

# Skewness Preference and the Popularity of Technical Analysis

Preliminary. Comments welcome.

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## ABSTRACT

Theoretical and empirical research has cast doubt on the profitability of technical trading strategies. We propose a simple model of how investors perceive the profits from technical trading, and show that investors' preference for positive skewness caters to the popularity of technical analysis. In particular, prospect theory helps explain the puzzle of why investors make extensive use of technical analysis. While behavioral finance is often invoked as the theoretical foundation of technical analysis, this paper shows that ideas from behavioral finance may rather explain the popularity of technical analysis despite its lack of a theoretical foundation and empirical success.

**Keywords:** Behavioral Finance, Market Timing, Moving Average, Prospect Theory, Skewness Preference, Technical Analysis

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# I. Introduction

Technical analysis – predicting future prices from past prices alone – is popular among institutional and individual investors alike. An extensive academic literature has investigated the profitability, with mostly negative conclusions. Therefore, the popularity of technical analysis constitutes a puzzle. The aim of this paper is to shed new light on this puzzle by providing an explanation that does not root in the (alleged) profitability of technical analysis. Instead, we offer a behavioral, or risk-preference based, explanation for the popularity of technical analysis.

Our argument roots in the psychology of how investors experience a technical trade. To this means, we propose a simple model of how an investor assesses a trading rule. The model takes into account ideas from narrow framing and mental accounting (Shefrin and Statman 1985, Thaler 1985) that were taken up, for example, by Barberis and Xiong 2012. The investor receives utility from gains and losses realized from the individual trades. In particular, he has preferences over the gain/loss distribution that a technical strategy induces, and this distribution is evaluated myopically just like a (static) gamble. This simple way of evaluating a technical trading rule is similar to the way casino visitors evaluate gambling strategies in Barberis’ 2012 model of casino gambling.

We think that these assumptions are particularly suited for the study of technical trading strategies. In their contemplation to trade, technicians wait for an attractive price pattern. When an attractive pattern emerges, they go for it. Once they close the position, they assess the trade through the gain or loss realized. The trading signals are inferred from price charts that are independent of the investor’s portfolio, which induces strong narrow framing on the traded asset. Doing many individual trades, the technician experiences a large number of gains and losses for each trading rule. We study the properties of this experienced gain/loss distribution for 7700 technical trading rules applied to a large number of stocks and more than 60 years of price data, to answer the following questions: Do all these technical trading rules, irrespective of the stocks and time periods they are applied to, induce gain/loss distributions with common stochastic properties?

The answer is yes. Irrespective of the stock that is traded, when it is traded, and the particular trading rule used, the gain/loss distribution is strongly skewed to the right. Technical trading yields frequent small losses paired with infrequent but large gains. In a Black-Scholes setting, we show that long position technical trades on a stock result in the same skewness as mildly in-the-money call options on the stock. Technical trading yields much higher skewness than dispensing with market timing, i.e., when trading buy-and-hold. We also show that winning trades typically take a long time during which the trader can savor, while the many small losses typically come quickly.

The reason for this asymmetric return pattern lies in the asymmetric sales timing that basically all technical trading rules have in common. Designed for chasing trends, winning stocks are held while stocks that start to fall are sold quickly. Such a strategy results in significant skewness irrespective of the underlying stock price dynamics covered by the large data set. In particular, technical strategies result in significant skewness even if there is no actual trend that could be chased. We illustrate this through a simple model that compares technical trading to a trailing stop-loss strategy, i.e., a stop-loss strategy whose stop-loss level increases if the stock price increases.

The sale timing from technical trades is similar to that of trailing stop-loss. This effect is pervasive, even though not readily apparent from looking at the various trading rules and their graphical representations. For the famous moving average trading rule, we thus illustrate the similarity to trailing stop-loss explicitly.

We show that technical trading skews to the right irrespective of the market environment, as is also evidenced by the number of stocks and years we cover. The effect is also persistent across time-periods and robust to sorting by market capitalization. We also show that trading short upon technical sell signals skews to the right. One could think that, if long technical trading skews to the right, then short technical trading should skew to the left. This is the case, for example, when trading buy-and-hold a stock following a geometric Brownian motion. Trend-chasing results in right-skewed profits though for both long and short positions.

This paper offers a risk preference-based – rather than profitability-based – explanation for the popularity of technical analysis. We show that skewness preference may play a major role in the susceptibility to technical trading rules, which we believe has not been realized before. Thereby, the paper builds upon a large literature (discussed below) that provides evidence for skewness preference, and adds to another large strand of literature that points out the relevance of skewness preference for financial decisions. For example, underdiversification and technical trading may both be a consequence of investors’ skewness preference. By tracing down the attractiveness of technical trading to a well-understood and established phenomenon, skewness preference, this paper further helps to consolidate our understanding of the origins of suboptimal financial decisions.

After reviewing the related literature below, Section II illustrates our results for the famous moving average trading rule and simulated data, because perfect knowledge of the underlying price process allows for some particularly clear insights. Section III describes our price data and the technical trading strategies we analyze. Section IV gives the main result that technical trading skews to the right for a 7700 strategies applied to different stocks and time periods. Section V provides a number of additional results. We study the prospect theory utility from technical trading, discuss short-selling and contrarian strategies, different reference returns of the investor, and compare the skewness from trading technically with that from buying a call option. Section VI concludes. The appendix contains precise definitions of the trading rules and the parameters we use.

## A. *Related Literature*

Technical analysis is popular among institutional and individual investors alike. According to a recent survey of 678 fund managers by Menkhoff (2010), 86% of fund managers rely on technical analysis. For 26% of surveyed fund managers technical analysis is the most important criterion when making investment decisions. Lease, Lewellen, and Schlarbaum (1974) and Hoffmann and Shefrin (2014) analyze survey responses from individual investors matched with trading data, and report that 27% (32%) use technical analysis. Etheber (2014) and Etheber, Hackethal, and Meyer (2015) show trading volume increases when salient technical trading rules give signals, in particular for individual investors. The individual investors in each of these datasets trade frequently and, in line

with Barber and Odean (2000), occur high fees and earn significantly lower returns.

Technical analysis is futile in light of the efficient market hypothesis (Fama 1970). Against this criticism, technicians bring forward that research in behavioral finance has questioned market efficiency and conclude that “The evidence provided by behavioral finance supports the use of technical analysis.” cf. Kirkpatrick and Dahlquist (2011, p.50). Markets are not fully rational, assets may be mispriced, and such mispricings may exist for a long time. However, one of the two building blocks of behavioral finance (cf. (Barberis and Thaler, 2003, abstract)) is the limits to arbitrage literature, which established that mispricings are not easily exploited.<sup>1</sup> In particular, we are not aware of a behavioral theory that argues that mispricings can be exploited through technical trading strategies.

The alleged profitability of technical analysis is sometimes linked to momentum.<sup>2</sup> Since technical trading rules are defined on individual stock prices, though, they may only capture time-series momentum. They do not capture cross-sectional momentum as considered by Jegadeesh and Titman (1993, 2001).<sup>3</sup>

On the empirical side, Park and Irwin (2007) provide an overview of studies on the profitability of technical trading. They note that there are many older studies that report positively on technical analysis, but that they often suffer from econometric deficiencies and data-snooping bias. The majority of technical trading rules we study are taken from Sullivan, Timmermann, and White (1999), who study their profitability over more than 100 years of data. Their rules also include those in the well-cited study of Brock, Lakonishok, and LeBaron (1992) on which they comment (Sullivan et al. (1999, p.1683)): “the superior performance of the best technical trading rule is not repeated in the out-of-sample experiment covering the 10-year period 1987–1996. In this sample the results are completely reversed”.

Using a different methodology, Bajgrowicz and Scaillet (2012, p.457) also test our rules taken from Sullivan et al. (1999), and state: “The Brock et al. (1992) results should be viewed as a statistical anomaly, discovered ex post by extensive data snooping.” They conclude that “an investor would never have been able to select ex ante the future best performing rules. Moreover, even in-sample, the performance is completely offset by the introduction of low transaction costs. Overall, our results seriously call into question the economic value of technical trading rules that has been reported for early periods.” As such, even though not directly relevant for the conclusions of our paper, we are reluctant to assume that the trading rules we study are profitable.

As is also noted by (Roscoe and Howorth, 2009, p. 207), the finance literature on technical analysis almost exclusively concentrates on its profitability. There is very little research on *why*

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<sup>1</sup>The textbook on technical analysis by Kirkpatrick and Dahlquist (2011) does not mention “limits to arbitrage” on any of its 636 pages.

<sup>2</sup>Momentum may arise, for example, because investors under- and overreact to news (Barberis, Shleifer, and Vishny 1998 Hong and Stein 1999) or because of cognitive biases that affect their belief formation. Grinblatt and Han (2005) argue that investors’ tendency to hold on to assets that have lost in value and holding on to those that have gained in value may generate momentum in asset returns.

<sup>3</sup>Lewellen (2002) provides a decomposition of momentum in cross-sectional and time-series components. Moskowitz, Ooi, and Pedersen (2012) find time-series momentum in the prices of futures contracts.

technical analysis is prevalent (other than arguing that the reason is the alleged profitability). Based on personal interviews with twelve individual investors who use technical analysis, (Roscoe and Howorth, 2009, p. 220) conclude that “[charting] allows investors to make sense of, manage and participate in the markets.” Further reasons could be that technical signals are attention-grabbing and serve as simple heuristics. Using these heuristics avoids search costs and gives an illusion of knowledge and control (cf. Etheber et al. (2015)). Such attributes have been shown to matter for stock-trading in general (Barber and Odean, 2002, 2008). To the best of our knowledge, no academic paper has hypothesized or shown that technical trading caters individual risk preferences, and skewness preference in particular.

Skewness preference has long been established as an integral part of individual risk preferences. For example, Golec and Tamarkin (1998) find that skewness preference can explain betting behavior for horse-race bets. Ebert and Wiesen (2011) and Ebert (2015) provide experimental protocols to delineate risk aversion from skewness preference, and find strong evidence for skewness preference. Ebert (2015) disentangles right-skew and left-skew and finds that individuals desire right-skew as well as dislike left-skew. Successful descriptive theories of decision making under risk, like prospect theory (Kahneman and Tversky (1979)) or the salience theory of choice under risk (Bordalo, Gennaioli, and Shleifer (2012)) imply skewness preference. For cumulative prospect theory (Tversky and Kahneman (1992)) we verify explicitly that investors may find technical trading desirable even when the stock price does not follow trends and offers zero expected return.

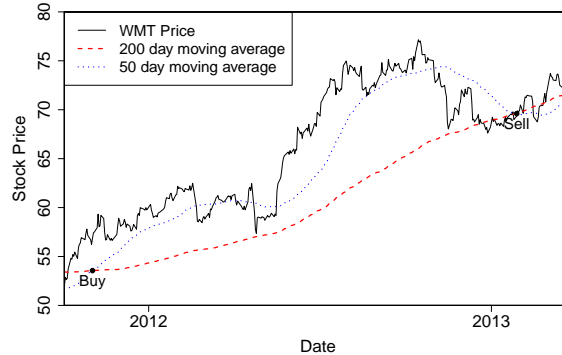
Our result that the popularity of technical analysis may be due to investors’ skewness preference adds to a substantial literature on the importance of skewness preference for financial behavior. Kumar (2009) finds that individual investors are more inclined to hold lottery-like stocks. Grinblatt and Keloharju (2009) find that overconfident and sensation-seeking investors trade more frequently. Conine and Tamarkin (1981) and Simkowitz and Beedles (1978) showed that skewness preference can explain underdiversification. In the latter two papers (in our paper), investors accept increased variance due to underdiversification (technical trading) to earn higher skewness. Mitton and Vorkink (2007) find empirical evidence that investors sacrifice mean-variance efficiency for skewness. Kraus and Litzenberger (1976) started an extensive literature over skewness in asset returns, which showed that skewed assets earn lower returns (e.g. Boyer, Mitton, and Vorkink (2010)). Barberis and Huang (2008) present a model where skewed securities are overpriced. Boyer and Vorkink (2014) find that lottery-like options earn lower returns.

## II. Preliminaries and introductory examples

### A. *The moving average trading rule*

Before we start, we first give a concrete example of a very popular technical trading rule: the double-crossover moving average (MA) strategy with a short-term moving average of 50 days and a

long-term moving average of 200 days.<sup>4</sup> The value of the 50-day (200-day) MA line at time  $t$  is given by the price average of the previous 50 (200) days. Figure 1 illustrates these moving averages for the Walmart common stock (ISIN: US9311421039) trajectory of daily closing prices on NYSE for the period 2008–2013. We observe that the 50-day MA is more responsive to recent price changes than the long-term MA. The MA strategy gives a *buy signal* when the short-term MA crosses the long-term MA *from below*, supposedly indicating an upward trend that abandons the long-term trend given by the long-term MA. Similarly, a *sell signal* occurs when the short-term MA crosses the long-term MA from above, indicating that the short-term upward trend is over. Figure 1 also gives the purchase and sale prices resulting from the MA strategy that goes long in the stock. We will consider short-sales later.



**Figure 1: Example buy and sell signal for Walmart from October 2011 to April 2013.** This graph shows the 50-day MA (dashed line) and 200-day MA (dotted line) lines computed from the Walmart stock's daily closing prices (solid line) on NYSE from October 2011 to April 2013. The position opens at 56.23 and closes at 69.

### B. A model of myopic stock trading

In the following, we propose a simple model of how an investor evaluates the attractiveness of a trading rule. The main ideas are that (i) the investor does mental accounting over individual trades (ii) evaluates each trade myopically, as the static gamble it generates (iii) the gain/loss distribution of this gamble is estimated as the one experienced from applying the trading rule in the past.

More specifically, the investor thinks of his investment history in terms of different investing episodes. Each episode is defined by the name of the investment, the purchase price, and the sale price; cf., e.g., Barberis and Xiong (2012). Rather than taking a portfolio view, the investor evaluates the individual trades in isolation. This view is consistent with Thaler's (1980) ideas of narrow framing and mental accounting. Shefrin and Statman (1985) argue that when an investor sells a stock, he closes a mental account that was opened when he first bought the stock. The moment of sale is therefore a natural time to evaluate the investment episode. The assumption of narrow framing seems particularly natural for technical trades, because all focus is on the past price

<sup>4</sup>This trading rule features a rather long holding time for the average trade. Following Sullivan et al. (1999), later on we will consider a wide range of parametrizations to include strategies with holding times of various lengths.

chart of a single stock (and not on summary statistics of a portfolio and how a newly purchased stock would add to it).

Suppose the investor invests an amount  $X_0$  in a stock at time  $t = 0$ , which is when he receives a buy signal from the technical rule he pursues. He sells the position when he receives the sell signal at time  $\tau$ , for  $X_\tau$ . Consider the net present value  $G_0$  of the gain (or loss) from his investment, which is given by:

$$G_0 = \frac{X_\tau}{1 + r_\tau} - X_0.$$

where  $r_\tau$  is the investor's reference return over the length of the trade. Note that  $r_\tau$  is a preference parameter that reflects, in a very simple way, how the investor adjusts for risk. Standard behavioral choices for  $r_\tau$  would be the risk-free rate, the market rate, or zero. In the latter case, the investor experiences a gain when he sells for more than what he bought for. Since (i) many individual brokerage accounts make the purchase price salient and compute changes in the position value relative to it and (ii) the time when a stock is bought may not be shown at all, we believe that zero is in fact a very relevant reference return for individual investors. Unless noted otherwise, we thus assume  $r_\tau = 0$ .

The empirical distribution of the gain  $G_0$  is obtained from all possible technical trades on a certain data set. In other words, this distribution is constructed from extensive sampling of individual trades and captures how the typical technical trade will turn out. In the simulation example below, the gains and losses are computed from a Monte Carlo sample. For real data, gains and losses are computed from the individual trades of different stocks in different time periods, to be collapsed into a single distribution. This distribution  $G_0$  is the investor's estimate of the gain/loss distribution that he will experience when trading technically, which is why we call it the *experienced distribution from technical trading*. We assume that the investor has preferences over this experienced distribution.

In our model, the investor evaluates technical trading rules similarly to the way gambling strategies are evaluated in Barberis' 2012 casino gambling model. For  $r_\tau = 0$ , the way we compute the gain/loss distribution of a technical strategy and the way Barberis computes the gain/loss distribution from a gambling strategy coincide. Both models imply that the investor is myopic over individual trades and the induced gambles. Since technical trades take longer than casino visits, we offer the investor a simple way to discount later gains from trading, which implies that he makes trading decisions according to a net present value criterion. (It turns out that different reference returns do not influence our results much, though.) In this paper, we are interested in whether the universe of technical trading rules generates gambles with similar properties, and whether these properties are attractive to behavioral investors.

### C. Simulation example

For simplicity, in this example we illustrate the experienced MA distribution for an exogenous price process. In particular, the stock price  $S_t$  follows a geometric Brownian motion

$$dS_t = S_t dt + \sigma S_t dW_t, \quad \text{with } S_0 > 0 \quad (1)$$

where  $W$  is a standard Brownian motion,  $S_0$  is the initial stock value and  $\sigma$  represents the volatility of the stock. The drift is zero such that the stock price follows a martingale. Studying the MA strategy in this abstract setup has some advantages as regards the interpretation of results. The geometric Brownian motion is Markovian and therefore, by assumption, the stock price does not move in trends. This renders the original purpose of trend-chasing trading strategies like MA moot. Due to the zero drift, Doob's optional sampling theorem implies that every trading strategy (and MA in particular) results in an expected profit of zero. Therefore, stock trading implies risk but no return. Therefore, no rational risk-averse expected utility maximizer would invest in this stock.

While the MA buy and sell signals are not predictive of the future stock price itself, trading MA is not without effect. The MA buy and sell signals determine which price histories lead to the purchase of the stock and which price developments after purchase result in an earlier or later sale. Put technically, technical trading strategies are not Markovian (irrespective of whether the stock price is). In particular, this path-dependent timing of buying and selling determines the length of a trade. The simulation setting allows for the study of the effect of this sales timing in isolation, thereby abstracting from the actual purpose of trading MA, which is catching trends and making profits.

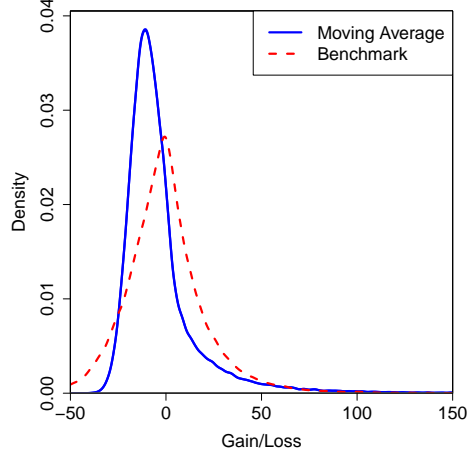
For comparative reasons, we also consider the experienced distribution from random stock trading according to a strategy that does not involve this path-dependent buy and sell timing. That is, the holding time of this *benchmark strategy* is identical in distribution to that of MA, but it is *independent* of the stock price evolution. In other words, the benchmark strategy is a *buy-and-hold strategy* with stochastic and exogenous holding time.<sup>5</sup> Therefore, the benchmark strategy abstracts from the particular buy and sell timing of the MA strategy. When applying a technical strategy and random trading to the same asset, a comparison between the gain/loss distributions nets out the impact of the asset dynamics, and isolates the impact of the technical strategy's characteristic market timing.

Figure 2 shows the MA gain/loss distribution (solid line) and the benchmark strategy (dashed line) computed using Monte-Carlo methods. Unless noted otherwise, we consider an initial investment of  $X_0 = 100$  so that gains and losses may likewise be interpreted as holding period percent returns. Figure 2 shows the MA gain/loss distribution (solid line) and the benchmark strategy (dashed line) computed using Monte-Carlo methods. While trading MA cannot generate excess return in this setting, it has a strong effect on the shape of the gain/loss distribution. Compared to

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<sup>5</sup>Considering a buy-and-hold strategy with a constant holding time, which would result in a log-normal distribution in the current setting, yields the same results and conclusions. The crucial difference is really the sales timing to be discussed below, which is path-dependent for MA and not path-dependent for random trading.





**Figure 2: Gain/Loss Distribution of the MA strategy for simulated data.** This graph shows the gain/loss distribution for the MA(50,200) strategy (solid line) and the benchmark strategy (dashed line) for an initial investment of  $X_0 = 100$ . The stock price follows a geometric Brownian motion with drift  $\mu = 0$  and a volatility of  $\sigma = 0.3$ . The expected profit of both strategies is zero, and the average holding time is 148 days. The third standardized central moment (the quantile-based skewness) is 5.52 (0.65) for the MA(50,200) strategy and 1.33 (0.22) for the benchmark strategy.

the benchmark strategy, the distribution of gains and losses is strongly skewed to the right. Trading MA reduces the probability of losses larger than 35 to almost zero (0.029%). At the same time, the probability of moderate losses is substantial: While the left tail of the distribution is short, it is also very thick. The right tail of the distribution, on the other hand, is long but very lean. The far right tail lies slightly above that of the benchmark strategy, while the probability of moderate gains is smaller. The third standardized central moments compute to 5.52 and 1.33 for the benchmark and the MA strategy, respectively. For the empirical part we will use the more robust, tail- or quantile-based measure of skewness by Hinkley (1975):<sup>6</sup>

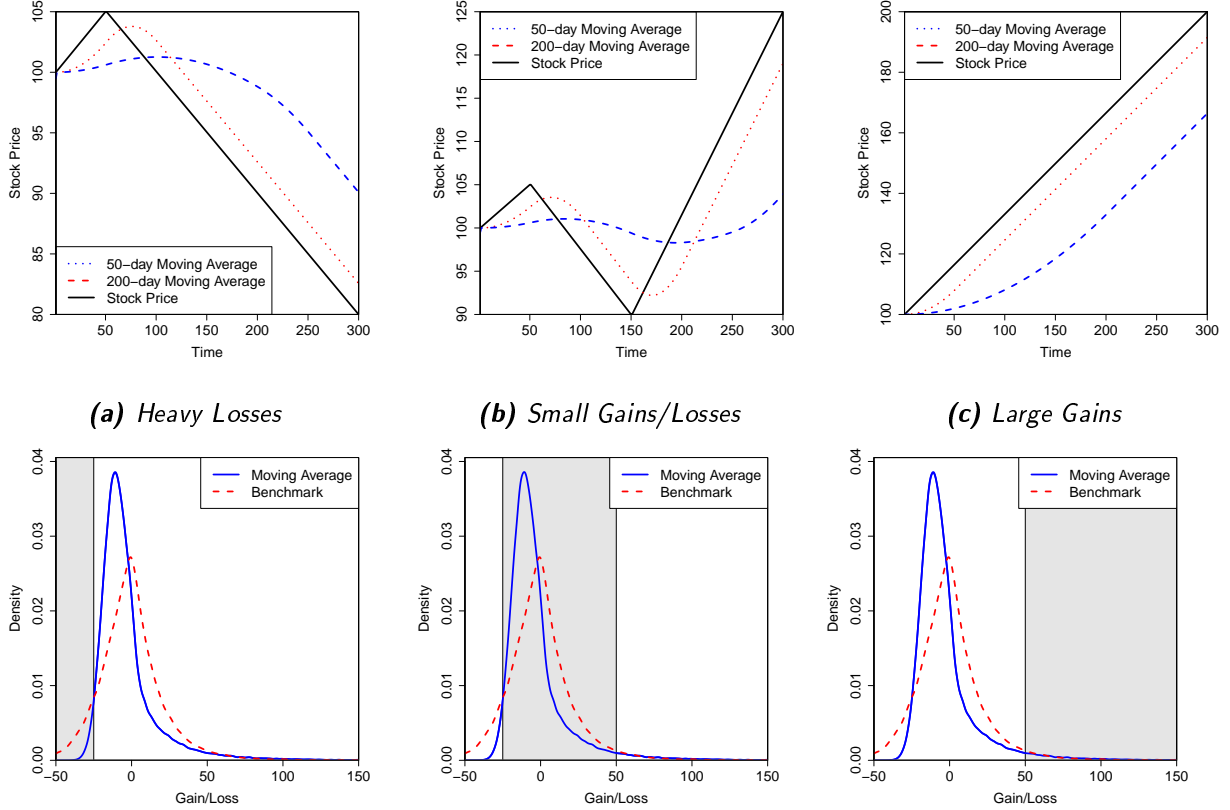
$$\nu := \frac{(P_{99} - P_{50}) - (P_{50} - P_1)}{P_{99} - P_1}$$

where  $P_j$  is the  $j$ th quantile of the gain/loss distribution. For the MA and benchmark gain/loss distribution, respectively,  $\nu_{\text{tech}} = 0.65$  and  $\nu_{\text{bench}} = 0.22$ .<sup>7</sup>

This pronounced skewness generated from trading MA offers a preference-based explanation for the popularity of MA trading: investors' strong preference for positive skewness (e.g., Kraus and Litzenberger (1976) for asset returns, Golec and Tamarkin (1998) for horse-race bets, and Ebert and Wiesen (2011) in a laboratory experiment). While expected utility theory and risk aversion cannot explain MA trading in the above setting, behavioral theories that imply a strong preference for skewness can. Below we illustrate this explicitly for cumulative prospect theory (CPT, Tversky and

<sup>6</sup>See e.g. Green and Hwang (2012) and Conrad, Dittmar, and Ghysels (2013) for applications in the finance literature.

<sup>7</sup>Just as the third standardized central moment, this measure is translation invariant and symmetric. Translation invariance implies that skewness is independent of the initial investment and is the same no matter whether we consider gains and losses, returns, or payoffs. Moreover, skewness is measured independently of mean and variance.



**Figure 3: Sales timing implied by trading MA.** The top row shows stylized stock price trajectories (solid line) and corresponding evolutions of 50-day (dotted line) and 200-day (dashed line) MA lines. The bottom row highlights in gray different parts of the MA(50,200) return distribution shown in Figure 2. The shape of the gain/loss distribution in the highlighted parts can be related to the time of sale that the MA strategy dictates for stock price evolutions as in the above panel.

Kahneman 1992). Moreover, the example shows that a strong preference for skewness can explain the popularity of technical analysis even when technical trading is not profitable. Therefore, while some investors might argue that they trade MA because they believe that prices move in trends, it may also be the case that they appreciate the right-skewed trading experience MA subtly imposes.

#### D. Intuition for why trading MA trading yields skewed profits

Why does trading MA skew the distribution of gains and losses to the right? Figure 3 provides the intuition for this result by considering three stylized stock price trajectories subsequent to a buy signal (shown in the upper panels of Figures 3a, 3b, and 3c).<sup>8</sup> For each of the three scenarios, the lower panel shows again the MA gain/loss distribution from Figure 2. Each scenario explains why this distribution differs in the highlighted, gray area from that of random trading as given by the benchmark strategy.

In the scenario depicted in Figure 3a, the stock price increases at first and then declines substan-

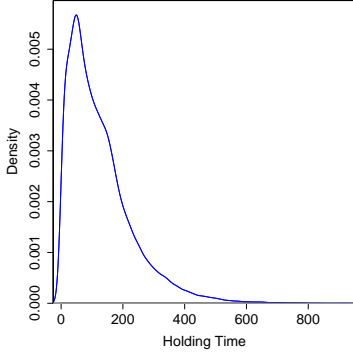
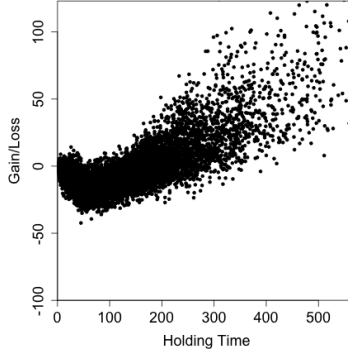
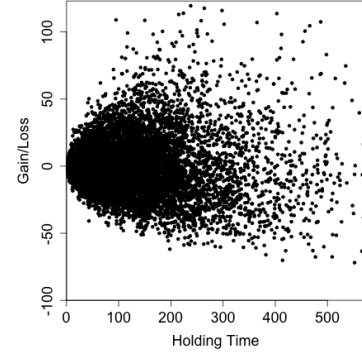
<sup>8</sup>On the 199 trading days prior to the buy signal, for each of the three scenarios, the stock traded constantly at 100 while on day 200 before the buy signal it traded at 50. Note that this indeed results in a buy signal at  $t = 0$ .

tially. The 50-day MA line picks up the initial upward trend and rises quickly, while the increase of the 200-day MA is less pronounced. Likewise, once the stock price starts to decline, the 50-day MA adjusts quickly and turns downward. The 200-day MA is yet increasing when the price decline starts; only slowly is the 200-day MA turning downward. The sell signal occurs when the 50-day MA crosses the 200-day MA at a value above 100. At that time, the stock price has decreased to about 98. Therefore, trading MA yields a small loss of  $-2$ . This first example illustrates that the MA strategy sells a stock after an episode of sufficiently rapid price decline, and explains why there is almost no probability mass on substantial losses (the highlighted area in the lower panel of Figure 3a). Only when prices decline steadily for a long time, at a rate small enough to avoid a sell-signal, MA may result in large losses.

The scenario in Figure 3b starts out just like that in Figure 3a, but after the decline in prices, from day 51 to 150, the stock recovers. As the stock has been sold by then, the investor misses upon the subsequently high returns. Instead, he has realized a moderate loss just as in the previous scenario. This explains why trading MA shifts probability mass from moderate gains to moderate losses. Again, whenever the stock price decreases sufficiently within a short period of time the stock is sold. Thus all scenarios with such an early price decline result in small losses. This latter effect takes probability mass from both severe losses (scenarios as depicted in the upper panel of Figure 3a) and moderate gains (scenarios as depicted in the upper panel of Figure 3b) to mild losses (the lower panel of Figure 3b). This explains the thick but short left tail of the MA return distribution. In fact, the probability of a loss between  $-30$  and  $0$  in Figure 2 equals  $69.25\%$ .

Finally, Figure 3c shows that for a continuously increasing price without large setbacks, the MA lines never cross. The sluggish 200-day MA never catches up with the 50-day MA line. Therefore, the fact that the MA strategy buys into the stock when the short-term MA lies above the long-term MA *and* that the short-term MA is more flexible in adjusting to recent stock price movements implies a systematic asymmetry in the way stocks are sold. Stocks that are constantly rising are never sold, which implies a pronounced upside. Losing stocks are sold quickly, which implies a restricted downside. Effectively, therefore, trading MA results in skewing the distribution of the overall trading experience strongly to the right.

The previous discussion provides us with several testable predictions not only for the gains or losses realized from MA trading, but also for the corresponding trade durations. Losing trades are typically short while the very successful trades will take a long time. Figure 4 confirms this intuition. The left panel shows the distribution of holding times for the MA trading rule and the right panel shows a scatter plot of the realized gain/loss (x-axis) and corresponding holding time (y-axis). Holding times from trading MA are themselves rather right-skewed. The mean (median) holding time is 126 (101) days. 90% of trades are shorter than 265 days and 5% of holding times are larger than 334 days. The scatter plot in Panel (b) illustrates that the success from trading and the holding time are indeed heavily correlated. Recall that this effect is not mechanical as we assumed a zero excess return in our simulations. We can see this from Panel (c), which illustrates the relationship between gains and holding time for the benchmark strategy. In that case, the

**(a) Holding Time Distribution****(b) MA Strategy****(c) Benchmark Strategy**

**Figure 4: Holding Times and Gains and losses.** Panel (a) shows the holding time distribution from MA(50,200) trades estimated from the simulated data. Panel (b) plots the gains and losses from MA trading together with the respective holding times. Panel (c) plots the gains and losses from the benchmark strategy together with the respective holding times. Holding times are heavily correlated with the gains obtained from the MA strategy ( $\rho = 72\%$ ). The benchmark strategy employs the same holding time distribution as the MA strategy, but does not feature the asymmetric sales timing of the MA strategy. Therefore, by definition the correlation between profits and holding times in Panel (c) is zero.

correlation is zero by definition: While the benchmark strategy and the MA strategy employ the same holding time distribution (shown in Panel (a)), the benchmark strategy does not feature the asymmetric sales timing of the MA strategy.

We thus observe the following stylized facts for trading MA(50,200):

- (i) trading MA results in frequent losses
- (ii) trading MA results only in small losses
- (iii) trading MA results infrequently in very large gains
- (iv) losing trades are quick while winning trades are lengthy

Note that the first three points are consistent with the observation that trading MA strongly skews to the right. The fourth point follows from our study of holding times. In summary, when trading MA, losses come frequently but are short and sweet (i.e., come quickly and in small amounts only).

#### *E. A simple model of trend-chasing and skewed profits*

We summarize the four stylized facts observed above within a simple model. The model shows that the experienced distribution from trading MA and other trend-chasing strategies studied below all feature a pronounced degree of skewness. As will be seen below, while the chart signals based on MAs, channels, bands, resistance levels, or other indicators that define the various technical strategies are very different, in the end they all follow the simple logic of the following simple model.

Consider an arithmetic random walk  $G = (G_t)_{t \in \mathbb{N}}$  that models the gain or loss from an investment. For simplicity, suppose the investor's reference return is  $r_\tau \equiv 0$  such that the investors perceives a trade's profitability independently of its length, as the difference between sale and purchase price:  $G_0 = X_\tau - X_0$ . With equal probability, in each period, the asset price increases or

decreases by 1. The investor believes that there is a trend at  $t = 0$  (even though we know that the random walk is Markovian and does not feature trends) and thus enters the gamble. His strategy is to sell when the trend is over, and the investor's indicator for this is simply that the asset price drops. Such a trading strategy is sometimes called trailing stop-loss or Azéma-Yor stopping time. Therefore, his investment strategy is to sell at  $\tau$  where

$$\tau = \inf\{t > 0 : G_t < G_{t-1}\}.$$

The distribution of selling the asset at price  $n$  is given by

$$\mathbb{P}(G_\tau = n) = \begin{cases} \frac{1}{2} & \text{if } n = -1 \\ \frac{1}{2^{n+2}} & \text{if } n \in \mathbb{N}_0. \end{cases}$$

The resulting distribution is heavily right-skewed as it can be shown that

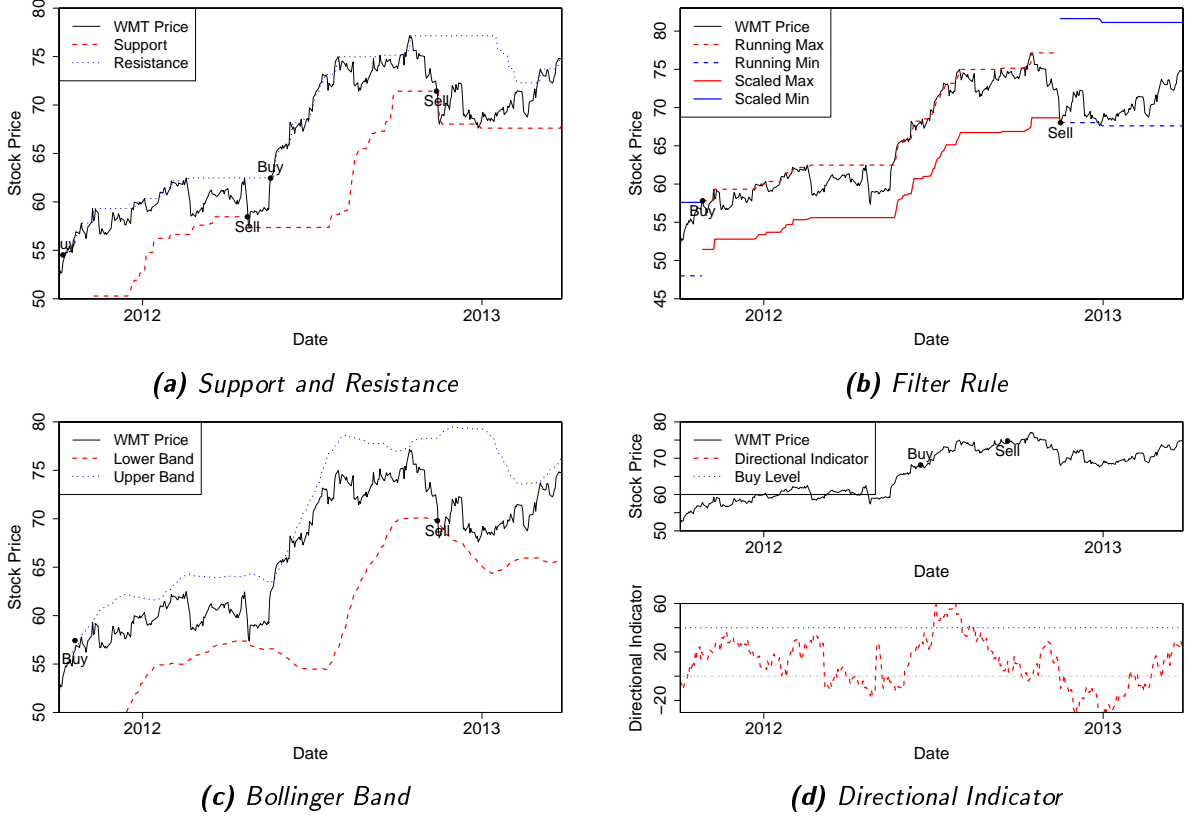
$$\mathbb{E}[(G_\tau - \mathbb{E}[G_\tau])^3] = \mathbb{E}[G_\tau^3] = \frac{1}{2}(-1)^3 + \frac{1}{4} \cdot 0^3 + \sum_{n=1}^{\infty} \frac{1}{2^{n+2}} n^3 = -\frac{1}{2} + \frac{1}{4} \sum_{n=1}^{\infty} \frac{n^3}{2^n} = -\frac{1}{2} + \frac{1}{4} \cdot 26 = 6$$

and standardized skewness equals  $3/\sqrt{2} \approx 2.1213$ . Computing the quantiles of  $G_\tau$  yields  $P_{99} = 5$  and  $P_{50} = P_1 = -1$  such that the quantile skewness measure computes to  $\nu(G_\tau) = 1$ . Note that there is a perfect linear relationship between the holding time  $\tau$  and the payoff  $G_\tau$ , which is  $G_\tau = \tau - 2$ . In this toy model, payoff and holding time are thus perfectly correlated, i.e.,  $\rho = \text{Corr}(G_\tau, \tau) = 1$ . Therefore, a trailing stop-loss strategy results in a gain/loss distribution that satisfies the same four properties we obtained for the MA(50,200) strategy.

### III. Data and strategies

#### A. Data

Our data set contains daily returns from 01/01/1962 up to 12/31/2013 for all CRSP common stocks (Sharecode 10 or 11) traded on the NYSE, the AMEX, and the NASDAQ. We remove stocks once delisted and stocks with an unreliable history as indicated by CRSP before a given date up to that date. Furthermore, stocks that are illiquid or that are traded for time periods too short to allow for technical trading are removed. A stock is defined as illiquid, if there are more than fifty prices unavailable or the stock is not actively traded for fifty days. We also remove stocks where trading is interrupted for unknown reasons by more than fifty days. Finally, we winsorize the returns at the 0.1% level. Risk-free and market discount rates are taken from Kenneth French's website. In order to keep the analysis computationally tractable, we follow Lo, Mamaysky, and Wang (2000) and focus on a stratified sample of 300 stocks. In particular, we double-sort the original sample into 30 strata built from six decades and five market capitalization quintiles. From each stratum, we select 10 stocks at random. In total, our analysis is thus based on 300 stocks and 86,385,812 daily



**Figure 5: Technical trading signals for Walmart from October 2011 to April 2013.** This figure illustrates buy and sell signals for Walmart common stock as implied by four different technical strategies: a Support and Resistance (SR) strategy, an Alexander Filter (ALX) Strategy, a Bollinger Band (BB) strategy, and a Directional Indicator (DI) strategy. They are computed from Walmart daily closing prices (solid line) on NYSE. The parameter choices are discussed in the main text. These four strategies and the MA(50,200) in Figure 1 are referred to later in the paper as “the five example strategies.” Appendix A discusses all rules and further parameter choices in detail.

returns.

## B. Technical strategies

In this section, we introduce two further categories of technical strategies as defined in Sullivan et al. (1999): support and resistance (SR) rules, and Alexander filter rules (ALX). In addition, we study Bollinger band (BB) rules and Directional Indicator (DI) rules. Appendix A defines all strategies formally, and discusses the many variations and parameter choices that we employ. Overall, we consider 7700 different technical trading strategies. For sake of concreteness, here we define explicit examples of each of the four strategies. Together with the MA(50,200), these comprise the set of “five example strategies” that we will focus on in some of our analysis.

Figure 5 shows buy and sell signals of the four new strategies for the Walmart stock from October 2011 to April 2013. The Support and Resistance strategy shown in the upper left panel of Figure 5 calculates the running minimum and maximum over the past 60 days. Buy signals are generated when breaking through the maximum, and sell signals occur when breaking through the minimum.

Alexander Filter rules as shown in the upper right panel of Figure 5 study fractions of the running maximum and minimum since trade inception. Buy signals occur upon a 20% price increase relative to the running minimum and sell signals occur upon an 11 % price decrease relative to the running maximum. The Bollinger Band strategy in the lower left panel of Figure 5 builds upon a moving average of 60 days. Around this moving average, an upper and a lower band are drawn, with distance of 2 times the moving average’s standard deviation. More volatile markets thus result in wider bands. The Bollinger Band employs a safety margin of 0.02, that is, the strategy buys (sells) if the current price exceeds the upper (lower) band by more than 2 %. In the following, we will refer to the four strategies depicted in Figure 5 and the MA (50,200) strategy shown in Figure 1 as the “five example strategies.”

## IV. Main results

This section establishes our main result that the vast majority of technical trading strategies consistently skew to the right, and that losses come small and quickly and that gains take time but may be large. We compute the skewness experienced from following 7700 technical trading strategies applied to 60 years of data and 300 stocks with different market capitalization.

### A. Methodology

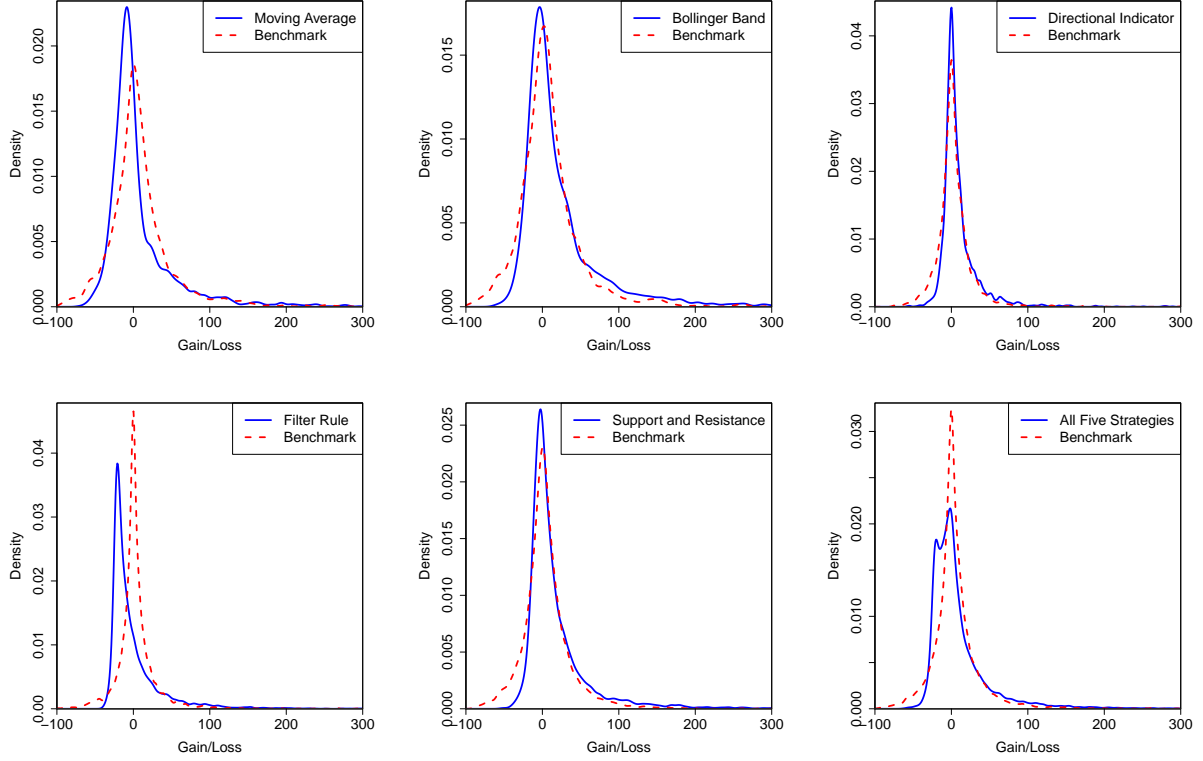
As before, for now we consider only long positions of a hypothetical investment of  $X_0 = 100$  and a reference return of zero. For the NYSE-AMEX-NASDAQ price data, we obtain the experienced distribution of a given technical trading rule as the empirical distribution of gains and losses that *each possible trade* on the dataset generates.<sup>9</sup>

The experienced distribution of the benchmark buy-and-hold strategy that reflects random trading is computed as follows. First, we randomly pick a stock-time observation at random. We then compute the return from buying the stock at that time for a random holding period. As in the simulation example, this holding period is identically and independently distributed to the one we obtained for the corresponding technical trading strategy under consideration.<sup>10</sup> Therefore, firstly, the benchmark strategy is not selective in the stocks it picks and the time when it buys them. For a technical strategy, in contrast, how often and when a stock is bought depends on the stock price history and the resulting trading signal. Secondly, as in the simulation example, for the technical strategy the time of sale also depends on the stock price evolution while for the benchmark strategy the time of sale is random and exogenous.

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<sup>9</sup>When studying the 7700 strategies in the next section, for numerical reasons we will restrict ourselves to a random sub-sample of all trades. This is also because many strategies yield a huge number of trades (more than 1 million). For the strategies in Figure 5, we compared the distribution obtained from all trades to that obtained from the respective sub-samples we construct. The sub-sampling does not have any effect on our results.

<sup>10</sup>If the holding time is longer than the period where prices are available (e.g., due to end of the sample period), the trade ends with a sale at the last available price. Removing these truncated trades instead does not change our results.



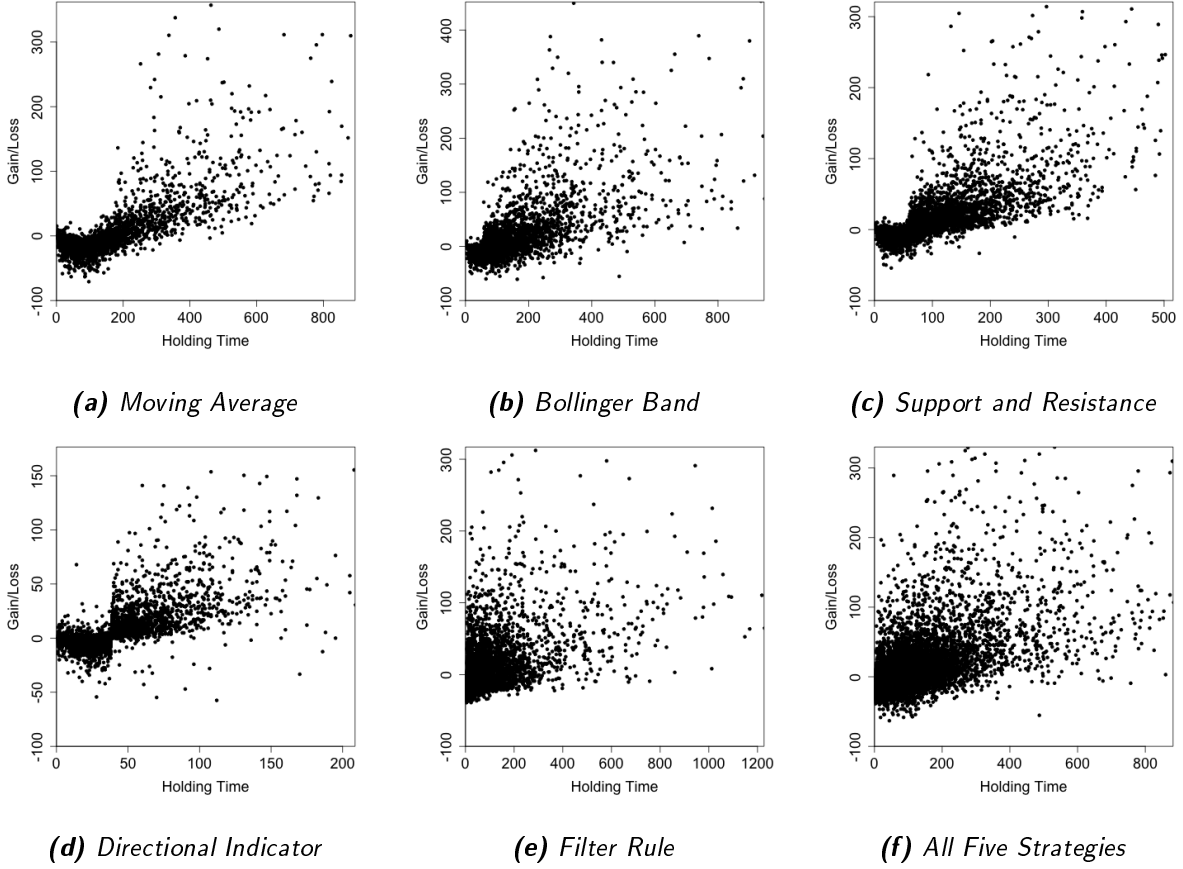
**Figure 6: Gain/loss distribution of long position technical strategies applied to NYSE-AMEX-NASDAQ data.** This figure shows the gain/loss distributions of the five example strategies (solid line) against their benchmark strategies (dashed line) when trading on historical price data. Only long position trades are considered.

### B. Results for a member of each strategy category

Figure 6 shows the realized gain/loss distribution for long position trades on NYSE-AMEX-NASDAQ stocks for the five strategies example strategies (illustrated in Figures 1 and 5). In the lower right panel, it also shows the gain/loss distribution from trading based on all five strategies simultaneously. The important insight is that, going from (i) the MA strategy to other strategies and (ii) going from simulated data to real data is does not change our result that technical trading skews to the right. Figure 7 shows the relationship between realized profit and holding time for the five example strategies. The general pattern for all five example strategies applied to real data is the same that we observed for the moving average applied to simulated data: Losses come quickly and are small in magnitude while gains take longer and can be large in magnitude.

We summarize our results in Table I. For all five strategies as well as their combination, technical trading results in significantly increased skewness (columns 2 to 4). We also confirm that realized gains and holding time are correlated, as evidenced by significantly positive Pearson correlation coefficients shown in columns 4 to 7 of Table I.





**Figure 7:** Correlation between holding time and realized profit for long position trades on NYSE-AMEX-NASDAQ stocks for the five example strategies and all rules combined.

### C. Experienced skewness of 7700 technical strategies

In this section, we study the skewness experienced from trading 7700 technical trading strategies on 60 years of NYSE-AMEX-NASDAQ data. The technical strategies and parameter choices are discussed in detail in Appendix A. By considering 7700 different specifications of these strategies in total, we want to establish the stylized fact “technical strategies skew heavily to the right.” This is similar to the approaches of Sullivan et al. (1999) or Bajgrowicz and Scaillet (2012) who adopt different methods in order to show that technical strategies are typically not profitable.

For each strategy, from all trades that the strategy generates, we compute the induced skewness  $\nu_{\text{tech}}$  of the technical strategy. We then also compute the skewness  $\nu_{\text{bench}}$  of the respective strategy’s benchmark strategy. Then, for each strategy, we compute the excess skewness generated from technical trading as

$$\nu_{\text{excess}} = \nu_{\text{tech}} - \nu_{\text{bench}}.$$

Figure 8 shows the distribution of excess skewness for all five strategy classes. The lower right panel of Figure 8 shows the distribution of excess skewness for all 7700 strategies we consider. The graphs

Example Strategy	Technical: $\nu$	Benchmark: $\nu$	p-value	Technical: $\rho$	Benchmark: $\rho$	p-value
Moving Average	0.71	0.38	<0.01	0.73	0.24	<0.01
Bollinger Band	0.76	0.36	<0.01	0.62	0.18	<0.01
Support and Resistance	0.75	0.29	<0.01	0.60	0.08	<0.01
Directional Indicator	0.61	0.23	<0.01	0.67	0.14	<0.01
Filter Rule	0.83	0.29	<0.01	0.64	0.26	<0.01
All Five Strategies	0.74	0.36	<0.01	0.63	0.21	<0.01

**Table I: Skewness and correlation between profit and holding time for long position trades.** The table shows, for long positions following the five example strategies and their benchmarks, the induced skewness  $\nu$ , the correlation between profits and holding time  $\rho$ , and p-values of bootstrap tests of whether these values are the same for technical trading and random trading. The table also shows results for trading on all five rules together.

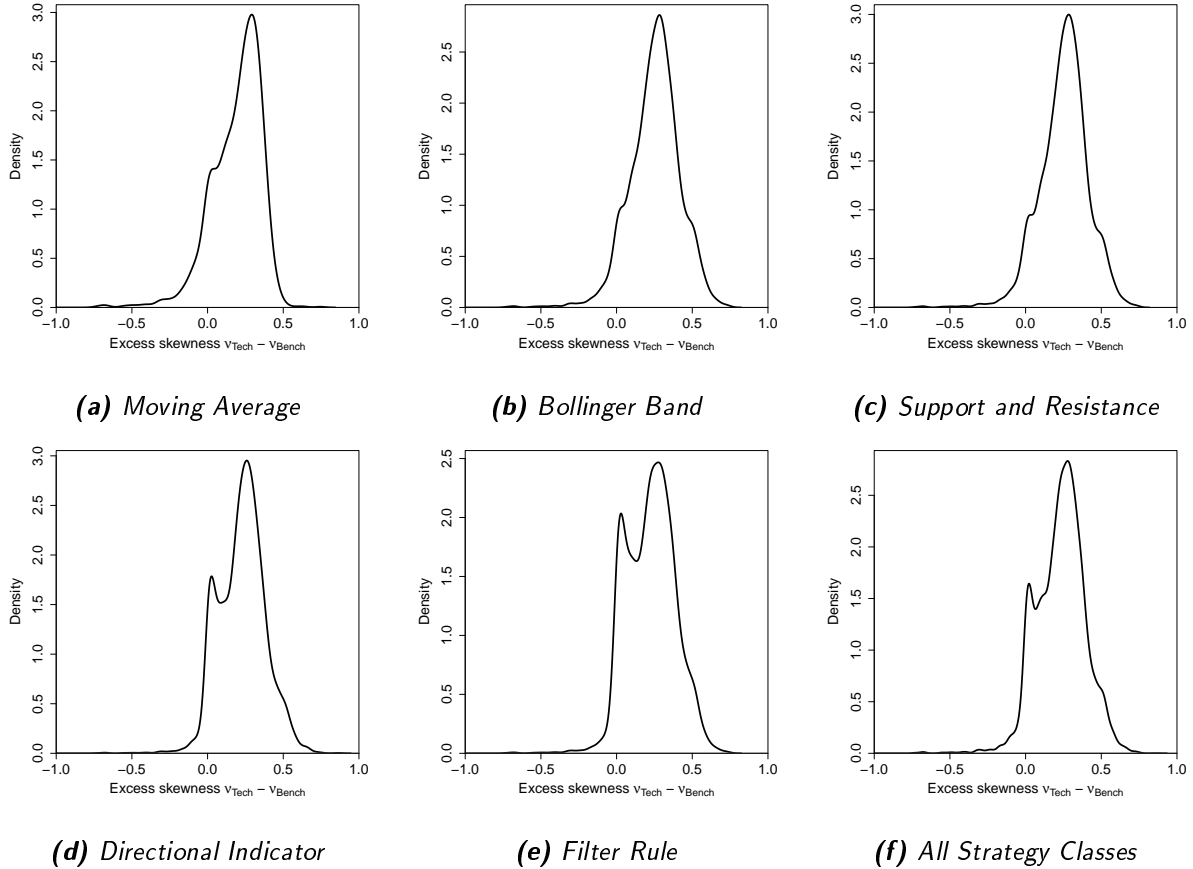
clearly indicate that in the large majority of cases excess skewness is positive, meaning that the technical strategy generates a larger skewness than random trading.

Table II shows the median skewness  $\bar{\nu}_{\text{tech}}$  for each strategy class and for all 7700 strategies. The median excess skewness  $\bar{\nu}_{\text{excess}}$  of all 7700 technical strategies is 0.34 ( $= 0.62 - 0.28$ ). For all five strategy classes, the difference is significant as indicated by a binomial test. Columns 5 to 7 of Table II document the analogous result for the correlation between realized gains realized and holding time. The average correlation for the 7700 strategies equals  $\bar{\rho}_{\text{tech}} = 0.54$  while for random trading the correlation equals only  $\bar{\rho}_{\text{bench}} = 0.12$ .

Strategy Class	Technical: $\bar{\nu}$	Benchmark: $\bar{\nu}$	p-value	Technical: $\bar{\rho}$	Benchmark: $\bar{\rho}$	p-value
Moving Average	0.61	0.32	<0.01	0.59	0.18	<0.01
Bollinger Band	0.68	0.33	<0.01	0.54	0.17	<0.01
Support and Resistance	0.55	0.24	<0.01	0.65	0.09	<0.01
Directional Indicator	0.67	0.33	<0.01	0.58	0.13	<0.01
Filter Rule	0.59	0.24	<0.01	0.32	0.07	<0.01
All Strategies	0.62	0.28	<0.01	0.54	0.12	<0.01

**Table II: Skewness and correlation between profit and holding time for long position trades.** The table shows, for long positions following all strategies classes and their benchmarks, the induced median skewness  $\nu$ , the median correlation between profits and holding time  $\rho$ , and p-values of binomial tests of whether these values are the same for technical trading and random trading by strategy class. The table also shows results for trading on all five strategy classes together.

In summary, the vast majority of the 7700 trading rules we consider yields significant excess skewness over random buy-and-hold trading. Realized gains correlate strongly with holding time, significantly more so than for random trading. These results were obtained from trades collected on a stratified sample of NYSE/AMEX/NASDAQ stocks that traded between 1963 and 2013. Table III shows the mean, median, and standard deviation of the experienced distribution when applying the strategy classes. We see that technical trading may or may not result in a higher unconditional mean than random trading according to the benchmark strategy. The standard deviation from technical trading is consistently higher. The fact that skewed gambles come along with higher standard deviation follows other settings of increased skewness such as underdiversification (Simkowitz and Beedles (1978), Conine and Tamarkin (1981), Mitton and Vorkink (2007)) or horse-race betting



**Figure 8:** Density of skewness for individual technical strategies and their benchmarks for long position trades on NYSE-AMEX-NASDAQ stocks for the five strategy classes and all rules combined.

(Golec and Tamarkin (1998)). Investors with a strong enough preference for skewness relative to risk aversion will thus find technical trading attractive. Empirical evidence has shown that skewness preference is indeed pronounced enough for many individuals so as to justify right-skewed low-mean, high-variance investments; the best example may be the extensive demand for lottery tickets.

## V. Further results and robustness

In this section, we obtain a number of additional results and robustness tests. For illustrative purposes and clarity of interpretation, we sometimes resort to (some of) the five example strategies and simulated data. In Section V.A, we show that the large skewness obtained from technical trading makes moving average trading attractive to prospect theory investors, even in the simulation setting where there is no trend and no momentum so that trading cannot be profitable. Section V.B analyzes technical trading based on sell signals, i.e., short selling. Section V.C analyzes the impact of the investor's reference point the discounting of gains and losses. Section V.E shows that trading a stock technically yields as much skewness as mildly in-the-money call options on the same stock.

Strategy Class	Mean			Median			Standard Deviation		
	Tech.	Bench.	p-value	Tech.	Bench.	p-value	Tech.	Bench.	p-value
Moving Average	4.77	5.05	<0.01	-2.10	0.75	<0.01	40.67	34.78	<0.01
Bollinger Band	11.12	5.62	<0.01	-0.09	1.23	<0.01	46.58	36.80	<0.01
Support and Resistance	4.51	3.13	<0.01	-0.73	0.73	<0.01	30.43	26.14	<0.01
Directional Indicator	10.36	5.44	<0.01	-0.54	1.21	<0.01	45.58	35.98	<0.01
Filter Rule	4.36	3.05	<0.01	-1.07	0.69	<0.01	30.92	25.80	<0.01
All Strategies	6.44	3.88	<0.01	-0.83	0.91	<0.01	36.60	30.00	<0.01

**Table III: Mean and standard deviation for long position trades.** The table shows, for long positions following all strategies classes and their benchmarks, the induced median of means, the median of medians, the median of standard deviation, and p-values of binomial tests of whether these values are the same for technical trading and random trading by strategy class. The table also shows results for trading on all five strategy classes together.

### A. Technical trading under cumulative prospect theory

As discussed, besides the empirical evidence on skewness preference, also successful descriptive theories of behavior imply strong skewness preference. In this section, as one important example, we show that the cumulative prospect theory (CPT) of Tversky and Kahneman (1992) can explain the popularity of technical trading—even in the simulation setting where there are no trends and when expected profits are zero. As will be seen, the link between prospect theory and technical trading is indeed the skewness preference implied by CPT through overweighting of small probabilities in combination with the skewness generation obtained by technical trading.

We assume an investment in the technical trade of  $X_0 = 100$  and compute the gains and losses from each trade as defined above. Denote by  $g_1 > g_2 > \dots g_k \geq 0 > g_{k+1} > \dots > g_n$  the gains ( $i = 1, \dots, k$ ) and losses ( $i = k + 1, \dots, n$ ) obtained from technical trading with probabilities (i.e., frequencies)  $p_1, \dots, p_n$ . The CPT-utility is given by

$$CPT(X) = \sum_{i=1}^n \pi_i u(g_i) \quad (2)$$

with *decision weights*  $\pi_i$  and a *utility function*  $u$  defined as follows. The value function  $u$  is given by

$$u(g) = \begin{cases} g^\alpha & \text{if } g \geq 0 \\ -\lambda(-g)^\alpha & \text{if } g < 0 \end{cases}$$

with “loss aversion parameter”  $\lambda \geq 1$  and utility curvature parameter  $\alpha \in (0, 1]$ .  $\alpha \in (0, 1]$  implies that the utility function is concave over the region of gains and convex over the region of losses. This implies diminishing sensitivity towards both gains and losses.  $\lambda \geq 1$  implies that the utility function is steeper in the region of losses than in the region of gains, which implies that losses loom larger than gains. Finally, CPT does not process objective probabilities linearly as does EUT, but

replaces the objective probabilities  $p_i$  with decision weights  $\pi_i$ . The  $\pi_i$  in equation (2) are given as<sup>11</sup>

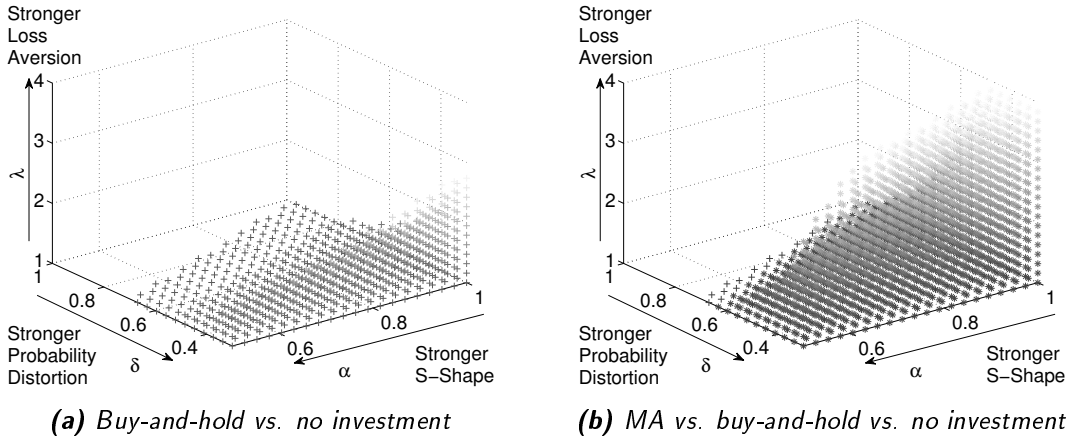
$$\begin{aligned}\pi_i &= w(p_1 + \dots + p_i) - w(p_1 + \dots + p_{i-1}), & i = 1, \dots, k \\ \pi_i &= w(p_i + \dots + p_n) - w(p_{i+1} + \dots + p_n), & i = k + 1, \dots, n\end{aligned}$$

where  $w$  is called *(probability) weighting function*. Tversky and Kahneman (1992) propose the following weighting function:

$$w(p) = \frac{p^\delta}{(p^\delta + (1-p)^\delta)^{\frac{1}{\delta}}}$$

with a probability distortion parameter  $\delta \in (0.3, 1]$ . For  $\delta < 1$  the function is inverse-S-shaped. This results in decision weights that overweight the probabilities of small and extreme outcomes, i.e., the tails of the evaluated distribution are overweighted. Inverse-S-shaped probability weighting results in a very strong preference for skewness; see Ebert and Strack (2015) for a formal result.

Estimates for the CPT parameters vary significantly within studies and across subjects, but benchmark values often reported are the median values of subjects analyzed in the seminal Tversky and Kahneman (1992) study:  $\lambda = 2.25$ ,  $\alpha = 0.88$ , and  $\delta = 0.65$ . To account for the observed heterogeneity in CPT preferences as well as to study the proneness of technical trading to loss aversion, S-shape, and probability weighting, we analyze 8000 parameter combinations that span the relevant parameter regions defined above.



**Figure 9: Prospect theory utility from Moving Average (MA) trading.** This graph illustrates the parameter values for which a CPT investor finds trading MA attractive. For comparative reasons, part (a) indicates with a “+” the 915 out of the 8000 considered parameter values for which trading the stock randomly according to the benchmark strategy is preferred over no investment. Part (b) compares preference between a stock investment according to the benchmark strategy, the MA strategy, and no stock investment. In that case, the benchmark strategy is optimal for only 15 parameter combinations (indicated by a “+”) while the MA(50,200) strategy is preferred for 2541 parameter combinations (indicated by a “\*”).

The results of these computations are visualized in Figure 9. Figure 9a indicates by “+” signs the parameter triples  $(\alpha, \delta, \lambda)$  for which trading the stock randomly according the MA benchmark

<sup>11</sup>In the computations of  $\pi_1$  and  $\pi_n$ , let  $w(p_1 + \dots + p_0) = w(p_{n+1} + \dots + p_n) \equiv 0$ .

(buy-and-hold) strategy yields higher CPT utility than no investment, i.e., positive CPT utility. Trading this stock with zero expected profit randomly is attractive to only few CPT investors (for 926 out of the 8000 parameter triples). These CPT investors are characterized by a mildly S-shaped utility function (large  $\alpha$ ), pronounced probability distortion (small  $\delta$ ), and mild loss aversion (small  $\lambda$ ). The intuition is as follows. Stock investment according to the benchmark strategy is risky and may result in losses bounded by the initial investment, but also in unbounded gains. A mild S-shape of the utility function implies that the marginal utility of gains decreases less rapidly. Probability weighting implies that the unbounded right tail of the distribution is significantly overweighted. And low loss aversion ensures that the investor is not too afraid of the potential losses of a risky investment.

Figure 9b illustrates the investors' decision when his investment opportunity set is enriched by the MA strategy. In Figure 9b, a "+" still marks the parameter triples for which buy-and-hold yields the highest CPT utility. A "\*" sign marks the parameter triples for which the CPT utility of trading MA is highest. If the space for a parameter triple is left blank, the investor decides against investment because the CPT utility of buying the stock is negative for both trading it MA or buy-and-hold.

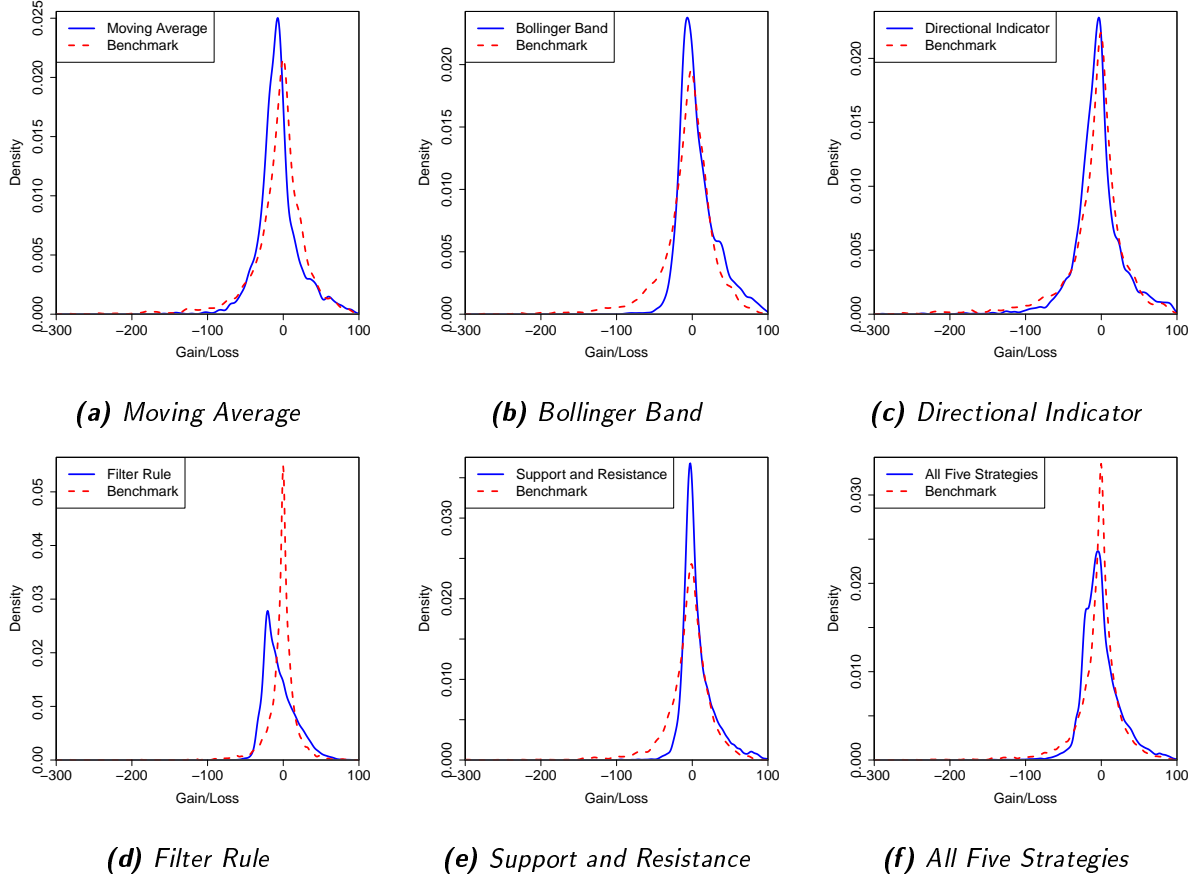
From Figure 9b we see that, firstly, investing in the stock is attractive for much more CPT preference parameter triples (2535 of 8000). Secondly, almost all (2506) of these triples are "\*" triples. This means that those CPT investors who prefer to invest in the stock prefer trading it MA rather than randomly. Only 22 out of the 2535 stock investors prefer to stay with random trading when also MA is available. The key to understanding this result is to recall what trading MA does to the distribution of trading proceeds (Figure 2).

Both MA and random trading result in right-skewed distribution of trading proceeds. This is why both strategies are generally favored by investors with a mildly S-shaped utility function, mild loss aversion, and pronounced probability weighting. Trading MA, however, results in a much more right-skewed distribution than trading randomly. This increased skewness makes MA attractive to investors with pronounced probability weighting even when they are quite loss averse or when they have a pronounced diminishing sensitivity towards large gains. Probability weighting is in fact necessary for skewness preference since with S-shaped utility typically prefer left-skewed return distributions. The fact that CPT investors with mild probability weighting prefer less skewness is also the reason why, for 22 parameter combinations, we find that the mild skew obtained from random trading is more attractive than the strong skew from MA. Note that these 22 parameter triples indeed feature moderate levels of probability weighting.

### *B. Short-selling and contrarian trading*

In this section, we analyze realized gains and losses from trading short subsequent to technical sell signals. The short position is closed when observing a buy signal. The upside from a short position is limited to 100% (in case the stock becomes worthless), while the downside is unbounded (because the potential stock price increase is unbounded). This makes the gains from short positions more

left-skewed for mechanical reasons. In the geometric Brownian motion case, for example, holding a stock long for a fixed time results in a right-skewed (log-normal) payoff distribution, but the payoffs from short positions are left-skewed. Moreover, if the market offers a risk premium, trading profits from short positions should correlate negatively with holding time. The question is whether these changed circumstances for short positions reversed the result of positive excess skewness from technical trading that we obtained for long positions. Moreover, is the effect of technical trading on skewness offset for investors who engage in both long and short positions?



**Figure 10: Gain/loss distribution of short positions according to technical strategies applied to NYSE-AMEX-NASDAQ data.** This figure shows the profit distributions of the five example strategies (solid line) against their benchmark strategies (dashed line) when trading on historical price data. Only short position trades are considered.

The answer is no. Figure 10 shows that trading on technical sell signals in the NYSE-AMEX-NASDAQ dataset likewise skews to the right. In particular, while random short-selling results indeed in left-skewed gain/loss distributions (red curves), trading technically results in right-skewed distribution. Table IV shows the skewness measure  $\nu$  and the correlation of profits and holding time  $\rho$  when selling short upon technical sell signals and closing the position at the subsequent buy signal. Results are very similar to that of the long case. While both skewness and profit-holding time correlations are overall lower for short positions, the excess skewness obtained from technical trading is in fact even larger.

Example Strategy	Technical: $\nu$	Benchmark: $\nu$	p-value	Technical: $\rho$	Benchmark: $\rho$	p-value
Moving Average	0.11	-0.40	<0.01	0.65	-0.19	<0.01
Bollinger Band	0.37	-0.36	<0.01	0.63	-0.15	<0.01
Support and Resistance	0.42	-0.34	<0.01	0.00	-0.31	<0.01
Directional Indicator	-0.05	-0.45	<0.01	0.79	-0.15	<0.01
Filter Rule	0.40	-0.22	<0.01	0.39	-0.11	<0.01
All Five Strategies	0.19	-0.35	<0.01	0.27	-0.27	<0.01

**Table IV: Skewness and correlation between profit and holding time for short position trades.** The table shows, for short positions following the five example strategies and their benchmarks, the induced skewness  $\nu$ , the correlation between profits and holding time  $\rho$ , and p-values of bootstrap tests of whether these values are the same for technical trading and random trading. The table also shows results for trading on all five rules together.

We can also study a technician who enters both long and short positions when observing buy and sell signals, respectively. Table V shows the results for this “mixed case.” As is intuitive, the numbers lie somewhat between those of the short case and the long case. The overall picture that technical trades yield more skewed gains and losses and that gains correlate significantly with holding time is preserved.

Example Strategy	Technical: $\nu$	Benchmark: $\nu$	p-value	Technical: $\rho$	Benchmark: $\rho$	p-value
Moving Average	0.56	0.07	<0.01	0.70	0.09	<0.01
Bollinger Band	0.71	0.10	<0.01	0.61	0.09	<0.01
Support and Resistance	0.69	-0.00	<0.01	-0.03	-0.32	<0.01
Directional Indicator	0.06	-0.36	<0.01	0.67	0.03	<0.01
Filter Rule	0.71	0.09	<0.01	0.62	0.21	<0.01
All Five Strategies	0.59	0.01	<0.01	0.52	-0.05	<0.01

**Table V: Skewness and correlation between profit and holding time for mixed position trades.** The table shows, for mixed positions following the five example strategies and their benchmarks, the induced skewness  $\nu$ , the correlation between profits and holding time  $\rho$ , and p-values of bootstrap tests of whether these values are the same for technical trading and random trading. The table also shows results for trading on all five rules together.

Why does turning from long to short positions not reverse the skewing effect of technical trading? The reason is that technical rules close a position once the *value of the position* – and not the stock price – declines sufficiently relative to a previous value. Therefore, short and long positions are treated alike as regards the timing of their closure. The closure timing (i.e., the “stopping time”) is, however, decisive for the skewness induced, as was also illustrated through the toy model above.

The trading heuristic that exactly reverses the skewness effect of long technical trading is not short technical trading but *contrarian technical trading*. A contrarian rule shorts upon buy signals and goes long upon sell signals. The short (long) contrarian gain is thus the long (short) technical trade’s loss, and symmetry of our skewness measure implies the skewness reversal effect. Therefore, trend-chasing skews trading profits to the right while contrarian trading skews trading profits to the left. We have thus shown that contrarian trading corresponds to “penny-picking in front of a steamroller,” a phenomenon sometimes observed in repeated decisions that is at odds with the standard evidence on skewness preference.



### C. Different reference returns and discounting

In this section, we analyze the holding times of technical trading rules in more depth. In particular, since we have seen that generating gains through technical trading takes longer than realizing losses, the reference return the investor uses to discount his profits may have an asymmetric effect on our results. While discounting surely matters for profits, we will see that it does not matter much for skewness.

Example Strategy	Holding time		Reference: risk-free rate			Reference: market index		
	Mean	Median	Technical $\nu$	Benchmark $\nu$	p-value	Technical $\nu$	Benchmark $\nu$	p-value
Moving Average	176	132	0.71	0.38	<0.01	0.71	0.38	<0.01
Bollinger Band	167	119	0.76	0.36	<0.01	0.76	0.36	<0.01
Support and Resistance	106	78	0.75	0.29	<0.01	0.75	0.29	<0.01
Directional Indicator	45	39	0.61	0.23	<0.01	0.61	0.23	<0.01
Filter Rule	79	30	0.83	0.29	<0.01	0.83	0.29	<0.01
All Five Strategies	103	59	0.74	0.36	<0.01	0.74	0.36	<0.01

**Table VI: Holding time and skewness for different reference returns.** The table shows, for long positions following the five example strategies and their benchmarks, mean and median of trades' holding time and the induced skewness  $\nu$  for two different reference returns: the risk-free rate and the market return. *p*-values are for bootstrap tests that test whether these values are the same for technical trading and random trading. The table also shows results for trading on all five rules together.

Columns 2 and 3 of Panel of Table VI show the median holding time in days for the five example strategies. The means being larger indicate that the holding times of technical trades are themselves skewed to the right: There are many trades with short holding time, but a few trades take really long. As seen before, these long trades are the ones that yield the largest gains. Columns 4 to 5 (7 to 8) of Table VI show the skewness  $\nu$  from the experienced distribution when the proceeds at sale are discounted at the risk-free return (the market return). We see that the skewness is slightly smaller for the technical strategies and the benchmarks when discounting at the large market rate. The bootstrap tests confirm that the difference remains statistically significant. Overall, results are not economically different from the ones we obtained for investors who do not discount (Table I). Even if investors discount the very large gains from technical trading, which are realized infrequently and late, they will still make a very skewed trading experience.

### D. Persistence across time and stocks

In this section, following Lo et al. (2000), we study the persistence of excess skewness generated by technical trading strategies across two important dimensions: time and market capitalization. Small stocks are known to have more volatile returns, so there might as well be an impact on skewness. Table VII shows that technical trading generating significant excess skewness is not a small stock effect, but observed across all market capitalizations. Moreover, technical trading generated skewness during all time periods, thus being a reliable source of skewness for decades,

irrespective of the market environment.

Cap/decade	1963-1973	1974-1983	1984-1993	1994-2003	2004-2013	Whole period
0-20%	0.25 (<0.01)	0.34 (<0.01)	0.26 (<0.01)	0.21 (<0.01)	0.19 (<0.01)	0.26 (<0.01)
21-40%	0.32 (<0.01)	0.34 (<0.01)	0.23 (<0.01)	0.17 (<0.01)	0.27 (<0.01)	0.24 (<0.01)
41-60%	0.23 (<0.01)	0.29 (<0.01)	0.18 (<0.01)	0.09 (<0.01)	0.16 (<0.01)	0.16 (<0.01)
61-80%	0.24 (<0.01)	0.41 (<0.01)	0.18 (<0.01)	0.13 (<0.01)	0.17 (<0.01)	0.21 (<0.01)
81-100%	0.14 (<0.01)	0.36 (<0.01)	0.31 (<0.01)	0.22 (<0.01)	0.07 (<0.01)	0.20 (<0.01)
All caps	0.26 (<0.01)	0.34 (<0.01)	0.22 (<0.01)	0.15 (<0.01)	0.16 (<0.01)	0.22 (<0.01)

**Table VII: Excess skewness for different market capitalizations and across time.** The table shows the average excess skewness generated from technical trading over random trading when following all 7700 strategies. Each cell shows the average excess skewness for trades on ten stocks randomly selected from a different size quintile (rows 2-6) and for trades from a different decade (columns 2 to 6). Row 7 (column 7) shows the average excess skewness across market capitalizations (across time periods). The lower right cell shows the average excess skewness generated by all 7700 strategies across all market capitalizations and time periods. Each cell also shows the  $p$ -values of a two-sided binomial test whether the average excess skewness is zero.

#### E. Comparing the skew from technical trading with that obtained from a call option

How much do technical strategies skew to the right? Table VIII shows for the five example strategies the skewness of an investment in a call option with maturities of six and three months, respectively. We use the simulated geometric Brownian motion data defined in Section II.C so that the exact option prices are given by the Black-Scholes formula. Column 1 of Table VIII shows the value of the quantile-based skewness measure  $\nu$  we obtained for each strategy in this case. Columns 2 and 3 show the strike-to-spot ratio of a call option which yields the same skewness as the technical trading strategy. For the quantile-based measure  $\nu$ , strike-to-spot ratios from about 81% to 94% yield option payoffs with the same skewness than our technical strategies.

It is worth to note that for higher prices the median option payoff readily approaches zero, in which case  $P_{50} - P_{01} = 0$ . This implies that  $\nu$  already attains its maximum value of 1. Due to their point masses at zero, our measure  $\nu$  judges option payoffs as extremely skewed. For this reason, in unreported results we thus also obtained the strike-to-spot ratios that match the third moments of our technical strategies. In that case, we observe strikes above 100%, so that the skewness from technical trading would even compare to that of out-of-the money options. Moreover, note that a call option with a strike of 0% is equivalent to buying the underlying stock and trading it buy-and-hold until maturity. Trading technically rather than buy-and-hold with fixed maturity thus corresponds to an increase in skewness  $\nu$  similar to that of pushing the strike of an option from 0% to more than 80%. Therefore, indeed, trading technically can generate highly right-skewed, lottery-like payoffs, and the skewness generated by trading technically is economically significant.

Note that this paper does provide an explanation for why investors seek skewness precisely through technical trading strategies. For example, skewness seekers could buy options or penny stocks, gamble in the casino, play the lottery, underdiversify, go the horse-track, and pursue any possible combination thereof. Evidence indeed shows that all these different sources of skewness

Example Strategy	$\nu$	Strike to Spot, 6M	Strike to Spot, 3M
Moving Average	0.65	84.78%	89.83%
Bollinger Band	0.64	84.37%	89.54%
Support and Resistance	0.73	88.47%	92.35%
Directional Indicator	0.57	80.99%	87.23%
Filter Rule	0.79	90.87%	93.99%

**Table VIII Moneyness of call options that yield the same skewness as technically trading the underlying stock.** The table shows, for long positions following the five example strategies and their benchmarks, the strike-to-spot ratio (“moneyness”) of call options that have the same quantile-based skewness  $\nu$  that is induced by the technical strategies when applied to the simulated data set. The second column is for a maturity of six months (126 trading days) and the third column is for a maturity of three months (63 trading days).

coexist and seem to complement each other. Why some skewness seekers pursue some skewed risks over others, and why there is heterogeneity among individuals in how they choose to create skewness, is not understood yet. To the best of our knowledge, no paper to date has even approached this question. Our point is thus merely that technical trading should be added to the aforementioned group of skewness generators, which may help explain its popularity. This explanation for the popularity of technical analysis is provocative since it is a behavioral one – an explanation rooting in the bounded rationality of investors – at least to the extent that a strong preference for skewness (as implied, e.g., by prospect theory) is regarded a preference bias.

## VI. Conclusion

Academics have long been skeptical towards technical analysis. In fact, predicting future prices from past prices by drawing moving average lines or resistance levels directly on the stock price charts appears odd to many people. Most of the literature has focused on the profitability of technical trading rules. The prevalence of technical analysis, the doubt in its profitability, and the evidence that individuals lose significant amounts of money by using it makes the understanding of technical analysis better an important topic for research.

In this paper, we have taken a behavioral perspective on technical analysis. We have shown that a strong preference for skewness, as has been established as an integral element of individual risk preferences, contributes to the attractiveness of technical trading. Technical trading rules may be perceived as gambles that yield large gains with small probability, accompanied by frequent but small losses. This holds irrespective of the market environment, the stocks traded, and the time period. If investors like such lottery-like gambles, technical trading is a means to generate right-skewed gambling experiences.

It is interesting to have in mind that many technicians regard behavioral finance as the theoretical foundation to the “science” of technical analysis. As discussed, justifying the profitability of technical analysis by taking reference to behavioral finance is not immediate. On the other hand, this paper has illustrated that ideas from behavioral finance can help us understand the popularity of technical

analysis better, irrespective of its profitability.

## Appendix A. Definitions of technical trading strategies

In this section, we describe in detail the 7700 technical strategies studied in this paper.<sup>12</sup> As Sullivan et al. (1999), we study moving average strategies (MA), support and resistance strategies (SR), and Alexander filter strategies (ALX).<sup>13</sup> In addition to the strategies considered by Sullivan et al. (1999), we study the Bollinger Band (BB) (e.g. Bollinger (2002)) and the Directional Indicator (DI) for commonly used parameter values. Throughout, let  $S_t$  denote a stock's closing price at trading day  $t$ .

### Appendix A. Moving average double-crossover strategy

The value of the MA line of stock at a given time  $t$  with length  $n$  is the average closing price of the past  $n$  closing prices:

$$MA(t, n, S) = \frac{1}{n} \sum_{i=1}^n S_{t-i}. \quad (\text{A1})$$

The MA strategy indicates a *buy signal* at time  $t$  if the short-term MA line crosses the long-term MA line from below:

$$MA(t-1, n_{short}) < MA(t-1, n_{long}) \text{ and } MA(t, n_{short}) \geq MA(t, n_{long}) \quad (\text{A2})$$

A *sell signal* occurs at time  $t$  if the short-term MA line crosses the long-term MA line from above:

$$MA(t-1, n_{short}) > MA(t-1, n_{long}) \text{ and } MA(t, n_{short}) \leq MA(t, n_{long}). \quad (\text{A3})$$

In addition to studying more than hundred different combinations of long and short moving averages, like Sullivan et al. (1999) we employ various filters to the signals a trading rule predicts. First, a *time delay filter*  $d$  requires persistence of the trading signal for  $d$  days before the chartist acts on the trade signal. This applies to both buy and sell signals. Second, a *percentage band filter*  $b$  specifies a safety margin by which the shorter moving average has to exceed (succeed) the long moving average in order to create a buy (sell) signal. Third, a *minimum holding time filter*  $c$  requires a minimum holding time of  $c$  days for each trade. Only after that time a strategy's sell signal results in an actual sale. We apply these three filtering rules to the MA as well as to the subsequent trading strategies. All parameters employed and combined in our analysis of the MA rule are shown in Table IX. Considering  $N$  moving averages of different length yields  $N(N-1)/2$  long-short combinations. Denoting the number of parameters used for each filter with capital letters  $D$ ,  $B$ , and  $C$ , respectively, yields

$$\left( \sum_{i=1}^{N-1} i \right) \times (B + D + C + 1) = 2040 \quad (\text{A4})$$

<sup>12</sup>To be precise, we study 7700 technical strategies in total.

<sup>13</sup>Since we focus on technical strategies that generate signals based on past price data, we do not study the volume-based strategy of Sullivan et al. (1999). Moreover, we do not study the channel breakout strategy because this strategy yields no sell signals; Sullivan et al. (1999) thus assume that the position is held for a pre-specified number of days. In practice, sell signals for channel strategies are often taken from other strategies such as MA or DI; see "Channeling: Charting A Path To Success" by Justin Kuepper (published online in investopedia, <http://www.investopedia.com/articles/trading/05/020905.asp>).

Parameter	Description	Values
$n$	length of moving average	1,2,5,10,15,20,25,30,40,50,75,100,125,150,200,250
$b$	fixed band multiplier	0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, 0.05
$d$	time delay	2, 3, 4, 5
$c$	minimal holding time days	5, 10, 25, 50

**Table IX Parameters employed for the moving average trading rule.**

different moving average strategies. Like Sullivan et al. (1999), we further employ nine more strategies with very long MA and very short long MAs. Overall, this yields 2,049 MA trading rules; see Sullivan et al. (1999) for more details.

### Appendix B. Support and Resistances

Chartists interpret breakthroughs of certain market support and resistance levels as buy or sell signals. A resistance level is computed as the running maximum of the past  $n$  closing prices. Hence, the chartist observes a buy signal at time  $t$  if

$$S_t > \max\{S_{t-n}, \dots, S_{t-1}\} \text{ and } S_{t-1} \leq \max\{S_{t-n-1}, \dots, S_{t-2}\} \quad (\text{A5})$$

A sell signal occurs if the chart breaks the lower resistance in form of the running minimum at time  $t$ :

$$S_t < \min\{S_{t-n}, \dots, S_{t-1}\} \text{ and } S_{t-1} \geq \min\{S_{t-n-1}, \dots, S_{t-2}\} \quad (\text{A6})$$

The same filters discussed before can be applied to the SR rule. In case of the time delay filter, acting upon the trading signal requires its persistence over  $d$  trading days. For the percentage band filter, to create a trading signal the current price needs to exceed the running maximum (or minimum) by more than a specified percentage  $b$ . In addition, Sullivan et al. (1999) consider an alternative definition of extrema where the maximum and minimum in equations (A5) and (A6) is replaced by the most recent closing price that is greater (less) than the previous  $e$  closing prices. Formally, the first maximum in equation (A5) and the first maximum in equation (A6) are replaced by, respectively,

$$S_{\bar{t}} \text{ where } \bar{t} := \max\{\tilde{t} < t : S_{\tilde{t}} < \max\{S_{\tilde{t}-1}, \dots, S_{\tilde{t}-e}\}\} \text{ and} \quad (\text{A7})$$

$$S_{\underline{t}} \text{ where } \underline{t} := \max\{\tilde{t} < t : S_{\tilde{t}} < \min\{S_{\tilde{t}-1}, \dots, S_{\tilde{t}-e}\}\} \quad (\text{A8})$$

and analogously for the two other extrema in equations (A5) and (A6) that refer to time  $t-1$ . The parameters we employ are shown in Table X and combined as in Sullivan et al. (1999) to yield a total of

$$(1 + C) \times (N + E) + B \times (N + E) + B \times (N + E) + D \times C \times (N + E) = 340 \quad (\text{A9})$$

parameter combinations.

Parameter	Description	Values
$n$	support and resistance range	5, 10, 15, 20, 25, 50, 100, 150, 200, 250
$e$	alternative extrema parameter	2, 3, 4, 5, 10, 20, 25, 50, 100, 200
$b$	fixed band multiplier	0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, 0.05
$d$	time delay	2, 3, 4, 5
$c$	minimal holding time days	5, 10, 25, 50

**Table X Parameters employed for the support and resistance trading rule.**

### Appendix C. Filter Rules

Building on the description in Alexander (1961) and Fama and Blume (1966), the ALX strategy yields buy and sell signal as follows. A buy (sell) signal occurs once the closing price has risen by  $x\%$  (fallen by  $y\%$ ) compared to the minimum (maximum) price observed since a time  $t_0$ .<sup>14</sup> In particular, suppose we have entered a long position at time  $t_0$ . We then sell once  $S_t$  has fallen by  $y\%$  compared to this subsequent maximum, i.e., if

$$S_t < (1 - y) \max\{S_{t_0}, \dots, S_{t-1}\}. \quad (\text{A10})$$

The sell signal is likewise the signal to open a short position. Redefining  $t_0$  as the opening time of a short position, we compute the subsequent minimum,  $\min\{S_{t_0}, \dots, S_{t-1}\}$ , and close the short position once the stock price has risen  $x\%$  above it, i.e., once

$$S_t > (1 + x) \min\{S_{t_0}, \dots, S_{t-1}\}. \quad (\text{A11})$$

Like Sullivan et al. (1999) we combine the ALX rule with a minimum holding time filter  $c$  and implement it with the alternative definition of extrema (using the parameter  $e$ ); see the explanations for the MA and SR strategies. The parameters we employ in our study of the ALX rule are shown in Table XI.

Parameter	Description	Values
$x$	price change ( $x \cdot$ price) to initiate a long position	0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.035, 0.04, 0.045, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.12, 0.14, 0.16, 0.18, 0.2, 0.25, 0.3, 0.4, 0.5
$y$	price change ( $y \cdot$ price) to initiate a short positions	0.005, 0.01, 0.015, 0.02, 0.025, 0.03, 0.04, 0.05, 0.075, 0.1, 0.15, 0.2
$e$	length alternative extrema	1, 2, 3, 4, 5, 10, 15, 20
$c$	minimal holding time in days	5, 10, 25, 50

**Table XI Parameters employed for the Alexander filter rules.**

The Alexander filter rule parameters  $X$  and  $Y$  for the price changes which open and close a position require the value of  $X$  to be larger than the value of  $Y$ . Hence, we consider a total amount

<sup>14</sup>Except for when initiating the strategy where  $t_0$  indicates the beginning of the dataset,  $t_0$  will always be the time when entering a long position or a short position.

of  $XY = 185$  combinations of  $X$  and  $Y$ . We combine them to a total of

$$X \times (1 + E) \times (1 + C) + XY \times (1 + C) = 2005 \quad (\text{A12})$$

strategy combinations.<sup>15</sup>

#### Appendix D. Bollinger Band

The Bollinger Band is defined by two lines, one above and one below of the price path's moving average of some length  $n$ . For a moving average line  $MA(t, n, S)$ , which we defined in equation (A1), a Bollinger Band is defined as

$$BB(t, S_t) = MA(t, n, S) \pm B \times \sigma_t, \quad (\text{A13})$$

where the *Bollinger Band factor*  $B$  describes the width of the bands and  $\sigma_t$  denotes the stock's volatility at time  $t$  computed from the same number of observations as the moving average,  $n$ . The Bollinger Band strategy is not part of Sullivan et al. (1999)'s analysis. We thus take commonly used parameters similar to examples discussed in Bollinger (2002), and also employ the percentage band, time delay, and minimal holding time filters; see Table XII.

Parameter	Description	Values
$n$	moving average length	2,5,10,15,20,25,30,40,50,75,100,125,150,200,250
$f$	bollinger factor	1,1.3, 1.5, 1.8. 2, 2.5, 3
$b$	fixed band multiplier	0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, 0.05
$d$	time delay	2, 3, 4, 5
$c$	minimal holding time days	5, 10, 25, 50

**Table XII Parameters employed for the Bollinger band trading rule.**

In total, for the Bollinger band strategy we study

$$N \times F \times (1 + B + C + D) = 15 \times 7 \times 17 = 1785 \quad (\text{A14})$$

parameter constellations.

#### Appendix E. Directional Indicator

The directional indicator computes, for a fixed channel length  $n$ , the net price change relative to the total price change. The net price change is given by

$$\Delta P_{net}(t, n) = S_{t-1} - S_{t-n}$$

and the total price change is the sum of the absolute price changes, i.e.,

$$\Delta P_{tot}(t, n) = \sum_{i=1}^{n-1} |S_{t-i} - S_{t-i-1}|$$

<sup>15</sup>We deviate slightly from Sullivan et al. (1999) by adding the minimal holding time filter to all strategy combinations instead of applying it only to a narrow subset.



. The *directional indicator* is then computed as

$$DI(t, n) = \frac{\Delta P_{net}(t, n)}{\Delta P_{tot}(t, n)} \times 100.$$

The directional indicator strategy gives a buy signal when the net price change exceeds the total price change by a certain threshold  $u$ . Once it falls below a lower threshold  $l$ , the strategy gives a sell signal. The same filters discussed before can also be applied to the directional indicator strategy. In total, for the Directional Indicator strategies we use

Parameter	Description	Values
$n$	channel length	10, 20, 30, 40, 50, 75, 100, 150, 200, 250
$u$	upper limit	30, 40, 50
$l$	lower limit	0, 5, 10
$b$	fixed band multiplier	0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, 0.05
$d$	time delay	2, 3, 4, 5
$c$	minimal holding time days	5, 10, 25, 50

**Table XIII Parameters employed for the directional indicator trading rule.**

$$= C \times U \times L \times (1 + B + C + D) = 1530 \quad (\text{A15})$$

parameter constellations.

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