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HIGH-FREQUENCY MOMENTUM AND CONTRARIAN STRATEGIES IN U.S. BLUE CHIPS

Abstract

A high-frequency enough dataset may be able to identify very short-term opportunities that can potentially generate significant profits. The present study aims to test the performance of momentum and contrarian trading strategies in a high-frequency setting. To this end, tick-by-tick data from Refinitiv (TRTH) are employed, and 288 strategies are tested across a sample of 28 highly liquid U.S. blue chip stocks during the period 2020–2021, a timeframe marked by significant market volatility, notably the COVID-19-induced crash of February–March 2020 and the subsequent recovery phase from April 2020 to December 2021. The analysis reveals that, although certain strategies exhibit superior performance relative to the benchmark strategy both prior to and following adjustments for risk, data snooping, and luck, none outperform the benchmark strategy once reasonable transaction costs are accounted for. These findings suggest that sophisticated retail traders may be unable to exploit underreaction or overreaction in stock prices at high frequency. The main contribution of this study lies in the application of stringent robustness checks, including a robustness check based on luck within the context of intraday trading strategies.

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INTRODUCTION

While empirical research has gradually shifted from low to high frequency, progressing from monthly to intraday data, the decline or disappearance of the return premia from momentum and contrarian trading strategies at lower frequencies has been noted (Chordia et al., 2014; Hwang & Rubesam, 2015). Schulmeister (2009) also highlighted a potential shift in profitability toward higher frequencies. However, few studies explore these strategies at high frequency. As Herberger et al. (2020) emphasize, high-frequency datasets may reveal short-term opportunities with profit potential. This study addresses that gap by analyzing both strategies at the tick-by-tick level, restricting holding periods to a few minutes. The aim is to determine whether momentum and contrarian effects can be exploited in a high-frequency setting by sophisticated retail traders with coding skills, once transaction costs, risk, data snooping, and chance are properly accounted for. More precisely, understanding whether classic trading anomalies like momentum and contrarian patterns persist at very high frequencies, and whether they can be harnessed by non-institutional traders, is crucial for both academic research and real-world trading practices. In an era where retail traders increasingly access high-frequency data and algorithmic tools, it becomes essential to revisit these strategies under realistic conditions.

The present study builds on Herberger et al. (2020), who test 16 momentum and 16 contrarian strategies on 30 German blue-chip stocks over the period from 11/01/2013 to 12/23/2014, using holding periods

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from 15 to 300 minutes. They argue that algorithmic trading compresses the momentum and contrarian effects to shorter timeframes by accelerating information flow. It also relates to Chordia et al. (2014), who claim that increased liquidity should enhance anomaly-based arbitrage. If true, profits from these strategies may vanish once transaction costs are factored in. Finally, the methodology follows the methodologies proposed by Duvinage et al. (2014) and Harvengt (2022).

1. LITERATURE REVIEW AND HYPOTHESES

The origins of momentum and contrarian effects remain debated. Some attribute them to misreaction to information, a notion which emerged in behavioral finance and which implies that if stock prices indeed underreact or overreact to information, then a trader can select stocks based on past returns and profit from it (Barberis et al., 1998; Daniel et al., 1998; Hong & Stein, 1999). Others argue that momentum and contrarian abnormal returns are simply a compensation for the risk taken (Conrad & Kaul, 1998). As for Lo and MacKinlay (1990), they suggest momentum arises from security lead-lag effects. This study does not aim at favoring one explanation, though if these effects occur at sub-second speeds, risk-based explanations may seem more plausible.

Momentum and contrarian effects, which correspond to the continuation and reversal of the direction of preceding stock returns, are well documented. Many studies show stock returns are predictable via past performance, so that it is possible for traders to generate abnormal returns using either momentum (relative strength) or contrarian (mean reversion) strategies. The 'loser/winner ranking' method is most commonly employed, whereby stocks are ranked according to their recent performance over a defined 'formation period', and those exhibiting either the highest or lowest returns are subsequently purchased to capture the momentum or contrarian effects, and held for a specified 'holding period'. Alternatively, some rely solely on technical systems (e.g., Schulmeister, 2008), which is the approach adopted in this study.

Levy (1967) first showed 'relative strength' strategies, later called 'momentum' by Jegadeesh and Titman (1993), yield abnormal returns. Jegadeesh and Titman (1993) found that past winners outperform losers over 3-12 months in the U.S. market. This anomaly persisted in later studies (e.g., Chan et al., 1996; Jegadeesh & Titman, 2001) and was linked to behavioral underreaction. The momentum effect is present in international markets (Rouwenhorst, 1998; Rouwenhorst, 1999; Chui et al., 2000), commodities (Miffre & Rallis, 2007), bonds (Jostova et al., 2013), cryptocurrencies (Liu et al., 2022), and over multiple timeframes (Schiereck et al., 1999; Wing-Shing Lam et al., 2007; McInish et al., 2008; Schulmeister, 2008; Venter, 2009; Zhang et al., 2019). Wiest (2023) offers a comprehensive review.

De Bondt and Thaler (1985) showed contrarian strategies were profitable over 3-5 year periods. Jegadeesh (1990) and Lehmann (1990) found them effective at weekly/monthly levels. Conrad et al. (1994) observed stronger reversals in high-transaction stocks, while Cooper (1999) found weaker reversals with high volume growth. Avramov et al. (2006) reconciled both studies by showing that reversals strengthen with activity weekly, but weaken monthly, and illiquidity increases reversals. Finally, Chiang et al. (2021) found that reversals decline with expected turnover. As with the momentum effect, the contrarian effect is present globally (Baytas & Cakici, 1999; Gaunt, 2000), in commodities (Caporale & Plastun, 2021), cryptocurrencies (Kosc et al., 2019), and across timeframes (McInish et al., 2008).

Most prior studies focus on weekly/monthly frequencies. Few examine intraday effects. Among the studies focusing on the momentum and contrarian effects at the intraday level, Gao et al. (2018) find that the first half-hour return on the SPY predicts the last hour return. Similarly, Zhang et al. (2019) find that morning returns forecast afternoon returns in the Chinese stock market, Fung et al. (2000) find that price reversals can be exploited to give rise to profitable opportunities after transaction costs in both U.S. and Hong Kong index futures, and Kang (2005) identifies intraday momentum and contrarian effects in NYSE stocks. Venter (2009), however, finds no significant intraday effects on the JSE.

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This study advances prior research by conducting an analysis at the tick-by-tick level, in which reliance is placed on a technical trading system, considered more appropriate for high-frequency settings, rather than on the traditional 'loser/winner ranking' method. Drawing upon the existing literature, the following hypotheses are formulated:

H1: *Momentum and contrarian effects are present and observable at high frequency.*

H2: *Some of the tested trading strategies generate significant profits prior to adjustments for risk, corrections for data snooping and luck, and the inclusion of transaction costs.*

H3: *Sophisticated retail traders possessing coding proficiency are able to benefit from momentum and contrarian effects at high frequency, even when simple and easily implementable trading strategies are applied.*

2. METHOD

This study focuses on 28 highly liquid U.S. blue-chip stocks listed on Nasdaq over the period 2020–2021. Tick-by-tick data covering 476 trading days are sourced from Refinitiv (TRTH). The 28-stock sample is drawn from an initial set of 40 large-cap stocks with a market capitalization above $10 billion identified by Professors Terrence Hendershott and Ryan Riordan in the 2008–2010 Nasdaq HFT dataset.

From the original list, some stocks were excluded, such as those delisted by the end of 2021 (e.g., Allergan, Chubb, Celgene), those falling below the $10 billion threshold (e.g., Alcoa, Gap, Southwestern Energy), and those with unavailable or incomplete data on Refinitiv (e.g., Dell, Baker Hughes, Honeywell). The resulting sample consists of 28 large-cap U.S. stocks (see Table 1).

Table 1. Dataset

Stock Name	Ticker	Period	N
Apple	AAPL	01/01/2020 – 31/12/2021	476
Adobe	ADBE	01/01/2020 – 31/12/2021	476
Applied Materials	AMAT	01/01/2020 – 31/12/2021	476
Amgen	AMGN	01/01/2020 – 31/12/2021	476
Amazon	AMZN	01/01/2020 – 31/12/2021	476
American Express	AXP	01/01/2020 – 31/12/2021	476
Biogen	BIIB	01/01/2020 – 31/12/2021	476
Broadcom	BRCM	01/01/2020 – 31/12/2021	476
Comcast	CMCSA	01/01/2020 – 31/12/2021	476
Corning	GLW	01/01/2020 – 31/12/2021	476
Costco	COST	01/01/2020 – 31/12/2021	476
Cisco Systems	CSCO	01/01/2020 – 31/12/2021	476
Cognizant	CTSH	01/01/2020 – 31/12/2021	476
The Walt Disney Co	DIS	01/01/2020 – 31/12/2021	476
Ebay	EBAY	01/01/2020 – 31/12/2021	476
General Electric	GE	01/01/2020 – 31/12/2021	476
Gilead Sciences	GILD	01/01/2020 – 31/12/2021	476
Google	GOOG	01/01/2020 – 31/12/2021	476
Hewlett–Packard	HPQ	01/01/2020 – 31/12/2021	476
Intel	INTC	01/01/2020 – 31/12/2021	476
Intuitive Surgical	ISRG	01/01/2020 – 31/12/2021	476
Kimberly–Clark	KMB	01/01/2020 – 31/12/2021	476
Kroger	KR	01/01/2020 – 31/12/2021	476
3M	MMM	01/01/2020 – 31/12/2021	476
The Mosaic Company	MOS	01/01/2020 – 31/12/2021	476
Pfizer	PFE	01/01/2020 – 31/12/2021	476
Procter & Gamble	PG	01/01/2020 – 31/12/2021	476
PNC Financial Services	PNC	01/01/2020 – 31/12/2021	476

Table 1 presents the 28 U.S. blue chip stocks used in the study, including the Stock Name, Ticker, Period, and Number of trading days (N).

The exclusive focus on blue-chip stocks stems from the liquidity needs of trading in a high-frequency setting, which requires swift, low-cost execution of long and short positions. This aligns with the approach of Herberger et al. (2020), who restricted their sample to DAX 30 stocks to ensure sufficient liquidity and minimize irregular analyst coverage effects, as noted by Hong et al. (2000).

Across the 476 days, approximately 626 million transactions occurred, or about 2.2 million transactions per strategy, representing around 88 billion shares in total and $6.9 trillion in dollar volume. On average, 1.3 million transactions took place daily, involving 185 million shares and $14 billion in dollar volume. 140 shares were exchanged per transaction on average, with a standard deviation of 97 shares (see Table 2).

Table 2. Sample – Descriptive statistics

Number of days	476
Number of transactions	625,764,534
Total share volume	87,908,742,940
Total dollar volume	6,873,373,000,000
Trade size (mean)	140
Trade size (std dev)	97
Daily number of transactions (mean)	1,314,631
Daily share volume (mean)	184,682,233
Daily dollar volume (mean)	14,439,859,290

Table 2 reports the descriptive statistics of the sample.

The study tests momentum and contrarian trading strategies following Duvinage et al. (2014) and Harvengt (2022). Duvinage et al. (2014) focus on medium-term intraday contrarian strategies, while this study applies to both momentum and contrarian strategies at the tick-by-tick level, following Harvengt (2022). It is assumed that large price variations serve as relevant signals for both short-term market timing continuations (momentum strategies) and reversals (contrarian strategies), using the historical return distribution to identify such price swings.

Percentiles of historical returns are calculated over four time windows: the prior trading day, the previous 5, 10, and 20 days. These windows are consistent with volatility clustering, defined as the persistence of volatility over time, described by Mandelbrot (1997).

The trading strategy methodology is consistent throughout. For momentum strategies, a buy signal is triggered when the most recent tick-level return exceeds the 90th, 95th, or 99th percentile based on any of the four time windows. For contrarian strategies, a buy signal is triggered when the return falls below the 10th, 5th, or 1st percentile.

Of the 288 total strategies, 216 (three-quarters) use a confirmation signal, while 72 (one-quarter) do not. For those that do, a trend indicator, either the Volume Weighted Average Price (VWAP) or a pair of moving averages (5-minute with 13-minute or 5-minute with 21-minute), must confirm the buy signal. For strategies without trend indicators, confirmation is not required.

Additionally, 96 strategies (one-third) employ a temporary stop loss of -2% or -1%; the remaining 192 (Two-thirds) do not. If triggered, a temporary stop loss causes the algorithm to short the stock until a new buy signal appears. All strategies use a permanent –5% stop loss to prevent extreme losses, ending trading for the day if reached.

All strategies begin with a long (+1) position. The entry time varies depending on whether moving average combinations are used. Without MA-based confirmation, positions are taken immediately at the market open. With MA-based confirmation, entry is delayed by 13 minutes for the 5-13-minute pair and by 21 minutes for the 5-21-minute pair. All strategies end with a flat position at the market close (0).

In momentum strategies, once a buy signal is confirmed (if needed), the position remains long (+1). If a temporary stop loss triggers a sell, the position becomes a short position (–1) until a new buy signal appears. Upon a permanent stop loss, the position is closed for the rest of the day (0).

Contrarian strategies follow the same mechanics. Positions toggle between +1 and –1 based on signals, and are closed for the rest of the day if the –5% stop loss is hit.

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As in Duvinage et al. (2014), it is assumed that the trader always has sufficient cash to reinvest, even if closing positions results in losses. This allows the analysis to focus solely on return generation, independent of capital constraints.

Transaction costs are incorporated using a conservative 0.05% fee per trade, following Olson (2004), Duvinage et al. (2014), and Harvengt (2022). This estimate exceeds the actual fees offered by some brokers (as low as $0.0005 per trade at the time of writing).

In total, 144 momentum and 144 contrarian strategies are tested for a total of 288 strategies (see Table 3).

Table 3. Momentum and contrarian strategy combinations

Strategy	Momentum	Contrarian
Historical return distribution window	1 day 5 days 10 days 20 days	1 day 5 days 10 days 20 days
Percentiles	90th 95th 99th	10^{th} 5^{th} 1st
Trend indicator	None VWAP MA 5-13 MA 5-21	None VWAP MA 5-13 MA 5-21
Temporary stop loss	None –1% -2%	None –1% -2%
Permanent stop loss	–5%	–5%

Table 3 presents the strategy combinations used in the study. 288 trading strategies are tested in total (2 x 4 x 3 x 4 x 3 x 1).

To evaluate performance, the strategies are compared to a buy-and-hold benchmark strategy. The benchmark strategy goes long at the market open (+1) and goes flat at the market close (0), thus excluding overnight price changes that the tested strategies cannot capture. Risk-adjusted returns are assessed using the Sharpe and Sortino ratios, common in algorithmic and high-frequency trading. These are compared to the benchmark strategy to determine if any strategies yield excess returns.

The Sharpe ratio (Sharpe, 1966), which was originally named the 'reward-to-variability' ratio by William F. Sharpe, compares the excess return of the trading strategy to its level of risk (as defined by volatility) so as to assess the risk-adjusted performance of the trading strategy. The higher the Sharpe ratio, the better, since a higher Sharpe ratio implies a higher return per unit of risk (as measured by volatility).

The Sharpe ratio is defined as follows:

$$Sharpe\ ratio\ (p) = \frac{R_p - R_f}{\sigma_p}, \quad (1)$$

where R_p – Expected return of the trading strategy, R_f – Risk-free rate (or benchmark rate), σ_p – Standard deviation of the expected return of the trading strategy (total risk).

For the sake of simplicity, a risk-free rate of 0% is used in this study, which is very close to the U.S. 10-year bond yield observed in March 2020 (within the covered period).

The Sortino ratio, created by Frank Sortino at the beginning of the 1980s, is a modified version of the Sharpe ratio where negative volatility (downside deviation) is taken into account in place of total volatility (standard deviation). As such, the Sortino ratio only penalizes downside risk rather than total risk (both upside and downside). The first reference to the ratio can be found in *Financial Executive Magazine* (August 1980), and the first calculation of the ratio can be found in a series of articles published in *Journal of Risk Management* (September 1981). Complementary work on the downside framework includes Sortino & Price (1994). The higher the Sortino ratio, the better, since a higher Sortino ratio implies a higher return per unit of bad risk (as measured by downside deviation).

The Sortino ratio is defined as follows:

$$Sortino\ ratio\ (p) = \frac{R_p - R_f}{\sigma_d}, \quad (2)$$

where R_p – Expected return of the trading strategy, R_f – Risk-free rate (or benchmark rate), σ_d – Standard deviation of the negative returns of the trading strategy (downside risk).

Stringent robustness checks are applied to control for risk, data snooping, and luck, both before and after transaction costs.

To correct for the influence of data snooping and evaluate if some of the strategies significantly outperform the benchmark strategy once taking data snooping into account, the Stepwise Superior Predictive Ability (SSPA) test is applied following Hsu et al. (2010) and Hsu and Vincent (2022).

A luck-corrected peer performance analysis is then conducted following Ardia and Boudt (2018) and Ardia et al. (2020), which provides a way to correct the different strategies for the luck effect based on the Sharpe ratio to see if some of the strategies significantly outperform the benchmark strategy based on this metric.

Last but not least, the results are checked after taking transaction costs into account. Another SSPA test and luck-corrected peer performance analysis is thus performed using the returns obtained *after* transaction costs.

The problem when testing many trading strategies on past data is that some of them are significant by luck alone, which means these strategies are actually not reliable and have no forecasting ability. This is due to the so-called 'data-snooping effect', which is a statistical bias present in statistical tests, resulting in finding statistical significance when there is none. To quote White (2000): "even when no exploitable forecasting relation exists, looking long enough and hard enough at a given set of data will often reveal one or more forecasting models that look good, but are in fact useless" (p. 1097).

As pointed out by Hsu et al. (2005), two approaches are used in the literature to account for the data-snooping effect. The first approach focuses on the way the data is used, either by avoiding reusing the same data set as in Lakonishok et al. (1994) and Chan et al. (1998), or by creating subsamples of the data set as in Brock et al. (1992), Rouwenhorst (1998, 1999), or Gencay (1998). In this case, however, the data splitting is arbitrary and thus questionable. The second approach consists in using a test that properly controls test size so as to reduce the risk of committing a type I error by rejecting the null hypothesis while it is true. Four tests are mainly used in the literature. They are the Bootstrap Reality Check (BRC) test by White (2000), the Superior Predictive Ability (SPA) test by Hansen (2005), the Stepwise version of the Reality Check (SRC) test by Romano and Wolf (2005), and the Stepwise version of the Superior Predictive Ability (SSPA) test by Hsu et al. (2010).

The BRC test (White, 2000) tests the null hypothesis under which the best strategy within a large group of strategies cannot beat the benchmark strategy (has no predictive ability over the benchmark strategy). While this method tackles some of the data-snooping effect, it is not as effective when the sample contains too many underperforming strategies, in that the test power is greatly reduced. Moreover, this method is not able to identify the outperforming strategies. The SPA test proposed by Hansen (2005) tries to improve the original method by increasing the rejection rate of the null hypothesis via a reduction of the number of poor models in the sample. While Hansen's modifications improve the original method, it is again unable to identify the outperforming strategies beyond the best strategy, unless the tests are run repeatedly. The SRC test (Romano & Wolf, 2005) improves White's BRC test by making it possible to find more than one outperforming strategy, which rejects the null hypothesis in each round of the test. But again, the method is not as effective when the sample contains too many underperforming strategies, the test power being greatly reduced when too many poor strategies are present. Eventually, the SSPA test (Hsu et al., 2010) relies on Hansen's (2005) approach and improves the method by allowing the test to automatically drop very poor strategies from the universe being tested in each bootstrap.

The present study relies on the SSPA test, following Hsu et al. (2010) and Hsu & Vincent (2022), as it is believed to be the most robust method to control for data snooping when dealing with trading strategies, especially with trading strategies included in a sample containing many underperforming strategies.

In more detail, the data were resampled based on the stationary bootstrap of Politis and Romano (1994), which provides a way to extract a critical value that can then be compared to the t-stat gen-

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erated from the original data. The critical value is the value that controls the family-wise error rate (FWER), which is the probability of making one or more type I errors, that is to say, rejecting one or more null hypotheses when they are actually true, when performing multiple hypothesis tests at a certain confidence level α. In this study, K is set to 1 and α is set to 5%.

First, the following null hypothesis is tested:

$$H_0 = \overline{Strategy_i} - \overline{Benchmark} \le 0. \tag{3}$$

The rejection of the null hypothesis implies that the alternative hypothesis is true and that the tested strategy significantly outperforms the benchmark strategy after taking data snooping into account.

Second, the t stat is computed in the following way:

$$t\_stat = \sqrt{n} \cdot \frac{\overline{Strategy_i} - \overline{Benchmark}}{\sqrt{s_i^2 + s_{Benchmark}^2}}. \tag{4}$$

Third, the boot stat meant to find the critical value is computed in the following way.

A peer-performance evaluation of the tested trading strategies with luck-correction is also performed following Ardia and Boudt (2018) and Ardia et al. (2020).[1] In more detail, the peer performance of a strategy *i*, belonging to a peer universe of n + 1 strategies (including the benchmark strategy), is tested using three peer performance parameters:

- π_i^0 : the proportion of strategies in the peer group that perform equally well as strategy *i*,
- π_i^+ : the proportion of strategies in the peer group that are outperformed by strategy *i*,
- π_i^- : the proportion of strategies in the peer group that outperform strategy *i*.

These three performance parameters measure the percentage of peers a strategy outperforms and underperforms, after correcting for luck, and provide a way to estimate the percentage of strategies that have equal, lower, or greater risk-adjusted performance (based on the Sharpe ratio in this study) when compared to strategy *i*.

As pointed out by Ardia and Boudt (2018), the proposed peer performance ratios offer two major advantages. First, they require the relative performance between two strategies to cross a threshold of statistical significance to be counted as evidence of a difference in performance. Second, the false discovery rate methodology is used to obtain peer performance estimates that are robust to false positives.

3. RESULTS

For simplicity, metrics are aggregated across the 28 stocks, and the overall performance of each trading strategy, whether momentum or contrarian, is assessed. Emphasis is placed on the Sharpe and Sortino ratios.

Since each strategy relies on the historical return distributions of four time windows (previous day, 5, 10, and 20 days), the 144 momentum strategies are grouped into 36 general momentum strategies (M1–M36), and the 144 contrarian strategies into 36 general contrarian strategies (C1–C36), to ease result interpretation. A summary of each strategy is provided in the Appendix. The top 5 momentum and top 5 contrarian strategies are presented in Table 4.

A two-step analysis is conducted. First, mean metrics are extracted for all strategies, and momentum and contrarian strategies are analyzed separately. Second, the number of times each strategy outperforms the benchmark strategy is counted, initially without adjustments, then corrected for

$$boot\_stat = \sqrt{n} \cdot \frac{\left(\overline{Strategy_{boot,i}} - \overline{Benchmark_{boot}}\right) - \left(\overline{Strategy_i} - \overline{Benchmark}\right)}{\sqrt{s_i^2 + s_{Benchmark}^2}}. \tag{5}$$

1 The "PeerPerformance" Package in R developed by Ardia et al. (2020) is used. For more information: https://CRAN.R-project.org/package=PeerPerformanceю.

Table 4. Performance metrics of the top 5 momentum and contrarian strategies

Rank	Momentum	Historical return distribution (HRD)	Sharpe ratio	Sortino ratio
1	M2	HRD20	0.23	0.28
2	M30	HRD20	0.01	0.02
3	M29	HRD20	0.01	0.01
4	M21	HRD20	0.01	0.01
5	M20	HRD20	0.01	0.01
Rank	**Contrarian**	**Historical return distribution (HRD)**	**Sharpe ratio**	**Sortino ratio**
1	C3	HDR10	0.21	0.23
2	C3	HRD5	0.21	0.24
3	C9	HRD10	0.21	0.23
4	C9	HRD5	0.21	0.24
5	C6	HRD10	0.21	0.23

data snooping using the SSPA test, and for luck via a Sharpe ratio-based luck-corrected peer performance analysis.

Table 4 presents the top 5 momentum and contrarian strategies.

Contrarian strategies tend to show better Sharpe ratios than momentum ones. Except for strategy M2, the Sharpe ratios of top momentum strategies are close to zero. When focusing on downside risk instead of total risk, contrarian strategies again show better Sortino ratios.

The key finding is that some of the strategies outperform the benchmark strategy after adjusting for risk. This initially suggests they may generate significant profits. However, corrections for data snooping, luck, and transaction costs are necessary to confirm their predictive power.

To correct for data snooping, the SSPA test (Hsu et al., 2010; Hsu & Vincent, 2022) is applied. Results are presented in Table 5.

Table 5. Stepwise superior predictive ability test before and after transaction costs

Strategy type	Nb of outperforming strategies (before costs)	Nb of outperforming strategies (after cost)
Momentum	37	0
Contrarian	43	0

Table 5 reports the strategies that outperform the benchmark strategy after correcting for data snooping, both *before* transaction costs and *after* transaction costs. A 0.05% transaction fee per transaction is used.

Without accounting for transaction costs, 37 momentum and 43 contrarian strategies outperform the benchmark strategy after correcting for data snooping, suggesting some forecasting ability. When transaction costs (0.05% per trade) are included, no strategy outperforms the benchmark. This implies that, in a high-frequency setting, the returns of both strategy types do not offset the costs incurred.

The analysis is extended using the luck-corrected peer performance method proposed by Ardia and Boudt (2018) and Ardia et al. (2020). Results are presented in Table 6.

Table 6. Luck-corrected peer performance before and after transaction costs

Strategy type	Nb of outperforming strategies (before costs)	Nb of outperforming strategies (after cost)
Momentum	63	0
Contrarian	69	0

Table 6 reports the strategies that outperform the benchmark strategy after correcting for luck, both *before* transaction costs and *after* transaction costs. The outperforming strategies are the strategies that have a better Sharpe ratio than their peers, including the benchmark strategy.

As noted by Ardia et al. (2020), a strategy can outperform in a pairwise test purely by chance. To correct for this, all pairwise Sharpe ratio comparisons are performed using Ledoit and Wolf's (2008) bootstrap method. For N strategies, N(N–1)/2 tests are run. Storey's (2002) false discovery rate method is then applied to classify strategies as over-, equally-, or underperforming based on Sharpe ratios.

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Similar to the SSPA test, this method shows some strategies beat the benchmark strategy after adjusting for luck, but none do so once transaction costs are included. It is noted, however, that some of these strategies could possess forecasting ability in a zero transaction cost environment, which may become prevalent in the future.

The main conclusion is that both the SSPA test and the luck-corrected peer performance analysis reach the same outcome, i.e., none of the strategies yield excess returns once transaction costs are factored in.

4. DISCUSSION

Overall, this study confirms the findings of Harvengt (2022), that is to say, momentum and contrarian trading strategies are unlikely to yield significant profits after transaction costs at the tick-by-tick level. It is important to note that both the study proposed by Harvengt (2022) and the present study use datasets where volatility is omnipresent (the Great Financial Crisis of 2008-2009 in the case of Harvengt (2022) and the Covid-19 crash of 2020 in the present analysis), an environment that is likely to be favorable to this type of strategy.

Moreover, the findings echo Lesmond et al. (2004), who, studying low-frequency momentum strategies, argue that the magnitude of abnormal returns often creates a false appearance of profitability. Likewise, in this study, excess returns from top-performing strategies appear illusory, as none outperform the benchmark strategy after accounting for transaction costs. The results are also consistent with Venter (2009), who finds intraday strategies nearly profitable under minimal brokerage rates, and with Herberger et al. (2020), who observe that contrarian strategy returns do not offset transaction costs. Similarly, the conclusions align with Chordia et al (2014), who assert that increased liquidity supports anomaly-based arbitrage. Given the prevalence of algorithmic and high-frequency traders in the U.S. blue chip stock market, true arbitrage opportunities are likely rare, explaining why the tested strategies fail to beat the benchmark strategy after transaction costs. Hence, retail traders may be unable to exploit both underreaction and overreaction in stock prices at high frequency.

It is important to highlight some limitations present in this study so as to suggest several directions for future research. First, transaction prices are used instead of mid-quote prices to compute returns, as only transaction price data are available. As a result, the strategies examined are subject to the bid-ask spread bounce, wherein stock prices oscillate between the best bid and ask prices. Consequently, the 'true' volatility may differ from the volatility measured in this study, potentially affecting the Sharpe and Sortino ratios.

Second, the analysis is restricted to U.S. blue-chip stocks to ensure that strategies are tested on some of the most liquid securities globally, an approach considered most appropriate in a high-frequency setting. Nevertheless, better performance might be achieved on less liquid stocks, such as mid- and small-cap equities, although a trade-off exists between liquidity and transaction costs. More liquid stocks typically incur lower transaction costs, whereas less liquid stocks may involve higher costs. In addition, superior performance may be observed in markets with lower penetration by algorithmic and high-frequency traders, where arbitrage opportunities are likely to be more abundant.

Third, transaction costs are incorporated at a rate of 0.05% per trade, which is a conservative estimate. At the time of writing, commissions as low as $0.0005 per transaction are charged by certain brokers for U.S. equities. Consequently, some of the strategies analyzed may exhibit forecasting ability in a zero transaction cost environment, which may prevail in the future. Conversely, it could be contended that a zero-cost environment might coincide with the absence of arbitrage opportunities, and thus with the disappearance of profitable momentum and contrarian strategies.

Fourth, it is assumed that the trader (or algorithm) operates with ample capital reserves. While this assumption may lead to an overestimation of the returns generated, it also underscores the effectiveness of the SSPA test and the luck-corrected peer performance analysis in filtering out strategies whose apparent outperformance is due to luck.

Fifth, the study relies on trading strategies that are relatively simple to implement, which implies that more sophisticated strategies may yield better results and potentially generate significant profits even after transaction costs. In this regard, it is argued that institutional algorithmic and high-frequency traders, equipped with more advanced strategies, are well-positioned to be able to exploit underreaction and overreaction in stock prices at high frequency.

Sixth, potential industry effects are not accounted for in this analysis. This limitation is acknowledged, and it is suggested that future research address this aspect.

Seventh, the data used in this study cover a 24-month period marked by considerable market volatility (specifically, the COVID-19 crash of February–March 2020 and the post-COVID recovery from April 2020 to December 2021). It is therefore possible that different results would be obtained under more stable market conditions. Further research encompassing a longer and more diverse observation period is encouraged to validate and extend the findings. It is also important to note that the scope of analysis is limited to two years due to the substantial computational time required to run all 288 trading strategies on tick-by-tick data.

Eighth, the analysis is limited to 28 highly liquid stocks listed on Nasdaq due to liquidity constraints inherent to trading in a high-frequency setting. As such, further investigations involving a broader set of stocks would be welcomed.

CONCLUSION

In a world where sophisticated retail traders increasingly rely on algorithms and real-time data, it is important to know whether classical anomalies, like buying recent winners or betting against recent losers, can genuinely help them make money or instead lose money once all real-world costs are considered. This study takes up that question by using tick-by-tick data for 28 U.S. blue-chip stocks over the 2020–2021 period. Specifically, it analyses the performance of momentum (relative strength) and contrarian (mean reversion) trading strategies based on significant market variations as determined by the historical return distribution to see whether some of the tested strategies can be profitable after applying restrictive conditions such as controlling for risk, correcting for data snooping, correcting for luck and taking transaction costs into account in a high-frequency setting. After performing these robustness checks, the results indicate that while some of the strategies outperform the benchmark strategy both before and after adjusting for risk, and while some strategies still outperform the benchmark strategy after correcting for data snooping and luck, none of them is able to beat the benchmark strategy once taking reasonable transaction costs into account. In other words, none of the strategies tested at the tick-by-tick level can generate significant profits after taking transaction costs into account. The results indicate that while very short-term opportunities seem to exist for momentum and contrarian traders, it is unlikely that retail traders can benefit from them.

AUTHOR CONTRIBUTIONS

Conceptualization: Floris Laly.
Data curation: Floris Laly.
Formal analysis: Floris Laly.
Methodology: Floris Laly.
Project administration: Floris Laly.
Software: Floris Laly.
Writing – original draft: Floris Laly.
Writing – review & editing: Floris Laly.

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APPENDIX A

Table A1. The 288 tested trading strategies

Momentum Strategies	Combinations
M1	Momentum, No Trend indicator, l dav, Percentile 99th, No Stop Loss
M2	Momentum, No Trend indicator, l dav, Percentile 95th, No Stop Loss
M3	Momentum, No Trend indicator, l dav, Percentile 90th, No Stop Loss
M4	Momentum, No Trend indicator, l dav, Percentile 99th, Stop Loss – l%
M5	Momentum, No Trend indicator, l day, Percentile 95th, Stop Loss – l%
M6	Momentum, No Trend indicator, l dav, Percentile 90th, Stop Loss – l%
M7	Momentum, No Trend indicator, l dav, Percentile 99th, Stop Loss – 2%
M8	Momentum, No Trend indicator, l dav, Percentile 95th, Stop Loss – 2%
M9	Momentum, No Trend indicator, l dav, Percentile 90th, Stop Loss – 2%
M10	Momentum, VWAP, l dav, Percentile 99th, No Stop Loss
M1l	Momentum, VWAP, l dav, Percentile 95th, No Stop Loss
M12	Momentum, VWAP, l dav, Percentile 90th, No Stop Loss
M13	Momentum, VWAP, l dav, Percentile 99th, Stop Loss – l%
M14	Momentum, VWAP, l dav, Percentile 95th, Stop Loss – l%
M15	Momentum, VWAP, l dav, Percentile 90th, Stop Loss – 1%
M16	Momentum, VWAP, l dav, Percentile 99th, Stop Loss – 2%
M17	Momentum, VWAP, l dav, Percentile 95th, Stop Loss – 2%
M18	Momentum, VWAP, l dav, Percentile 90th, Stop Loss – 2%
M19	Momentum, MA Crossing 5-13, l dav, Percentile 99th, No Stop Loss
M20	Momentum, MACrossine5-13, l dav, Percentile 95th, No Stop Loss
M21	Momentum, MA Crossing 5-13, l dav, Percentile 90th, No Stop Loss
M22	Momentum, MA Crossing 5-13, l day, Percentile 99th, Stop Loss – l%
M23	Momentum, MA Crossing 5-13, l dav, Percentile 95th, Stop Loss – l%
M24	Momentum, MA Crossing 5-13, l dav, Percentile 90th, Stop Loss – l%
M25	Momentum, MA Crossing 5-13, l dav, Percentile 99th, Stop Loss – 2%
M26	Momentum, MA Crossing 5-13, l dav, Percentile 95th, Stop Loss – 2%
M27	Momentum, MA Crossing 5-13, l dav, Percentile 90th, Stop Loss – 2%
M28	Momentum, MA Crossing 5-21, l dav, Percentile 99th, No Stop Loss
M29	Momentum, MA Crossing 5-21, l dav, Percentile 95th, No Stop Loss
M30	Momentum, MA Crossing 5-21, l dav, Percentile 90th, No Stop Loss
M31	Momentum, MA Crossing 5-21, l dav, Percentile 99th, Stop Loss – l%
M32	Momentum, MA Crossing 5-21, l dav, Percentile 95th, Stop Loss – l%
M33	Momentum, MA Crossing 5-21, l dav, Percentile 90th, Stop Loss – l%
M34	Momentum, MA Crossing 5-21, l dav, Percentile 99th, Stop Loss – 2%
M35	Momentum, MA Crossing 5-21, l dav, Percentile 95th, Stop Loss – 2%
M36	Momentum, MA Crossing 5-21, l dav, Percentile 90th, Stop Loss – 2%
M37	Momentum, No Trend indicator, 5 davs, Percentile 99th, No Stop Loss
M38	Momentum, No Trend indicator, 5 davs, Percentile 95th, No Stop Loss
M39	Momentum, No Trend indicator, 5 davs, Percentile 90th, No Stop Loss
M40	Momentum, No Trend indicator, 5 davs, Percentile 99th, Stop Loss – l%
M41	Momentum, No Trend indicator, 5 davs, Percentile 95th, Stop Loss – l%
M42	Momentum, No Trend indicator, 5 davs, Percentile 90th, Stop Loss – l%
M43	Momentum, No Trend indicator, 5 davs, Percentile 99th, Stop Loss – 2%
M44	Momentum, No Trend indicator, 5 davs, Percentile 95th, Stop Loss – 2%
M45	Momentum, No Trend indicator, 5 davs, Percentile 90th, Stop Loss – 2%
M46	Momentum, VWAP, 5 davs, Percentile 99th No Stop Loss
M47	Momentum, VWAP, 5 davs, Percentile 95th, No Stop Loss
M48	Momentum, VWAP, 5 davs, Percentile 90th, No Stop Loss
M49	Momentum, VWAP, 5 davs, Percentile 99th, Stop Loss – l%
M50	Momentum, VWAP, 5 davs, Percentile 95th, Stop Loss – l%
M51	Momentum, VWAP, 5 davs, Percentile 90th, Stop Loss – l%
M52	Momentum, VWAP, 5 davs, Percentile 99th, Stop Loss – 2%

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Table A1 (cont.). The 288 tested trading strategies

Momentum Strategies	Combinations
M53	Momentum, VWAP, 5 davs, Percentile 95th, Stop Loss – 2%
M54	Momentum, VWAP, 5 davs, Percentile 90th, Stop Loss – 2%
M55	Momentum, MA Crossing 5-13, 5 davs, Percentile 99th, No Stop Loss
M56	Momentum, MA Crossing 5-13, 5 davs, Percentile 95th, No Stop Loss
M57	Momentum, MA Crossing 5-13, 5 davs, Percentile 90th, No Stop Loss
M58	Momentum, MA Crossing 5-13, 5 davs, Percentile 99th, Stop Loss – l%
M59	Momentum, MA Crossing 5-13, 5 davs, Percentile 95th, Stop Loss – l%
M60	Momentum, MA Crossing 5-13, 5 davs, Percentile 90th, Stop Loss – l%
M61	Momentum, MA Crossing 5-13, 5 davs, Percentile 99th, Stop Loss – 2%
M62	Momentum, MA Crossing 5-13, 5 davs, Percentile 95th, Stop Loss – 2%
M63	Momentum, MA Crossing 5-13, 5 davs, Percentile 90th, Stop Loss – 2%
M64	Momentum, MA Crossing 5-21, 5 davs, Percentile 99th, No Stop Loss
M65	Momentum, MA Crossing 5-21, 5 davs, Percentile 95th, No Stop Loss
M66	Momentum, MA Crossing 5-21, 5 davs, Percentile 90th, No Stop Loss
M67	Momentum, MA Crossing 5-21, 5 davs, Percentile 99th, Stop Loss – l%
M68	Momentum, MA Crossing 5-21, 5 davs, Percentile 95th, Stop Loss – l%
M69	Momentum, MA Crossing 5-21, 5 davs, Percentile 90th, Stop Loss – l%
M70	Momentum, MA Crossing 5-21, 5 davs, Percentile 99th, Stop Loss – 2%
M71	Momentum, MA Crossing 5-21, 5 davs, Percentile 95th, Stop Loss – 2%
M72	Momentum, MA Crossing 5-21, 5 davs, Percentile 90th, Stop Loss – 2%
M73	Momentum, No Trend indicator, 10 davs, Percentile 99th, No Stop Loss
M74	Momentum, No Trend indicator, 10 davs, Percentile 95th, No Stop Loss
M75	Momentum, No Trend indicator, 10 davs, Percentile 90th, No Stop Loss
M76	Momentum, No Trend indicator, 10 davs, Percentile 99th, Stop Loss – l%
M77	Momentum, No Trend indicator, 10 davs, Percentile 95th, Stop Loss – l%
M78	Momentum, No Trend indicator, 10 davs, Percentile 90th, Stop Loss – l%
M79	Momentum, No Trend indicator, 10 davs, Percentile 99th, Stop Loss – 2%
M80	Momentum, No Trend indicator, 10 davs, Percentile 95th, Stop Loss – 2%
M81	Momentum, No Trend indicator, 10 davs, Percentile 90th, Stop Loss – 2%
M82	Momentum, VWAP, 10 davs, Percentile 99th, No Stop Loss
M83	Momentum, VWAP, 10 davs, Percentile 95th, No Stop Loss
M84	Momentum, VWAP, 10 davs, Percentile 90th, No Stop Loss
M85	Momentum, VWAP, 10days, Percentile 99th, Stop Loss – l%
M86	Momentum, VWAP, 10 davs, Percentile 95th Stop Loss – l%
M87	Momentum, VWAP, 10 davs, Percentile 90th, Stop Loss – l%
M88	Momentum, VWAP, 10 davs, Percentile 99th, Stop Loss – 2%
M89	Momentum, VWAP, 10 davs, Percentile 95th, Stop Loss – 2%
M90	Momentum, VWAP, 10 davs, Percentile 90th, Stop Loss – 2%
M91	Momentum, MA Crossing 5-13, 10 davs, Percentile 99th, No Stop Loss
M92	Momentum, MA Crossing 5-13, 10 davs, Percentile 95th, No Stop Loss
M93	Momentum, MA Crossing 5-13, 10 davs, Percentile 90th, No Stop Loss
M94	Momentum, MA Crossing 5-13, 10 davs, Percentile 99th, Stop Loss – l%
M95	Momentum, MA Crossing 5-13, 10 davs, Percentile 95th Stop Loss – l%
M96	Momentum, MA Crossing 5-13, 10 davs, Percentile 90th, Stop Loss – l%
M97	Momentum, MA Crossing 5-13, 10 davs, Percentile 99th, Stop Loss – 2%
M98	Momentum, MA Crossing 5-13, 10 davs, Percentile 95th, Stop Loss – 2%
M99	Momentum, MA Crossing 5-13, 10 davs, Percentile 90th, Stop Loss – 2%
M100	Momentum, MA Crossing 5-21, 10 davs, Percentile 99th, No Stop Loss
M101	Momentum, MA Crossing 5-21, 10 davs, Percentile 95th, No Stop Loss
M102	Momentum, MA Crossing 5-21, 10 davs, Percentile 90th, No Stop Loss
M103	Momentum, MA Crossing 5-21, 10 davs, Percentile 99th, Stop Loss – l%
M104	Momentum, MA Crossing 5-21, 10 davs, Percentile 95th, Stop Loss – l%
M105	Momentum, MA Crossing 5-21, 10 davs, Percentile 90th, Stop Loss – l%
M106	Momentum, MA Crossing 5-21, 10 davs, Percentile 99th, Stop Loss – 2%

Table A1 (cont.). The 288 tested trading strategies

Momentum Strategies	Combinations
M107	Momentum, MA Crossing 5-21, 10 davs, Percentile 95th, Stop Loss – 2%
M108	Momentum, MA Crossing 5-21, 10 davs, Percentile 90th, Stop Loss – 2%
M109	Momentum, No Trend indicator, 20 davs, Percentile 99th, No Stop Loss
MHO	Momentum, No Trend indicator, 20 davs, Percentile 95th, No Stop Loss
Mill	Momentum, No Trend indicator, 20 davs, Percentile 90th, No Stop Loss
M112	Momentum, No Trend indicator, 20 davs, Percentile 99th, Stop Loss – l%
M113	Momentum, No Trend indicator, 20 davs, Percentile 95th, Stop Loss – l%
M114	Momentum, No Trend indicator, 20 davs, Percentile 90th, Stop Loss – l%
M115	Momentum, No Trend indicator, 20 davs, Percentile 99th, Stop Loss – 2%
M116	Momentum, No Trend indicator, 20 davs, Percentile 95th, Stop Loss – 2%
M117	Momentum, No Trend indicator, 20 davs, Percentile 90th, Stop Loss – 2%
M118	Momentum, VWAP, 20 davs, Percentile 99th, No Stop Loss
M119	Momentum, VWAP, 20 davs, Percentile 95th, No Stop Loss
M120	Momentum, VWAP, 20 davs, Percentile 90th, No Stop Loss
M121	Momentum, VWAP, 20days, Percentile 99th, Stop Loss – l%
M122	Momentum, VWAP, 20 davs, Percentile 95th, Stop Loss – l%
M123	Momentum, VWAP, 20 davs, Percentile 90th, Stop Loss – l%
M124	Momentum, VWAP, 20 davs, Percentile 99th, Stop Loss – 2%
M125	Momentum, VWAP, 20 davs, Percentile 95th, Stop Loss – 2%
M126	Momentum, VWAP, 20 davs, Percentile 90th, Stop Loss – 2%
M127	Momentum, MA Crossing 5-13, 20 davs, Percentile 99th, No Stop Loss
M128	Momentum, MA Crossing 5-13, 20 davs, Percentile 95th, No Stop Loss
M129	Momentum, MA Crossing 5-13, 20 davs, Percentile 90th, No Stop Loss
M130	Momentum, MA Crossing 5-13, 20 davs, Percentile 99th, Stop Loss – l%
M131	Momentum, MA Crossing 5-13, 20 davs, Percentile 95th, Stop Loss – l%
M132	Momentum, MA Crossing 5-13, 20 davs, Percentile 90th, Stop Loss – l%
M133	Momentum, MA Crossing 5-13, 20 davs, Percentile 99th, Stop Loss – 2%
M134	Momentum, MA Crossing 5-13, 20 davs, Percentile 95th, Stop Loss – 2%
M135	Momentum, MA Crossing 5-13, 20 davs, Percentile 90th, Stop Loss – 2%
M136	Momentum, MA Crossing 5-21, 20 davs, Percentile 99th, No Stop Loss
M137	Momentum, MA Crossing 5-21, 20 davs, Percentile 95th, No Stop Loss
M138	Momentum, MA Crossing 5-21, 20 davs, Percentile 90th, No Stop Loss
M139	Momentum, MA Crossing 5-21, 20 davs, Percentile 99th, Stop Loss – l%
M140	Momentum, MA Crossing 5-21, 20 davs, Percentile 95th, Stop Loss – l%
M141	Momentum, MA Crossing 5-21, 20 davs, Percentile 90th, Stop Loss – l%
M142	Momentum, MA Crossing 5-21, 20 davs, Percentile 99th, Stop Loss – 2%
M143	Momentum, MA Crossing 5-21, 20 davs, Percentile 95th, Stop Loss – 2%
M144	Momentum, MA Crossing 5-21, 20 davs, Percentile 90th, Stop Loss – 2%

Contrarian Strategies	Combinations
C1	Contrarian, No Trend indicator, l dav, Percentile lst, No Stop Loss
C2	Contrarian, No Trend indicator, l dav, Percentile 5th, No Stop Loss
C3	Contrarian, No Trend indicator, l dav, Percentile l0th, No Stop Loss
C4	Contrarian, No Trend indicator, l dav, Percentile lst, Stop Loss – l%
C5	Contrarian, No Trend indicator, l dav, Percentile 5th, Stop Loss – l%
C6	Contrarian, No Trend indicator, l dav, Percentile l0th, Stop Loss – l%
C7	Contrarian, No Trend indicator, l dav, Percentile lst, Stop Loss – 2%
C8	Contrarian, No Trend indicator, l dav, Percentile 5th, Stop Loss – 2%
C9	Contrarian, No Trend indicator, l dav, Percentile l0th, Stop Loss – 2%
C10	Contrarian, VWAP, l dav, Percentile lst, No Stop Loss
C11	Contrarian, VWAP, l dav, Percentile 5th, No Stop Loss
C12	Contrarian, VWAP, l dav, Percentile l0th, No Stop Loss
C13	Contrarian, VWAP, l dav, Percentile lst, Stop Loss – l%
C14	Contrarian, VWAP, l dav, Percentile 5th, Stop Loss – l%

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Table A1 (cont.). The 288 tested trading strategies

Contrarian Strategies	Combinations
C15	Contrarian, VWAP, l dav, Percentile l0th, Stop Loss – l%
C16	Contrarian, VWAP, l dav, Percentile lst, Stop Loss – 2%
C17	Contrarian, VWAP, l dav, Percentile 5th, Stop Loss – 2%
C18	Contrarian, VWAP, l dav, Percentile l0th, Stop Loss – 2%
C19	Contrarian, MA Crossing 5-13, l dav, Percentile lst, No Stop Loss
C20	Contrarian, MACrossine5-13, l dav, Percentile 5th, No Stop Loss
C21	Contrarian, MA Crossing 5-13, l day, Percentile l0th, No Stop Loss
C22	Contrarian, MA Crossing 5-13, l dav, Percentile lst, Stop Loss – l%
C23	Contrarian, MA Crossing 5-13, l dav, Percentile 5th, Stop Loss – l%
C24	Contrarian, MA Crossing 5-13, l dav, Percentile l0th, Stop Loss – l%
C25	Contrarian, MA Crossing 5-13, l dav, Percentile lst, Stop Loss – 2%
C26	Contrarian, MA Crossing 5-13, l dav, Percentile 5th, Stop Loss – 2%
C27	Contrarian, MA Crossing 5-13, l dav, Percentile l0th, Stop Loss – 2%
C28	Contrarian, MA Crossing 5-21, l dav, Percentile lst, No Stop Loss
C29	Contrarian, MA Crossing 5-21, l dav, Percentile 5th, No Stop Loss
C30	Contrarian, MA Crossing 5-21, l dav, Percentile l0th, No Stop Loss
C31	Contrarian, MA Crossing 5-21, l dav, Percentile lst, Stop Loss – l%
C32	Contrarian, MA Crossing 5-21, l dav, Percentile 5th, Stop Loss – l%
C33	Contrarian, MA Crossing 5-21, l dav, Percentile l0th, Stop Loss – l%
C34	Contrarian, MA Crossing 5-21, l dav, Percentile lst, Stop Loss – 2%
C35	Contrarian, MA Crossing 5-21, l dav, Percentile 5th, Stop Loss – 2%
C36	Contrarian, MA Crossing 5-21, l dav, Percentile l0th, Stop Loss – 2%
C37	Contrarian, No Trend indicator, 5 davs, Percentile lst, No Stop Loss
C38	Contrarian, No Trend indicator, 5 davs, Percentile 5th, No Stop Loss
C39	Contrarian, No Trend indicator, 5 davs, Percentile l0th, No Stop Loss
C40	Contrarian, No Trend indicator, 5 davs, Percentile lst, Stop Loss – l%
C41	Contrarian, No Trend indicator, 5 davs, Percentile 5th, Stop Loss – l%
C42	Contrarian, No Trend indicator, 5 davs, Percentile l0th, Stop Loss – l%
C43	Contrarian, No Trend indicator, 5 davs, Percentile lst, Stop Loss – 2%
C44	Contrarian, No Trend indicator, 5 davs, Percentile 5th, Stop Loss – 2%
C45	Contrarian, No Trend indicator, 5 davs, Percentile l0th, Stop Loss – 2%
C46	Contrarian, VWAP, 5 davs, Percentile lst, No Stop Loss
C47	Contrarian, VWAP, 5 davs, Percentile 5th, No Stop Loss
C48	Contrarian, VWAP, 5 davs, Percentile l0th, No Stop Loss
C49	Contrarian, VWAP, 5 davs, Percentile lst, Stop Loss – l%
C50	Contrarian, VWAP, 5 davs, Percentile 5th, Stop Loss – l%
C51	Contrarian, VWAP, 5 davs, Percentile l0th, Stop Loss – l%
C52	Contrarian, VWAP, 5 davs, Percentile lst, Stop Loss – 2%
C53	Contrarian, VWAP, 5 davs, Percentile 5th, Stop Loss – 2%
C54	Contrarian, VWAP, 5 davs, Percentile l0th, Stop Loss – 2%
C55	Contrarian, MA Crossing 5-13, 5 davs, Percentile lst, No Stop Loss
C56	Contrarian, MA Crossing 5-13, 5 davs, Percentile 5th, No Stop Loss
C57	Contrarian, MA Crossing 5-13, 5days, Percentile l0th, No Stop Loss
C58	Contrarian, MA Crossing 5-13, 5 davs, Percentile lst, Stop Loss – l%
C59	Contrarian, MA Crossing 5-13, 5 davs, Percentile 5th, Stop Loss – l%
C60	Contrarian, MA Crossing 5-13, 5 davs, Percentile l0th, Stop Loss – l%
C61	Contrarian, MA Crossing 5-13, 5 davs, Percentile lst, Stop Loss – 2%
C62	Contrarian, MA Crossing 5-13, 5 davs, Percentile 5th, Stop Loss – 2%
C63	Contrarian, MA Crossing 5-13, 5 davs, Percentile l0th, Stop Loss – 2%
C64	Contrarian, MA Crossing 5-21, 5 davs, Percentile lst, No Stop Loss
C65	Contrarian, MA Crossing 5-21, 5 davs, Percentile 5th, No Stop Loss
C66	Contrarian, MA Crossing 5-21, 5 davs, Percentile l0th, No Stop Loss
C67	Contrarian, MA Crossing 5-21, 5 davs, Percentile lst, Stop Loss – l%
C68	Contrarian, MA Crossing 5-21, 5 davs, Percentile 5th, Stop Loss – l%

Table A1 (cont.). The 288 tested trading strategies

Contrarian Strategies	Combinations
C69	Contrarian, MA Crossing 5-21, 5 davs, Percentile l0th, Stop Loss – l%
C70	Contrarian, MA Crossing 5-21, 5 davs, Percentile lst, Stop Loss – 2%
C71	Contrarian, MA Crossing 5-21, 5 davs, Percentile 5th, Stop Loss – 2%
C72	Contrarian, MA Crossing 5-21, 5 davs, Percentile l0th, Stop Loss – 2%
C73	Contrarian, No Trend indicator, 10 davs, Percentile lst, No Stop Loss
C74	Contrarian, No Trend indicator, 10 davs, Percentile 5th, No Stop Loss
C75	Contrarian, No Trend indicator, 10 davs, Percentile l0th, No Stop Loss
C76	Contrarian, No Trend indicator, 10 davs, Percentile lst, Stop Loss – l%
C77	Contrarian, No Trend indicator, 10 davs, Percentile 5th, Stop Loss – l%
C78	Contrarian, No Trend indicator, 10days, Percentile l0th, Stop Loss – l%
C79	Contrarian, No Trend indicator, 10 davs, Percentile lst, Stop Loss – 2%
C80	Contrarian, No Trend indicator, 10 davs, Percentile 5th, Stop Loss – 2%
C81	Contrarian, No Trend indicator, 10 davs, Percentile l0th, Stop Loss – 2%
C82	Contrarian, VWAP, 10 davs, Percentile lst, No Stop Loss
C83	Contrarian, VWAP, 10 davs, Percentile 5th, No Stop Loss
C84	Contrarian, VWAP, 10 davs, Percentile l0th, No Stop Loss
C85	Contrarian, VWAP, 10 davs, Percentile lst, Stop Loss – l%
C86	Contrarian, VWAP, 10 davs, Percentile 5th, Stop Loss – l%
C87	Contrarian, VWAP, 10 davs, Percentile l0th, Stop Loss – l%
C88	Contrarian, VWAP, 10 davs, Percentile lst, Stop Loss – 2%
C89	Contrarian, VWAP, 10 davs, Percentile 5th, Stop Loss – 2%
C90	Contrarian, VWAP, 10 davs, Percentile l0th, Stop Loss – 2%
C91	Contrarian, MA Crossing 5-13, 10 davs, Percentile lst, No Stop Loss
C92	Contrarian, MA Crossing 5-13, 10 davs, Percentile 5th, No Stop Loss
C93	Contrarian, MA Crossing 5-13, 10 davs, Percentile l0th, No Stop Loss
C94	Contrarian, MA Crossing 5-13, 10 davs, Percentile lst, Stop Loss – l%
C95	Contrarian, MA Crossing 5-13, 10 davs, Percentile 5th, Stop Loss – l%
C96	Contrarian, MA Crossing 5-13, 10 davs, Percentile l0th, Stop Loss – l%
C97	Contrarian, MA Crossing 5-13, 10 davs, Percentile lst, Stop Loss – 2%
C98	Contrarian, MA Crossing 5-13, 10 davs, Percentile 5th, Stop Loss – 2%
C99	Contrarian, MA Crossing 5-13, 10 davs, Percentile l0th, Stop Loss – 2%
C100	Contrarian, MA Crossing 5-21, 10 davs, Percentile lst, No Stop Loss
C101	Contrarian, MA Crossing 5-21, 10 davs, Percentile 5th, No Stop Loss
C102	Contrarian, MA Crossing 5-21, 10 davs, Percentile l0th, No Stop Loss
C103	Contrarian, MA Crossing 5-21, 10 davs, Percentile lst, Stop Loss – l%
C104	Contrarian, MA Crossing 5-21, 10 davs, Percentile 5th, Stop Loss – l%
C105	Contrarian, MA Crossing 5-21, 10 davs, Percentile l0th, Stop Loss – l%
C106	Contrarian, MA Crossing 5-21, 10 davs, Percentile lst, Stop Loss – 2%
C107	Contrarian, MA Crossing 5-21, 10 davs, Percentile 5th, Stop Loss – 2%
C108	Contrarian, MA Crossing 5-21, 10 davs, Percentile l0th, Stop Loss – 2%
C109	Contrarian, No Trend indicator, 20 davs, Percentile lst, No Stop Loss
C110	Contrarian, No Trend indicator, 20 davs, Percentile 5th, No Stop Loss
C111	Contrarian, No Trend indicator, 20 davs, Percentile l0th, No Stop Loss
C112	Contrarian, No Trend indicator, 20 davs, Percentile lst, Stop Loss – l%
C113	Contrarian, No Trend indicator, 20 davs, Percentile 5th, Stop Loss – l%
C114	Contrarian, No Trend indicator, 20days, Percentile l0th, Stop Loss – l%
C115	Contrarian, No Trend indicator, 20 davs, Percentile lst Stop Loss – 2%
C116	Contrarian, No Trend indicator, 20 davs, Percentile 5th, Stop Loss – 2%
C117	Contrarian, No Trend indicator, 20 davs, Percentile l0th, Stop Loss – 2%
C118	Contrarian, VWAP, 20 davs, Percentile lst, No Stop Loss
C119	Contrarian, VWAP, 20 davs, Percentile 5th, No Stop Loss
C120	Contrarian, VWAP, 20 davs, Percentile l0th, No Stop Loss
C121	Contrarian, VWAP, 20 davs, Percentile lst, Stop Loss – l%
C122	Contrarian, VWAP, 20 davs, Percentile 5th, Stop Loss – l%

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Table A1 (cont.). The 288 tested trading strategies

Contrarian Strategies	Combinations
C123	Contrarian, VWAP, 20 davs, Percentile l0th, Stop Loss – l%
C124	Contrarian, VWAP, 20 davs, Percentile lst, Stop Loss – 2%
C125	Contrarian, VWAP, 20 davs, Percentile 5th, Stop Loss – 2%
C126	Contrarian, VWAP, 20 davs, Percentile l0th, Stop Loss – 2%
C127	Contrarian, MA Crossing 5-13, 20 davs, Percentile lst, No Stop Loss
C128	Contrarian, MA Crossing 5-13, 20 davs, Percentile 5th, No Stop Loss
C129	Contrarian, MA Crossing 5-13, 20 davs, Percentile l0th, No Stop Loss
C130	Contrarian, MA Crossing 5-13, 20 davs, Percentile lst, Stop Loss – l%
C131	Contrarian, MA Crossing 5-13, 20 davs, Percentile 5th, Stop Loss – l%
C132	Contrarian, MA Crossing 5-13, 20 davs, Percentile l0th, Stop Loss – l%
C133	Contrarian, MA Crossing 5-13, 20 davs, Percentile lst, Stop Loss – 2%
C134	Contrarian, MA Crossing 5-13, 20 davs, Percentile 5th, Stop Loss – 2%
C135	Contrarian, MA Crossing 5-13, 20 davs, Percentile l0th, Stop Loss – 2%
C136	Contrarian, MA Crossing 5-21, 20 davs, Percentile lst, No Stop Loss
C137	Contrarian, MA Crossing 5-21, 20 davs, Percentile 5th, No Stop Loss
C138	Contrarian, MA Crossing 5-21, 20 davs, Percentile l0th, No Stop Loss
C139	Contrarian, MA Crossing 5-21, 20 davs, Percentile lst, Stop Loss – l%
C140	Contrarian, MA Crossing 5-21, 20 davs, Percentile 5th, Stop Loss – l%
C141	Contrarian, MA Crossing 5-21, 20 davs, Percentile l0th, Stop Loss – l%
C142	Contrarian, MA Crossing 5-21, 20 davs, Percentile lst, Stop Loss – 2%
C143	Contrarian, MA Crossing 5-21, 20 davs, Percentile 5th, Stop Loss – 2%
C144	Contrarian, MA Crossing 5-21, 20 davs, Percentile l0th, Stop Loss – 2%