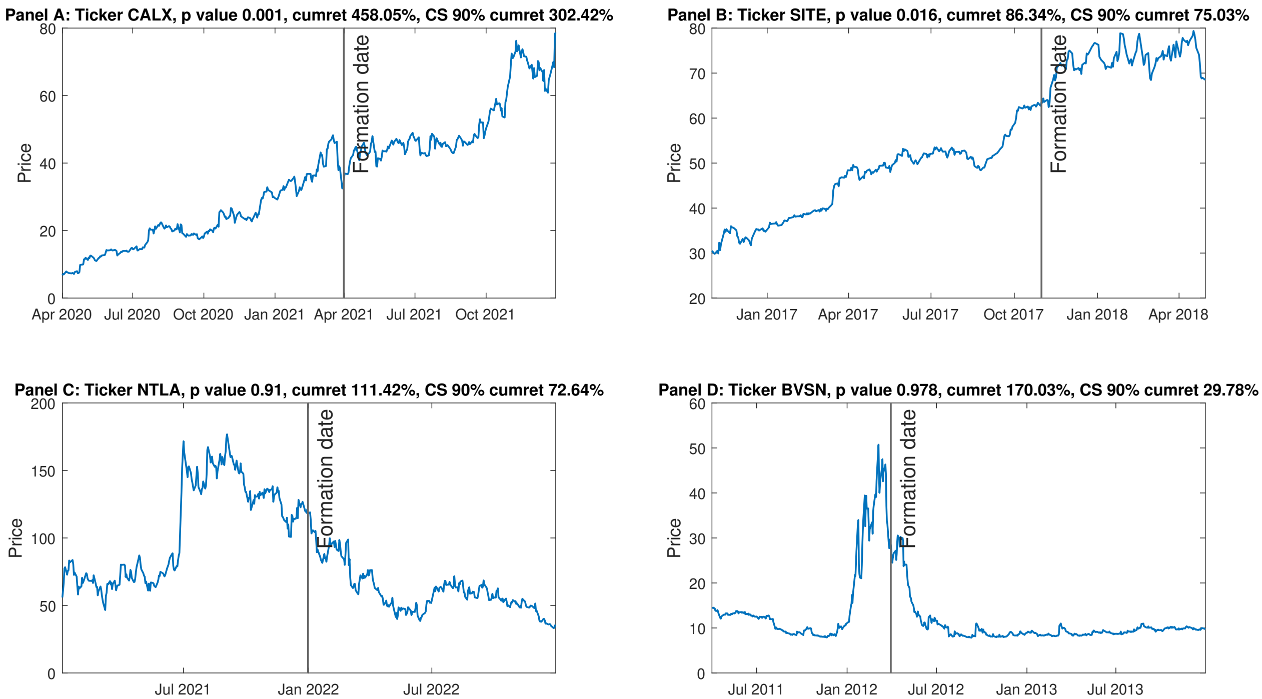

Figure 2: Momentum
The figure shows the median annualized average return and Sharpe ratio of taking a long position on winners and short position on losers. Note that for momentum, the zero-cost portfolio is formed by buying the top 10% of past winners and selling the bottom 10% of past losers. The horizontal axis represents 1- p value, so the significance increases from the left to right side.

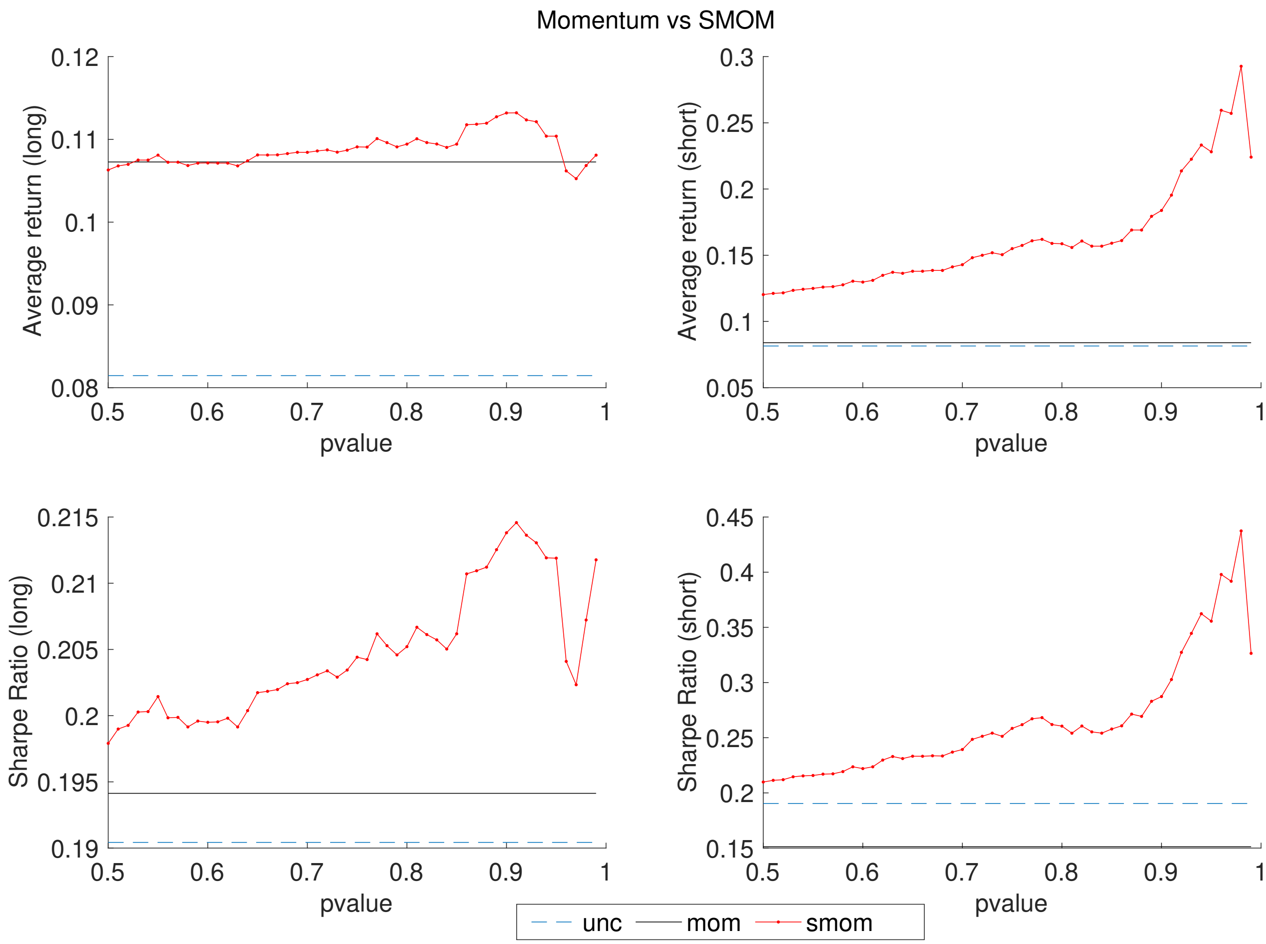

Figure 3: The number of significant stocks in momentum deciles at 10% significance level.
Panel A shows the number of significant stocks in the three deciles with lowest past returns. Decile 1 represent the decile with lowest 10% of stocks. Panel B shows the number of significant stocks in the three deciles with highest past returns. Decile 10 represent the decile with highest 10% of stocks. The shaded areas represent US recession periods reported by the National Bureau of Economic Research (NBER).

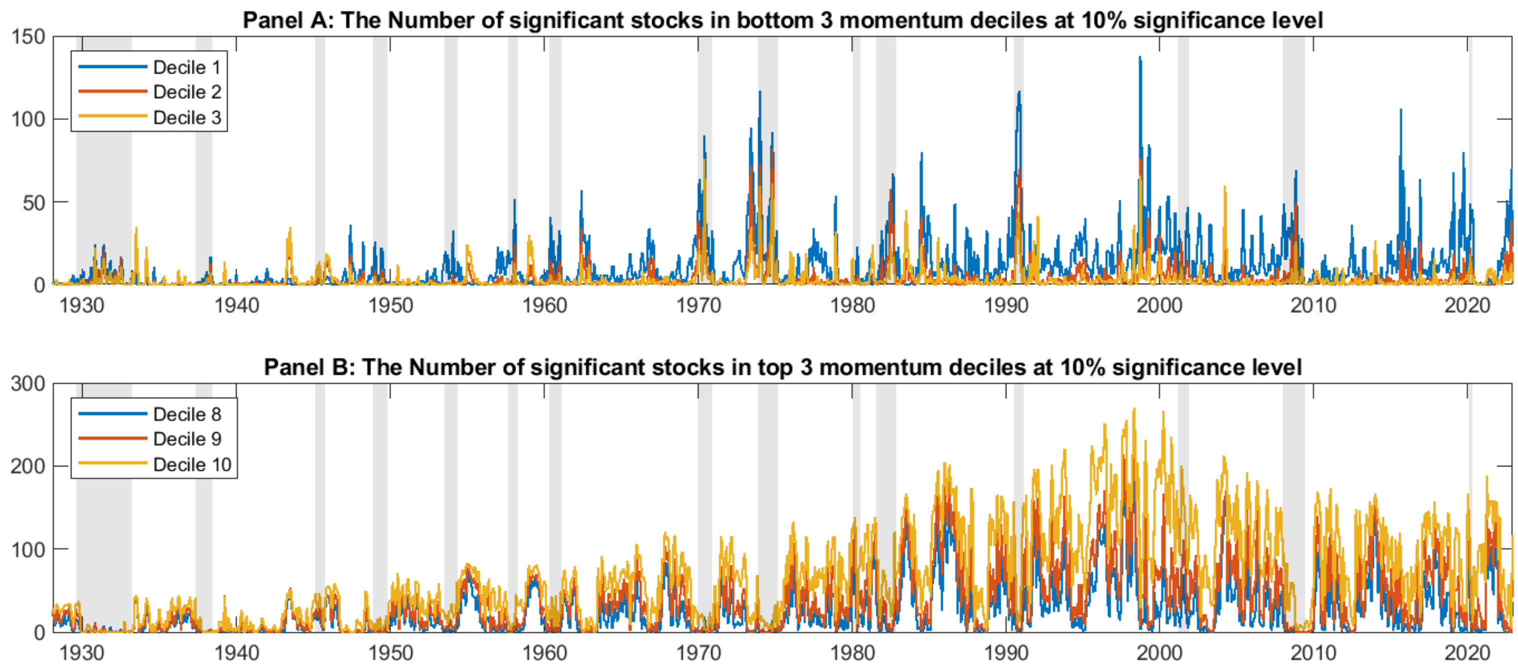

Figure 4: This figure shows distribution of p values for unconditional stock returns and stocks included in Decile 1 and 10 with bottom 10% and top 10% past cumulative returns respectively. The vertical axis represents the observed percentage.

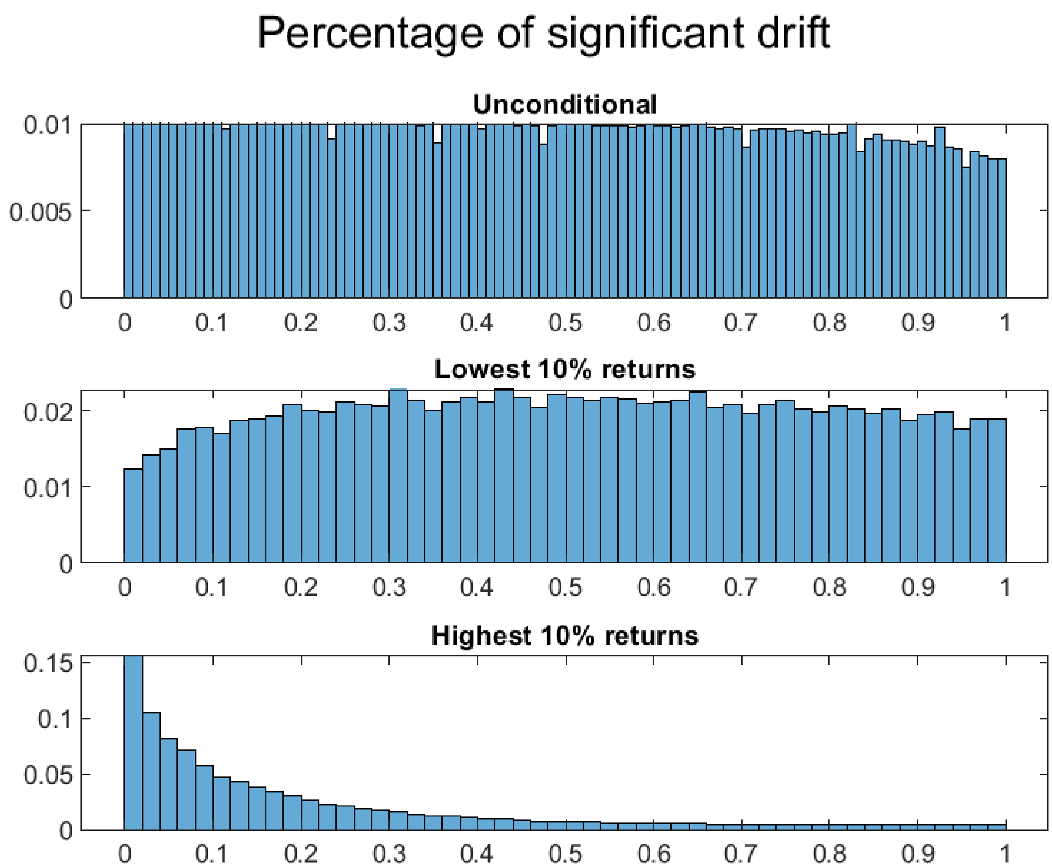

Figure 5: This figure shows the percentages of significant drift in the deciles of traditional momentum at the significance level of 5%, 10%, 25%, and 50% respectively.

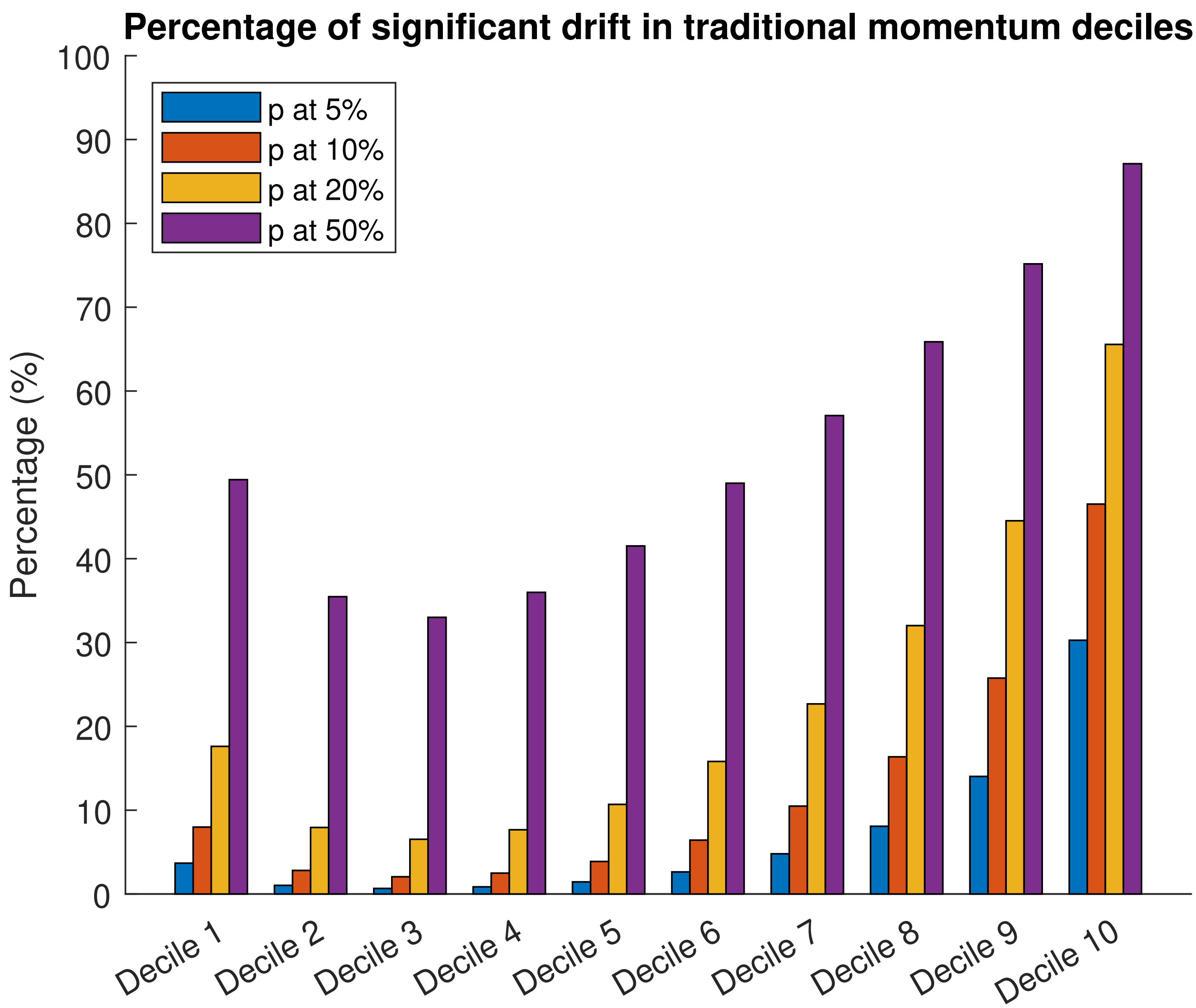

Figure 6: This figure shows the percentages of significant drift in the deciles of short-term reversal at the significance level of 5%, 10%, 25%, and 50% respectively.

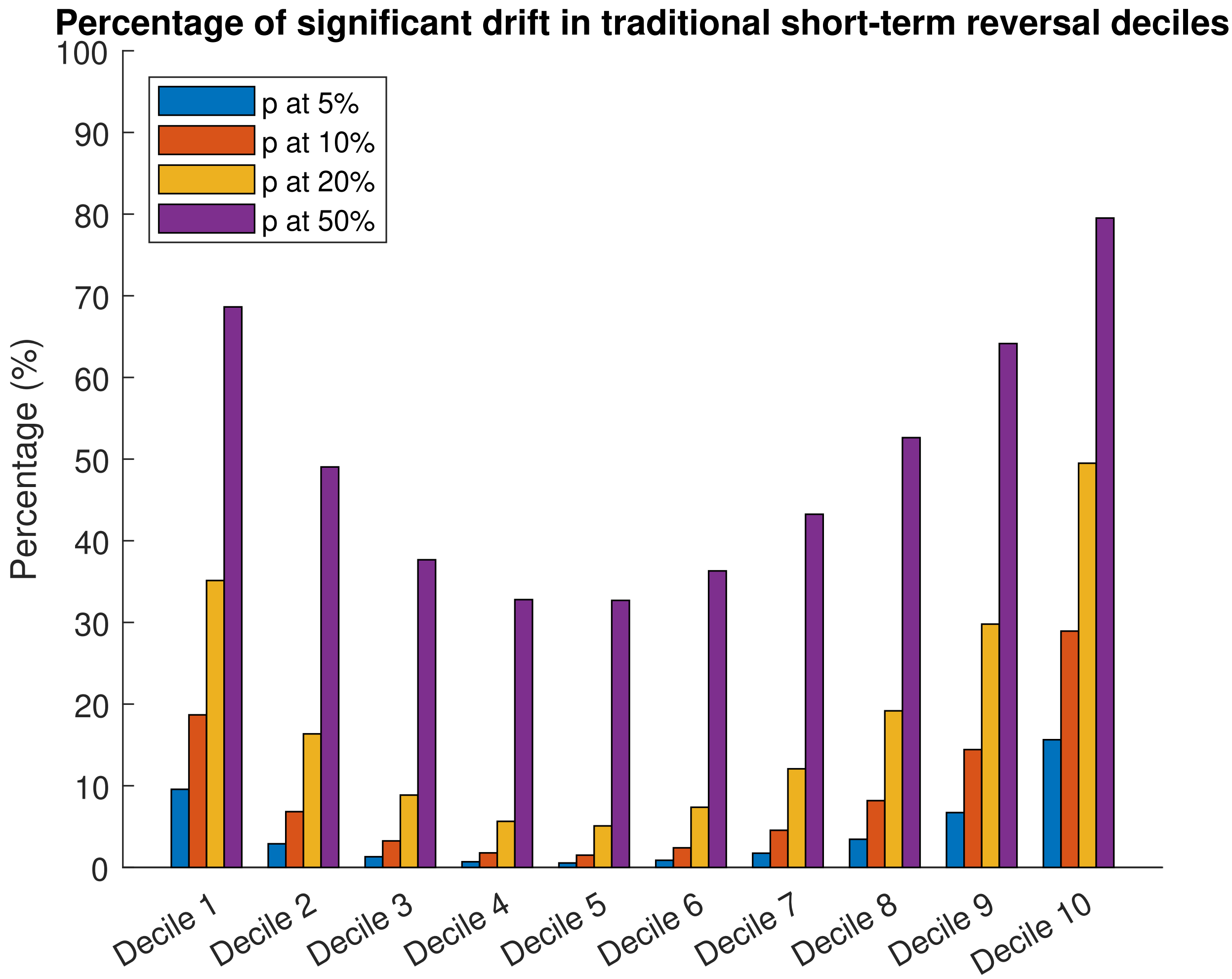

Figure 7: Time series of the number of stocks in the traditional momentum and pure momentum with p value of 5%, 10%, and 20%.

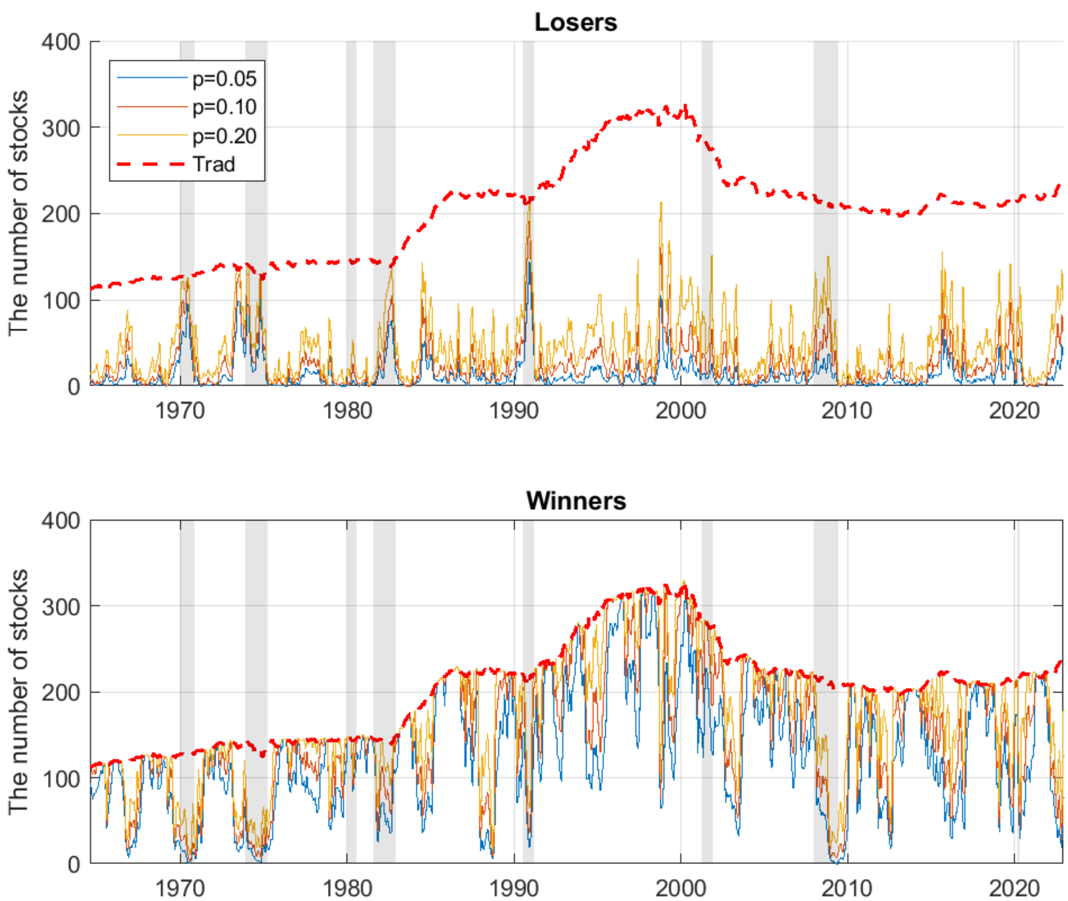

Figure 8: This figure compares the annualized equally-weighted return and Sharpe ratio of a long position in past winners, a short position in past losers, and the long-short portfolio as defined in traditional momentum and our pure momentum strategies across various p values ranging from 5% to 50%.

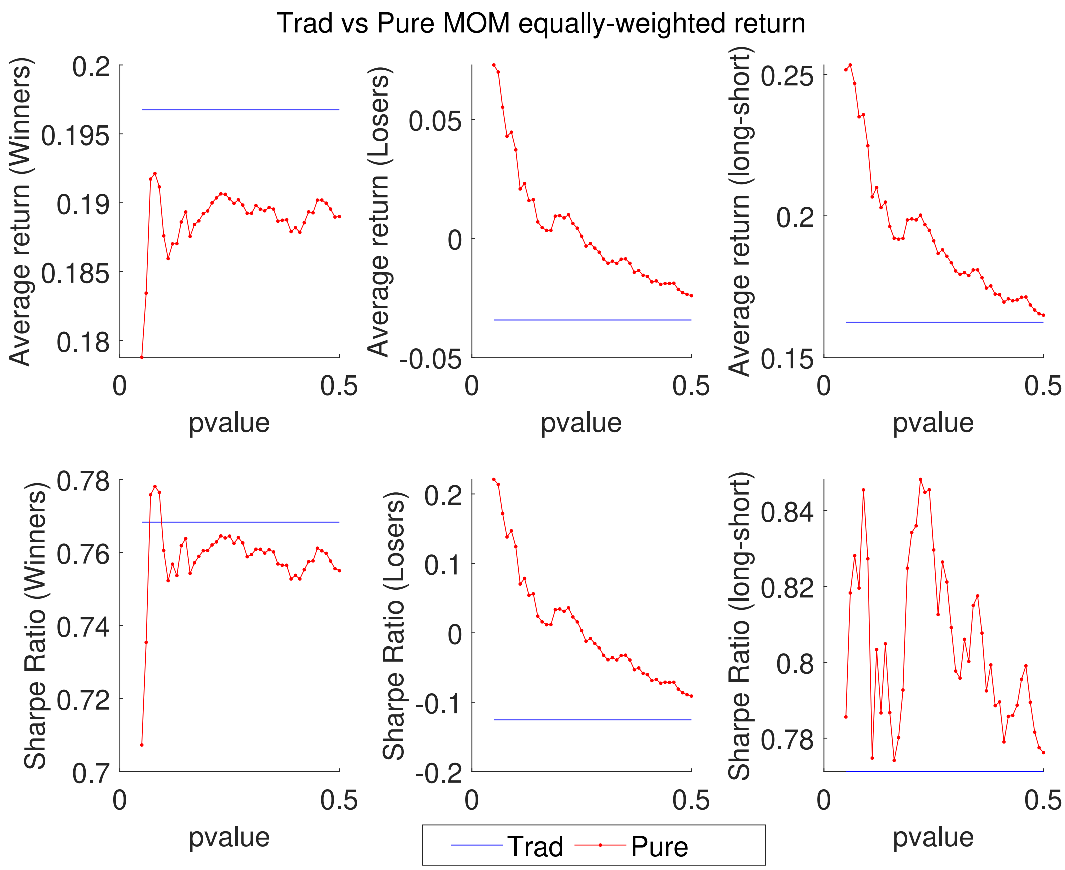

Figure 9: This figure compares the annualized net-of-cost equally-weighted return and Sharpe ratio of a long position in past winners, a short position in past losers, and the long-short portfolio as defined in traditional momentum and our pure momentum strategies across various p values ranging from 5% to 50%.

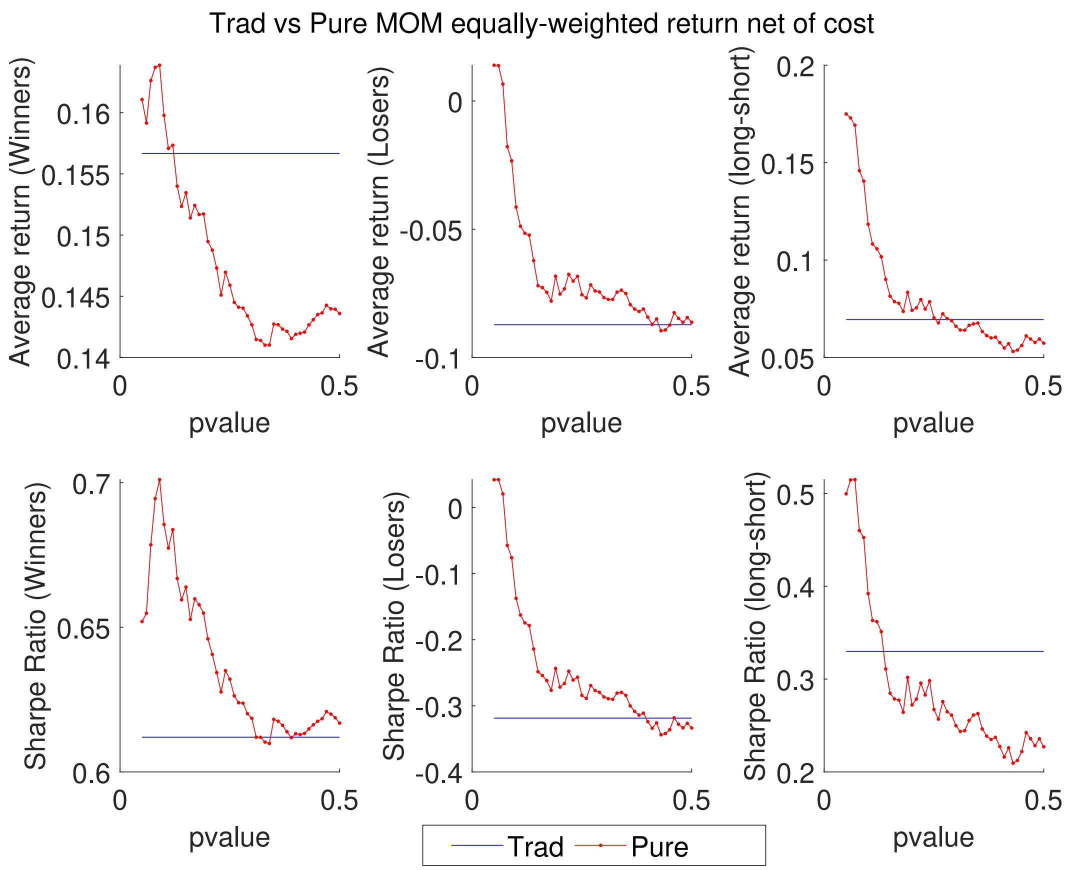

Figure 10: This figure compares the annualized value-weighted return and Sharpe ratio of a long position in past winners, a short position in past losers, and the long-short portfolio as defined in traditional momentum and our pure momentum strategies across various p values ranging from 5% to 50%.

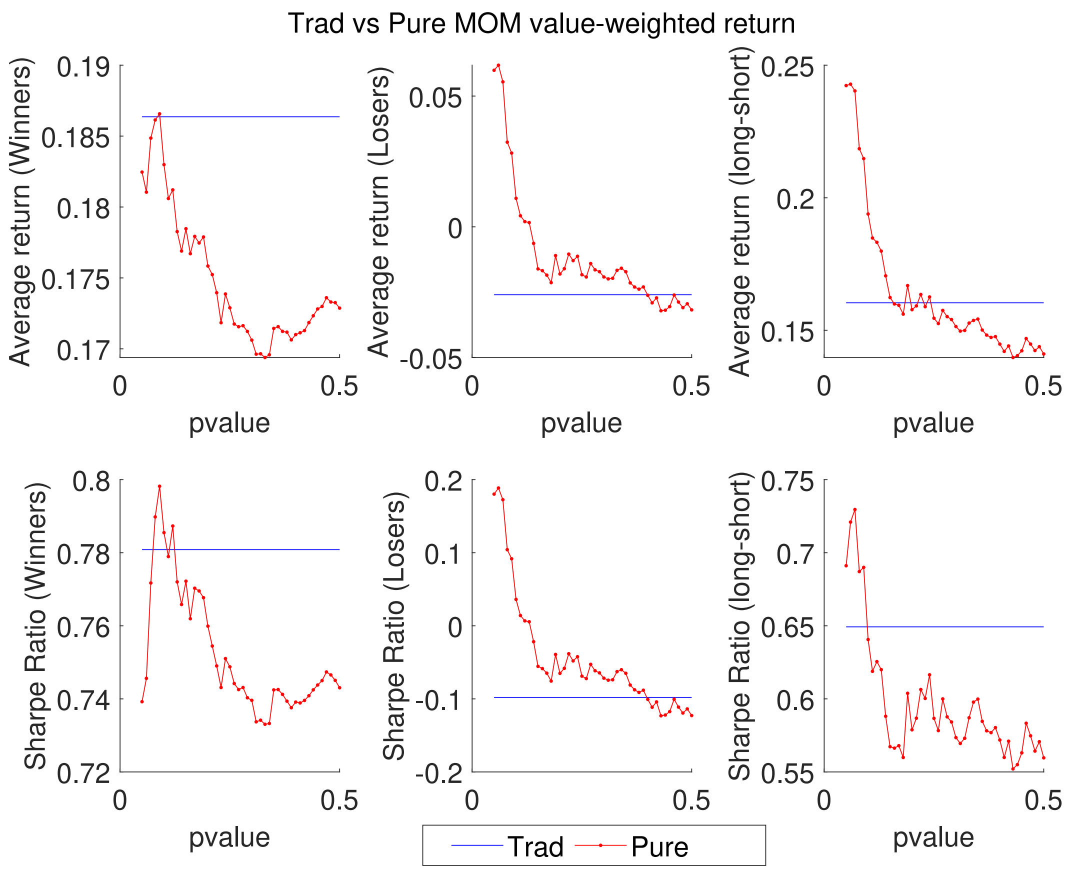

Figure 11: This figure compares the annualized net-of-cost value-weighted return and Sharpe ratio of a long position in past winners, a short position in past losers, and the long-short portfolio as defined in traditional momentum and our pure momentum strategies across various p values ranging from 5% to 50%.

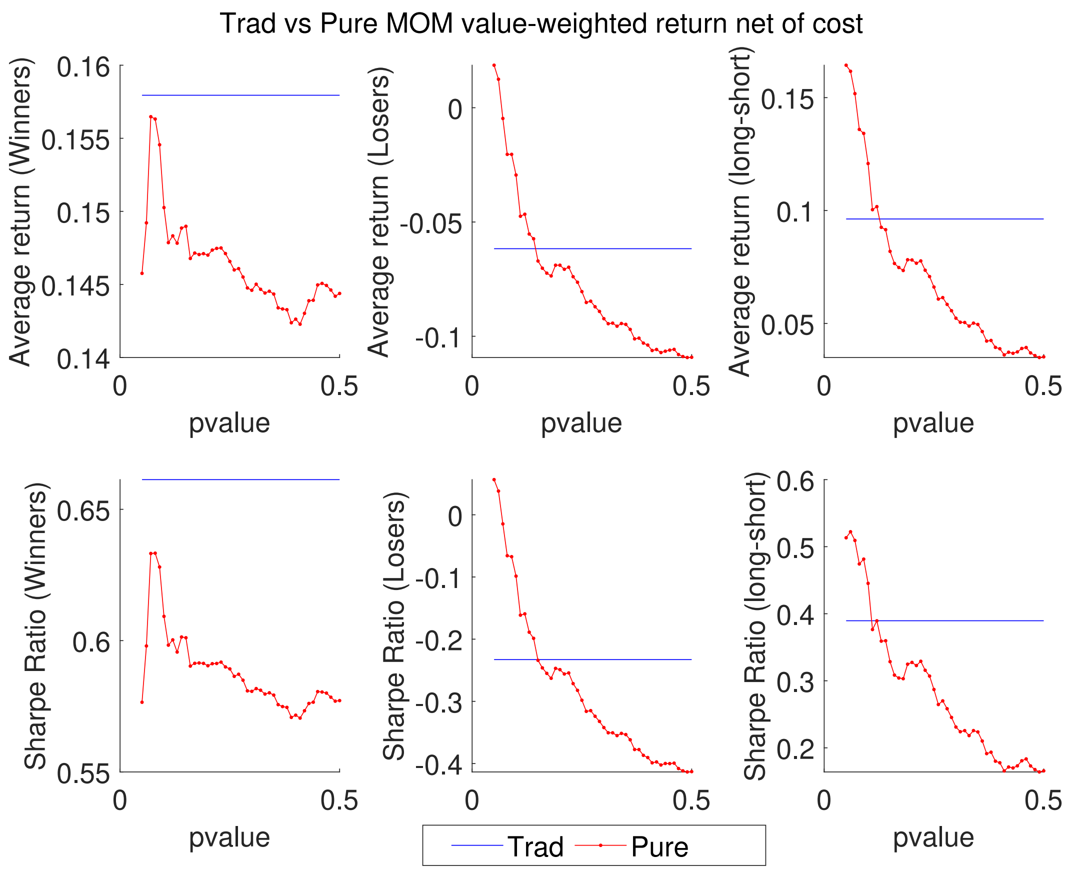

Figure 12: This figure compares the annualized equally-weighted return and Sharpe ratio of a long position in past winners, a short position in past losers, and the long-short portfolio as defined in traditional and our pure short-term reversal strategies across various p values ranging from 5% to 50%.

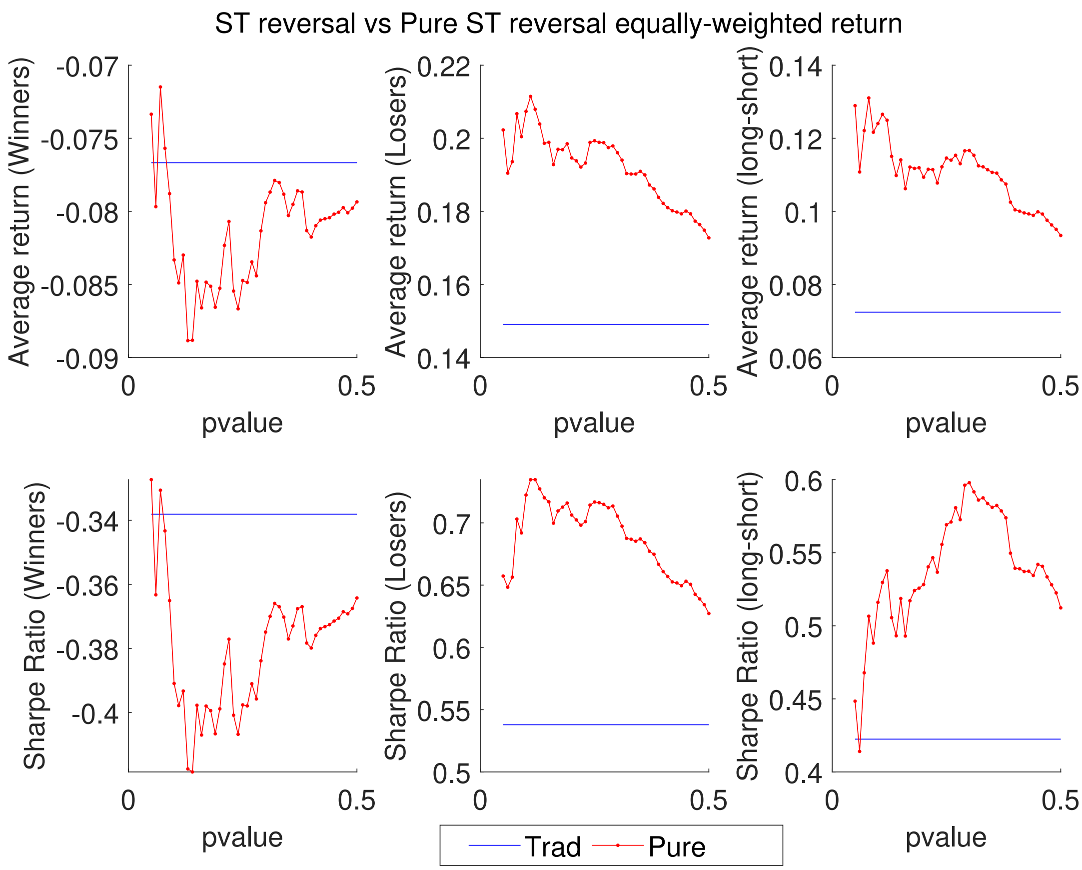

Figure 13: This figure compares the annualized net-of-cost equally-weighted return and Sharpe ratio of a long position in past winners, a short position in past losers, and the long-short portfolio as defined in traditional and our pure short-term reversal strategies across various p values ranging from 5% to 50%.

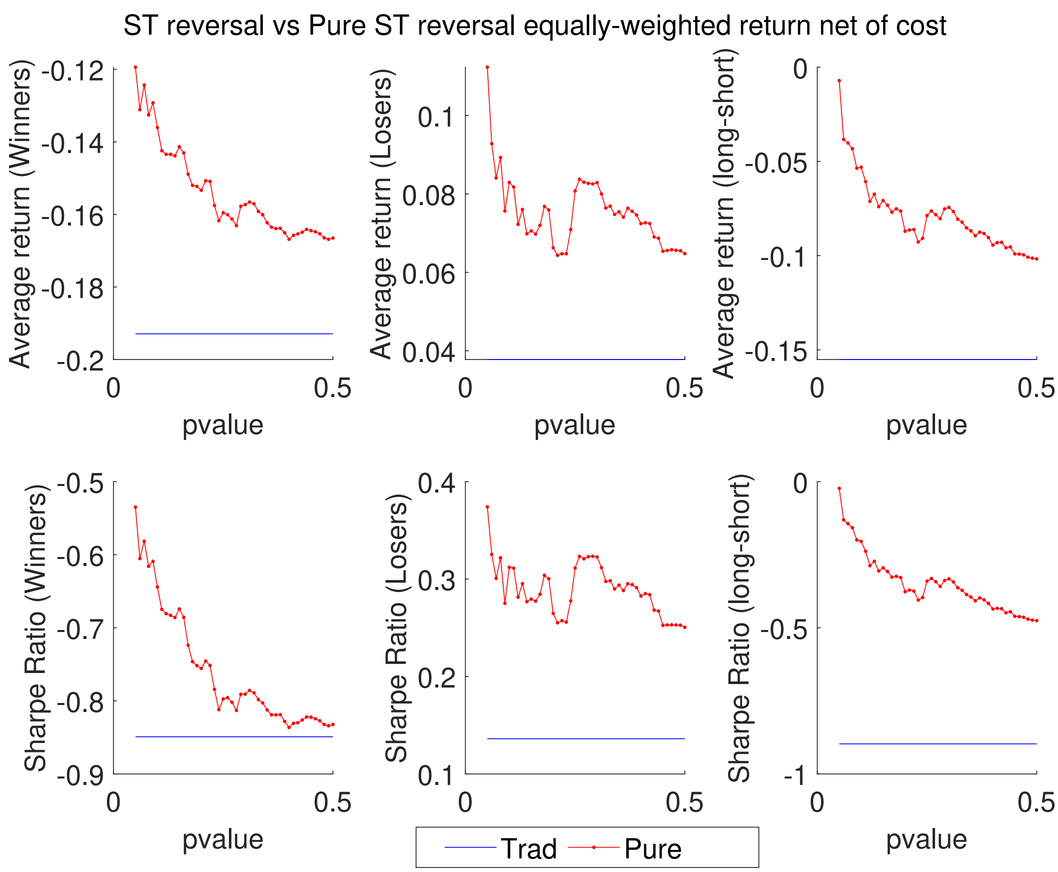

Figure 14: This figure compares the annualized value-weighted return and Sharpe ratio of a long position in past winners, a short position in past losers, and the long-short portfolio as defined in traditional and our pure short-term reversal strategies across various p values ranging from 5% to 50%.

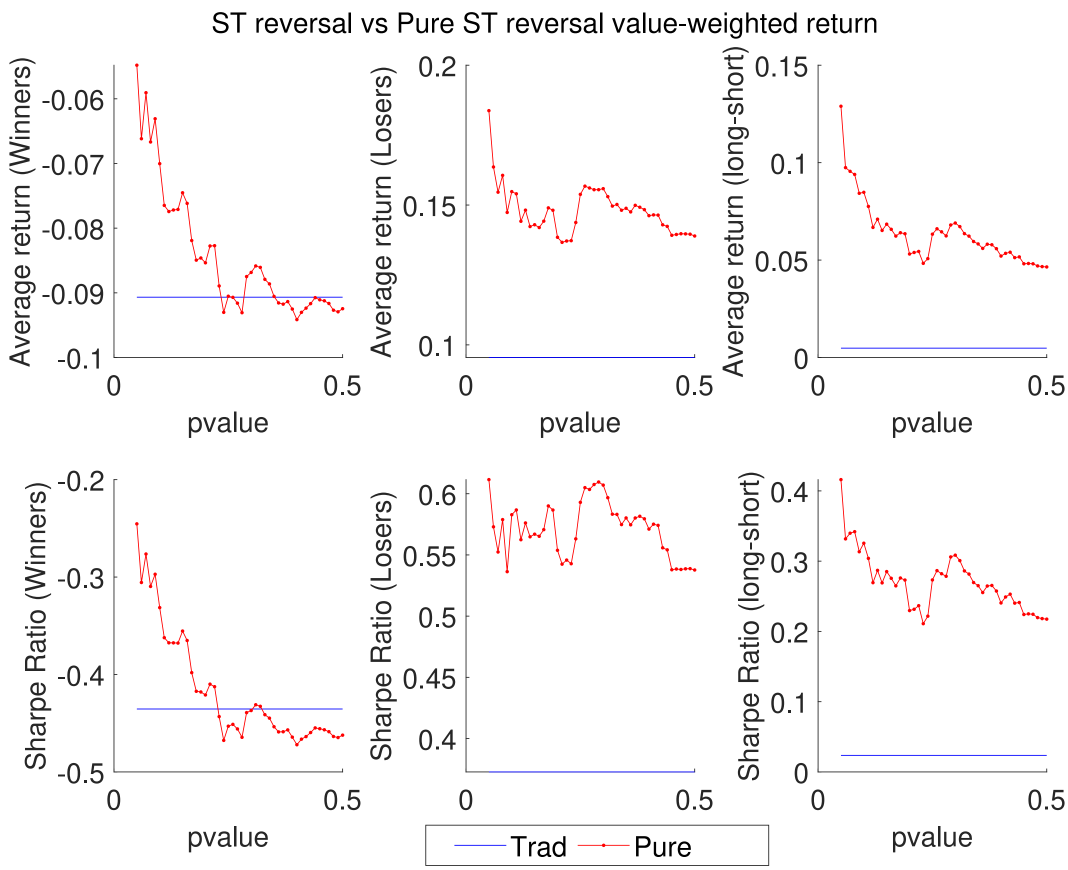

Figure 15: This figure compares the annualized net-of-cost value-weighted return and Sharpe ratio of a long position in past winners, a short position in past losers, and the long-short portfolio as defined in traditional and our pure short-term reversal strategies across various p values ranging from 5% to 50%.

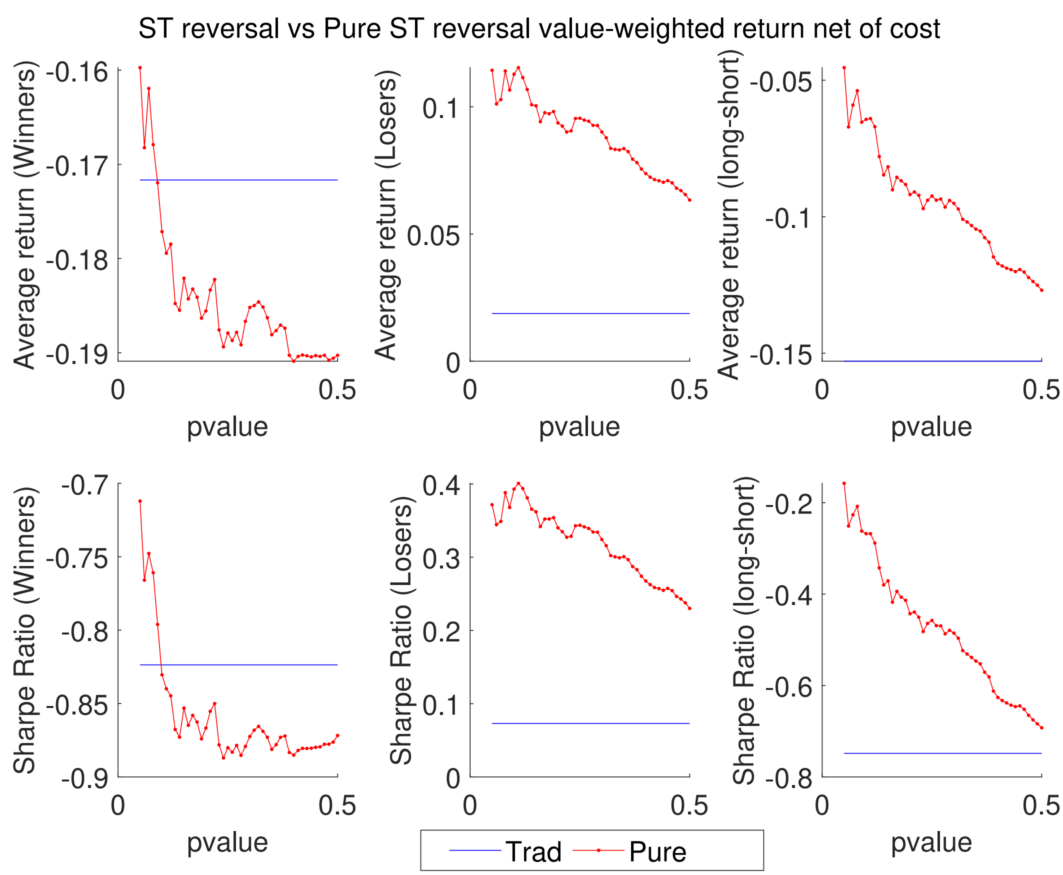

Figure 16: This figure compares the annualized equally-weighted return and Sharpe ratio of a long position in past winners, a short position in past losers, and the long-short portfolio as defined in traditional and our pure short-term reversal strategies across various p values ranging from 5% to 50%. **The results are from the whole stock universe without excluding penny stocks.**

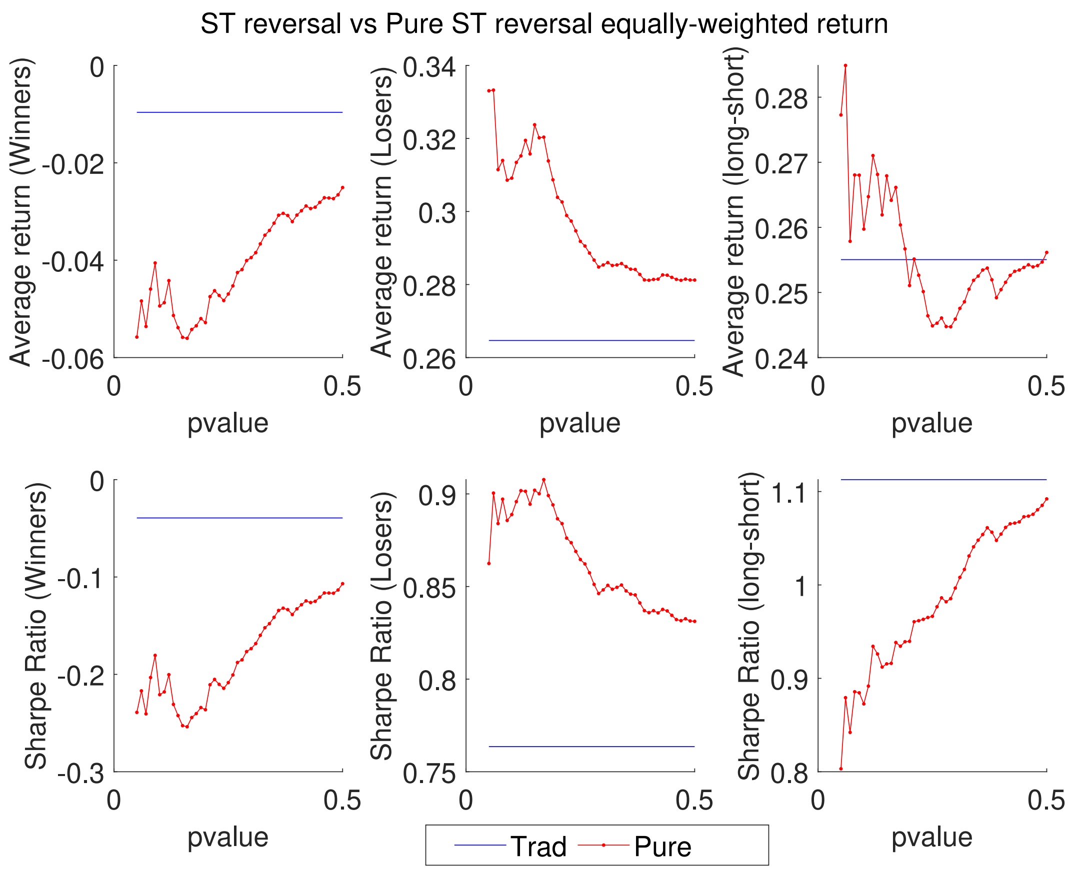

Figure 17: This figure compares the annualized net-of-cost equally-weighted return and Sharpe ratio of a long position in past winners, a short position in past losers, and the long-short portfolio as defined in traditional and our pure short-term reversal strategies across various p values ranging from 5% to 50%. **The results are from the whole stock universe without excluding penny stocks.**

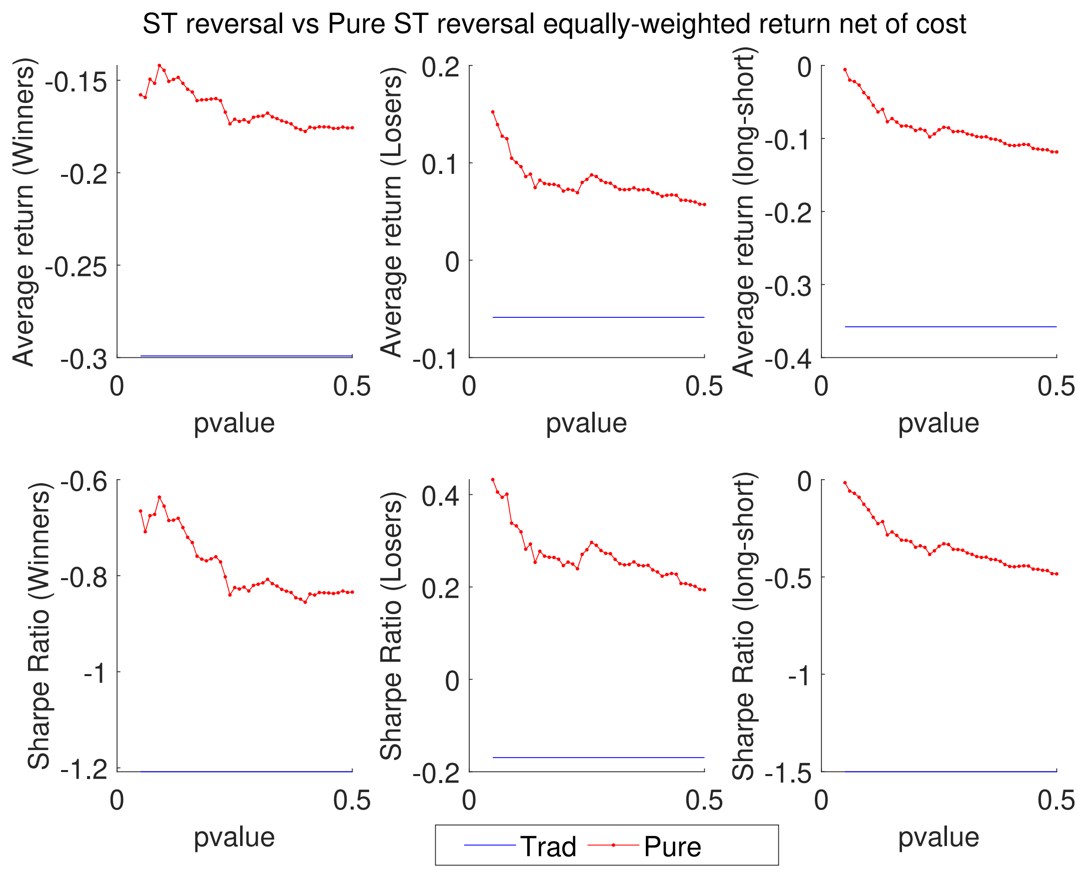

Figure 18: This figure compares the annualized value-weighted return and Sharpe ratio of a long position in past winners, a short position in past losers, and the long-short portfolio as defined in traditional and our pure short-term reversal strategies across various p values ranging from 5% to 50%. **The results are from the whole stock universe without excluding penny stocks.**

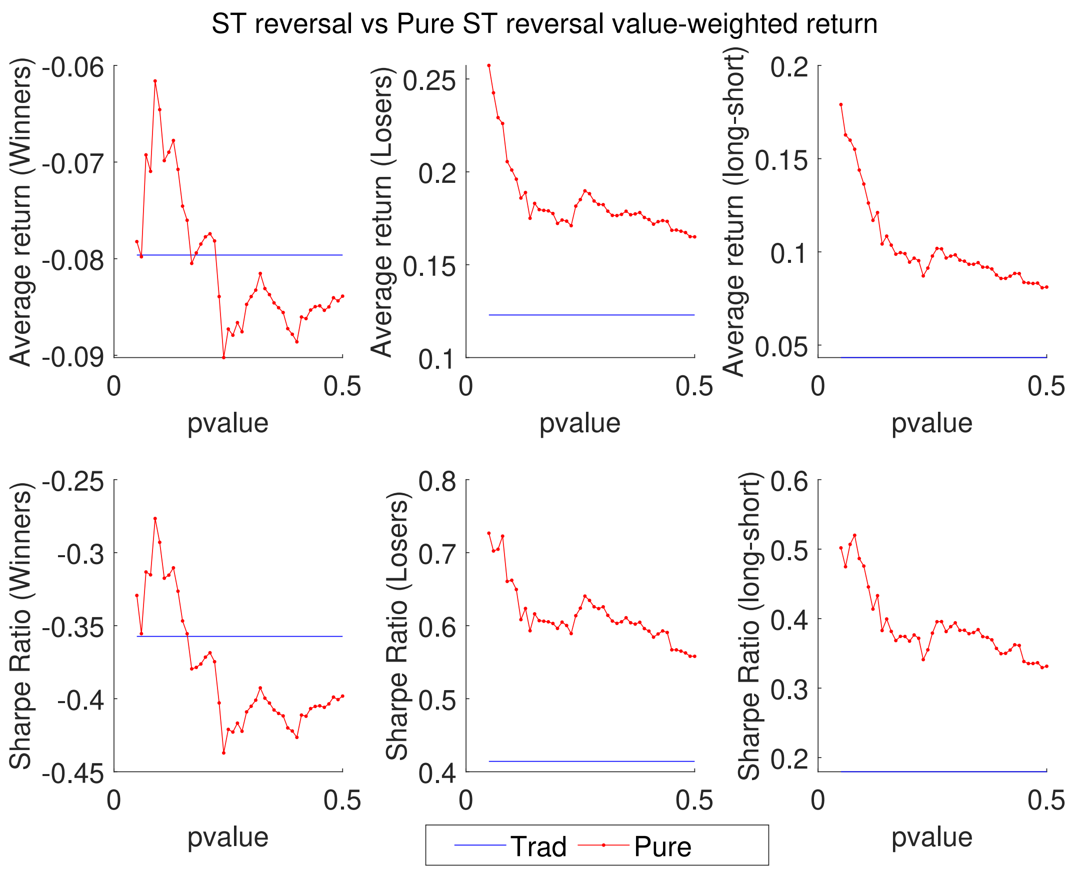

Figure 19: This figure compares the annualized net-of-cost value-weighted return and Sharpe ratio of a long position in past winners, a short position in past losers, and the long-short portfolio as defined in traditional and our pure short-term reversal strategies across various p values ranging from 5% to 50%. **The results are from the whole stock universe without excluding penny stocks.**