Testing the profitability of contrarian trading strategies based on the overreaction hypothesis

Matthieu Duvinage[a] Paolo Mazza[b] Mikael Petitjean[c]

September 17, 2014

Abstract

We develop 200 contrarian trading strategies based on significant market variations to test whether it is possible to benefit from the well-known psychological bias of overreaction that plagues investors. We conduct the most recent and appropriate statistical tests to ensure that none of these active strategies beats the buy-and-hold strategy due to pure luck only. Each of these strategies are tested on 13 different underlying assets, including exchange rates and stock indexes. When both transaction and borrowing costs are taken into account, our empirical results suggest that the use of significant market variations as daily reversal signals does not lead to any abnormal profit.

JEL Classification: G14

Keywords: Return predictability, high market variation, overreaction, behaviorial bias, SSPA

[a] National Bank of Belgium, 14 Boulevard de Berlaimont - 1000 Brussels (Belgium). Email: matthieu.duvinage@nbb.be.
[b] IESEG School of Management, 3 rue de la Digue - 59000 Lille (France). E-mail: p.mazza@ieseg.fr.
[c] Louvain School of Management & CORE, Université Catholique de Louvain, 151 Chaussée de Binche - 7000 Mons (Belgium). E-mail: mikael.petitjean@uclouvain.be.

We thank Mathieu Gorgerin for excellent research assistance. We are also grateful to an anonymous referee whose suggestions greatly improved the paper. We finally acknowledge the support from the ARC grant 09/14-025. Any remaining errors are solely the fault of the authors.

1 Introduction

Investors have always scouted throughout the globe to find the highest returns on their investment. Since the 1980's, this long-lasting quest for the Holy Grail has nevertheless been taking place in a constantly moving environment, accompanied by the rise and fall of new trading venues, participants, instruments, and technologies. In such market conditions, market variations can be extreme and even caused by exceptional events, the Black Monday (on October 19, 1987) and the Flash Crash (on May 6, 2010) being two notable examples. Not surprisingly, extreme explanations have also been proposed, from purely 'rational' computer-based trading to purely 'irrational' human behavior. It is nevertheless undisputable that investor psychology bears on the determination of market prices. On December 5, 1996, even Alan Greenspan who was a fierce advocate of the free market used the term 'irrational exuberance' to characterise the behavior of investors. Interestingly enough, markets kept rising until the middle of the year 2000. A more recent example concerns the European debt crisis when Mario Draghi, President of the European Central Bank (ECB), asserted on July 26, 2012 that the ECB was ready to do 'whatever it takes' to preserve the Euro. Following the speech, the mood turned upbeat as European stock exchanges started to rise, with the French CAC and the Spanish IBEX indexes closing 4.07% and 6.06% higher respectively. These two short examples remind us of the role that psychology plays in trading and investment decisions.

Applied psychology has considerably affected the way finance research is nowadays conducted. In behavioral finance, a particular attention is given to the degree of investor irrationality through the study of the effects of social, cognitive and emotional factors on market prices, returns and asset allocation. Market inefficiencies and anomalies are viewed as evidence of under- or over-reactions to information, leading to extended market trends or abrupt market reversals. Such market imperfections are attributed to a combination of cognitive biases such as bounded rationality, overconfidence, overreaction, representative bias, mimicry (herding instinct), and other predictable human errors in reasoning and information processing. Its increasing importance has been acknowledged by the 2002 and 2013 Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel, that has been attributed respectively to Daniel Kahneman and Robert Shiller.

We contribute to the literature on behavioral finance by investigating whether the well-known psychological bias of overreaction that plagues investors is predictable enough to lead to abnormal profits, justifying the claim that investor's behavior can be modeled appropriately. In particular, we test the predictive power of reversal signals based on significant market variations and control for transaction costs, borrowing costs, and randomness. The basic assumption is that investor overreaction drives excessive market movements that ultimately lead to price reversals. Under the null hypothesis (of no predictability), such reversal pattern cannot be anticipated and no abnormal profit can be realized. To the best of our knowledge, no previous work has studied overreaction-based strategies in the way we attempt to test them, using robust statistical procedures. To test the hypothesis of no predictability, we apply the Superior Predictive Ability (SPA) test and its stepwise version (SSPA), which corrects for data snooping. As in Duvinage et al. (2013), a double-or-out approach for trading strategies is used, which consists in following a benchmark by holding a long position modulated by one buy or sell transaction depending upon the previous day's price movement. This approach is recommended for SSPA tests since it delivers the same number of observations for each simulation.

The aim of the present paper is to test a comprehensive set of trading strategies based on both buy and sell signals. We do not address the differences between buy and sells signals, although some recent research evidence, such as Cooper et al. (2004) and Huang (2006), suggests that momentum profits depend on the up or down state of the market. We rather aim at testing trading strategies as a whole, correcting for data-snooping bias. Our results suggest that after controlling for transaction costs, borrowing costs, and data snooping (i.e. luck), active strategies based on investor overreaction do not provide significantly higher returns than the buy-and-hold benchmark strategy. Although evidence of significance is found in some cases, it remains too weak to be generalized.

The remainder of the paper proceeds as follows. In Section 2, we review some key findings of the literature on behavioral finance related to overreaction. Section 3 describes the methodology. In Section 4, we provide a brief description of the dataset and report the empirical results. The final section concludes.

2 Literature Review

Uncertainty plays a key role when it comes to making financial decisions. In the traditional finance literature, investors are able to make the best choice among all the possible alternatives by perfectly identifying the consequences associated with each of them. However, Simon (1955, 1957, 1959, 1979) argue that investors do not behave in a fully rational way. They have bounded rationality instead, i.e. they are limited in their capacity to process information. When making decisions, investors are argued to rely on a limited number of simplifying rules, failing to integrate the full logic of their decisions. For instance, when people have to choose between many possibilities, they just eliminate alternatives that do not present some predetermined characteristics, instead of thoroughly examining each alternative with its associated strengths and weaknesses (see Hong et al., 2005). Kahneman (1973) also argues that people are limited in their ability to perform several tasks at the same time. Miller (1956) further assesses that people can process only seven pieces of information simultaneously, implying that the cognitive load required for complex decisions overtakes their cognitive capabilities. For instance, the management of an investment portfolio is not an easy task since investors should not only put their attention on individual assets but also on the interactions between them.

Tversky and Kahneman (1981) and Kahneman and Lovallo (1993) argue that investors consider each decision in turn, instead of adopting a broader perspective. This decision process is called mental accounting. For instance, the decision to buy the stock of a company is separated from the decision on the amount of money to invest, thereby rejecting the influence between the two decisions. As outlined by Read and Rabin (1999), decision taking is impacted by the mental 'bracketing' of decisions, i.e. the fact that each decision is evaluated sequentially rather than in the global environment of all the decisions to make.

Such a 'narrow bracketing' depends on cognitive inertia. As outlined by Slovic (1972), the way decision problems are introduced (i.e. sequentially versus simultaneously or directly versus revealed after the cognitive process) bears on the investor choice. For instance, when people have to choose among several items, they choose more items when these choices are presented to them simultaneously rather than sequentially, as indicated by Redelmeier and Tversky (1992), Read and Rabin (1999) as well as Kahneman (2003).

Tversky and Kahneman (1974) document the fact that people often reduce the complex tasks of forming expectations and assessing probabilities to simpler judgmental operations. They identify a heuristic that is employed by people when they make decisions under uncertainty, called the 'representativeness heuristic'. When people evaluate the probability of an uncertain event belonging to a particular population, they often make probability judgments using similarities. In other words, when an event (e.g. a good performing stock) is highly representative of another class of events (i.e. a well-regarded company), the probability that the first originates from the second is judged to be (too) high (and vice versa). Kahneman and Tversky (1972, 1973) also suggest that too much weight is given to recent evidence, resulting in unrealistic forecasts. Barberis et al. (1998) also indicate that agents mistakenly extrapolate expectations from patterns in small samples. Barberis et al. (1998) show that this 'misconception of chance' bias leads investors to expect: higher (lower) returns after the release of good (bad) earnings announcements; and higher (lower) returns for recent winners (losers), while overreacting to prices over longer periods of time.

Investors also suffer from overconfidence and self-attribution, as outlined by Daniel et al. (1998, 2001). Overconfidence arises when investors think that they can predict the future better than they actually can, and are excessively optimistic about it. Self-attribution refers to the systematic attribution of success to skills, on the one hand, and failures to bad luck, on the other hand. Weinstein (1980) also suggests that most people have unrealistic views of their abilities, thereby engaging in wishful thinking. Daniel et al. (1998) and Barberis and Shleifer (2003) indicate that self-attribution maintains overconfidence. Odean (1999) also documents how overconfidence results in excessive trading. More recently, Barber and Odean (2008) show that investors tend to buy stocks that: appear in the press; exhibit high abnormal trading volumes; or display abnormally high returns.

Contrarian trading strategies have been widely analyzed in the literature over the last two decades. Yet, there is still no clear consensus on whether contrarian trading strategies are profitable once the luck effect has been removed, or whether the associated risk is the main cause of the excess returns. De Bondt and Thaler (1985) are the first to clearly lift the veil on market overreaction but it is Chan (1988) who provides a first comprehensive overview of what exactly implies a contrarian investment strategy. He suggests that the higher returns obtained by contrarians are a logical compensation for the higher risk they take by picking losers. He also finds no evidence that supports the overreaction hypothesis. Through the testing of return autocorrelations, Lo and MacKinlay (1990) provide evidence against overreaction being the only reason why contrarians make profits. However, Lakonishok et al. (1994) argue that the use of contrarian strategies can help beat the market: these strategies yield significantly higher returns even when risk is taken into account. Then, Dechow and Sloan (1997) argue against Lakonishok et al. (1994)'s findings, showing that biased forecasts and naive expectations are the key return drivers of contrarian trading strategies. The more recent release of David Dreman's book *Contrarian Trading Strategies: The Pyschological Edge* has led to new contributions, including Loughran (2012) who clearly argues in favor of contrarian trading strategies, as in the book.

All the behavioral biases identified in this section tend to move stock prices away from their economic fundamentals. Although the continuous adjustment of prices may be due to news arrivals and coherent with the efficient market hypothesis, it is also undeniable that some large unexplained fluctuations occur from time to time. Is it possible for contrarian investors to design profitable trading strategies based on these significant market variations? To answer this question, we test 200 contrarian strategies which are described in the next section.

3 Methodology

When significant market fluctuations occur, contrarian investors believe in the existence of irrational movements which are likely to be reversed by generating adaptation responses from market participants. The trading strategies that we test in this study are related to the overreaction bias which lies at the core of the literature on behavioral finance. These strategies are based on medium-term market timing: we buy (sell) at the close of very negative (positive) days and assume that large variations are relevant signals of medium-term market reversals. In the empirical analysis, we not only include periods of bubbles and crashes, but we also consider every market opening day as an opportunity to trade on unexpected and significant price variations.

The basic principle behind the tested strategies is straightforward: after a large market rise/drop, we bet on overreaction by investors and expect a price reversal movement. First, we consider various daily market drops/rises, from ± 1% to ± 10% as buy/sell signals. Second, we use a 5-year rolling window to compute percentile values. For instance, a buy signal is generated each time the last observed return is lower than the first percentile of the historical distribution built out of the previous five years of data. A sell signal is generated every time the last observed return exceeds the 99^{th} percentile computed over the previous five years. The 5-year time window rolls each day to include the most recent return in the distribution.

3.1 Data Snooping

Finance research has provided various statistical tools to test the profitability of trading rules. Using a bootstrap methodology, Brock et al. (1992) find that moving averages and trading-range breaks generate statistically significant abnormal returns compared to four benchmark models. The bootstrap resamples the original series n times in a systematic and random manner, thereby allowing to study the properties of the estimators. To some degree, this method controls for randomness by adjusting the p-values that were biased. Sullivan et al. (1999) go beyond Brock et al. (1992) by using White (2000)'s Reality Check bootstrap methodology which better controls for data snooping. When thousands of researchers and practitioners test thousands of trading strategies on the same time series, the null hypothesis of no abnormal profit is indeed very likely to be rejected at a given level of confidence because of pure luck only. Basic procedures of statistical hypothesis testing on single time series could therefore lead to wrong statistical decisions, e.g. committing a type-I error by rejecting the null hypothesis while it is true. If no correction for data mining is introduced, trading strategies cannot be tested seriously. As outlined by Hansen (2005), White (2000)'s Reality Check nevertheless suffers from two drawbacks. First, the RC test can be manipulated by the inclusion of poor and irrelevant strategies in the set of alternative strategies. Second, the RC test checks whether there is *any* model for which the null is rejected but it does not identify the outperforming model(s). Hansen (2005) and Hsu et al. (2010) provide new tools to circumvent these two drawbacks by developing the Superior Predictive Ability (SPA) test and its stepwise extension, respectively. These methods improve White (2000)'s Reality Check by comparing the performance of a benchmark model to n alternative models while adjusting explicitly for data-snooping.[1]

3.2 Double-or-Out

One of the requirements of the SPA test is the identical number of observations for each strategy, as indicated by Hansen (2005). In order to apply the SPA test and its stepwise extension, the double-or-out approach is considered (Duvinage et al., 2013). This method of investing starts by tracking the underlying asset (position +1). If there is no buy or sell signal (case 1), nothing more happens and we keep following the benchmark (position +1). If there is a large negative variation however (case 2), a buy signal is sent. We borrow money to double the position at the close of the day (position +2). We then wait for a large positive variation to close the whole position (going from position +2 to position 0).[2] If there is a large positive variation (case 3), we sell the long position in the underlying asset and get the cash back (going from position +1 to position 0). Consequently, the 'double-or-out' approach implies that the position is always 0, +1 or +2.[3]

[1]The interested reader should refer to Brock et al. (1992), Sullivan et al. (1999), White (2000), Hansen (2005), Hsu et al. (2010) and Duvinage et al. (2013) for additional technical information on these methods.

[2]In Section 4, we allow for the automatic return to the passive position (+1) after five days if no new signal is sent.

[3]Another alternative is to start by taking a short position in the benchmark asset. In this case, the position is 0, -1, or -2.

3.3 Signals

The computation of the buy and sell signals is done in two different ways. First, we use a predetermined percentage of daily price variation (from ±1% to ±10%). Second, we use the percentile function and a rolling window in order to add the most recent variation. We apply 10 different percentiles, from 0.1 to 0.0001 and from and 0.99 to 0.9999. For instance, if today's daily return is below (above) the return corresponding to the first (99^{th}) percentile based on the 5 previous years, we have a buy (sell) signal. The next day, the time window rolls forward to integrate the latest observation.

3.4 Cash Management

We also test two different philosophies regarding cash management: the 'full' and 'empty' approaches. Under the fist method, we assume that contrarian investors have sufficient cash, i.e. investors' pockets are 'full' of cash. When a position is closed, investors are always able to pay back even if they receive less money than the amount they initially invested. Under the second method, contrarian investors have no cash, i.e. investors' pockets are 'empty'. If investors have too little money to pay back the full amount of borrowing, they must generate cash out of the passive benchmark. In the event of a further market rise, they will not fully benefit from such a rise. In both cases, when there is more cash than required to pay back the borrowing, the cash surplus is reinvested.

3.5 Costs

We take both transaction and borrowing costs into account. At every step of the double-or-out system, we fully integrate transaction costs, i.e. 0.05% fees per transaction (e.g. Olson, 2004). Borrowing costs are also crucial in the performance of trading strategies and are often not included in research studies. To integrate them, we use the 3-month LIBOR with an additional 1% broker's call.

3.6 Strategy Classification

We also introduce stop loss orders. If the asset price at the end of the day is equal to (or lower than) the stop loss limit price, the position is closed in order to avoid excessive loss. Such stop loss orders are widely used by practitioners in order to minimize the impact of human psychology and emotions on trading decisions. We follow the well-known principle: "Cut the losses short and let the profits run". Finally, we make two different assumptions regarding the number of periods during which the contrarian investors remain fully invested in cash. Table 1 shows the different combinations of the tested strategies with respect to the stop loss and the cash-holding period.

Table 1: Stop loss and cash-holding period combinations

Features	Description
Combination 1: No stop loss, No waiting	1. In position +2, there is no stop loss order. 2. In position 0, we do not have to wait for the next buy signal to come back to position + 1. After a sell transaction and five days spent in position 0, we automatically come back to the benchmark tracking position (position +1).
Combination 2: No stop loss, Waiting	1. In position +2, there is no stop loss order. 2. In position 0, we have to wait for the next buy signal to come back to position + 1.
Combination 3: Stop loss, No waiting	1. In position +2, we use a stop loss of -2% (and -10%, alternatively). 2. In position 0, we do not have to wait for the next buy signal to come back. to position + 1. After a sell transaction and five days spent in position 0, we automatically come back to the benchmark tracking position (position +1).
Combination 4: Stop loss, Waiting	1. In position +2, we use a stop loss of -2% (and -10%, alternatively). 2. In position 0, we have to wait for the next buy signal to come back to position + 1.

The 200 tested strategies are classified in Table 2. There are 120 strategies with an arbitrary choice for the signals and 80 strategies based on rolling percentiles.

Table 2: Classification of all the strategies

Signals	Arbitrary								Rolling window							
Cash management	Full				Empty				Full				Empty			
Combination n°	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
Number	10	10	20	20	10	10	20	20	10	10	10	10	10	10	10	10
Total	10	20	40	60	70	80	100	120	130	140	150	160	170	180	190	200

4 Empirical analysis

Although research studies typically focus on one single asset class, we consider two different ones: Indexes and exchange rates. Table 3 presents the different assets that we examine, as well as the length of the daily historical series. For each asset, we include the same number of observations. 6301 daily returns correspond to a 20-year period, while 3774 records cover a 10-year period.

We apply Hansen (2005)'s SPA methodology and Hsu et al. (2010)'s stepwise extension to correct for data-snooping bias. The buy-and-hold strategy is compared to 200 active strategies. When testing for SPA, the question of interest is whether any alternative strategy performs better than the benchmark. The null hypothesis is that 'the benchmark is not inferior to any alternative model'. If the null is rejected, we identify the outperforming strategies through the Stepwise SPA procedure. We test this hypothesis with and without transaction costs. This will help detect whether significant results are due to the strategies themselves or to costs only.

Table 4 presents the lower and upper p-values associated with the SPA tests for each security. The p-value of a SPA test shows the relative performance of the benchmark strategy with respect to the k alternative models (i.e. the 200 active strategies). A low (high) p-value indicates that the null hypothesis is (not) rejected: Superior alternative strategies to the benchmark do (not) exist. Considering a significance level at $\alpha\%$, a strategy has a statistically significant predictive power if its associated p-value is lower than $\alpha\%$. Finally, Hansen (2005) proposes lower and upper p-value estimations because there is no perfect estimation of the mean distribution. Using the upper p-value leads to more conservative conclusions in the sense that it minimizes the risk of rejecting the null hypothesis while it is actually true.

Table 3: Dataset

Asset	Country	Period	N
Panel A : Indexes			
S&P 500	United-States	08/07/1987 - 06/07/2012	6301
FTSE 100	England	28/07/1987 - 06/07/2012	6301
DAX 30	Germany	25/08/1987 - 06/07/2012	6301
EURO STOXX 50	Europe	22/01/1988 - 06/07/2012	6301
HANG SENG 50	Hong-Kong	14/01/1987 - 06/07/2012	6301
IBOVESPA 50	Brazil	15/04/1997 - 06/07/2012	3774
MICEX 50	Russia	22/09/1996 - 06/07/2012	3774
BSE SENSEX 30	India	19/05/1997 - 06/07/2012	3774
SSE Comp 50	China	27/11/1996 - 06/07/2012	3774
NIKKEI 225	Japan	05/11/1986 - 06/07/2012	6301
Panel B : Exchange rates			
EUR/USD	Europe/U.S.	31/11/1999 - 06/07/2012	3268
EUR/JPY	Europe/Japan	07/12/1999 - 06/07/2012	3268
USD/JPY	U.S./Japan	07/03/1988 - 06/07/2012	6301

Source: Datastream.

Excluding transaction costs, the p-value is lower than 0.05 for the FTSE, EURO STOXX, and NIKKEI indexes. These results suggest that there is at least one of the 200 active strategies that beat the passive strategy in more than 95 cases out of 100. On the exchange rate markets, p-values are all higher than 10%, pointing to a very poor predictive power and a greater efficiency. Although emerging markets are often considered as less efficient, there is no evidence that contrarian strategies lead to abnormal profits. Regarding the influence of transaction costs, p-values are logically smaller and several results become insignificant.

The main drawback of the SPA test lies in the fact that it fails to identify the outperforming active strategie(s). This identification task is done by carrying out the SSPA test. Results before transaction costs are reported in Table 5.

Table 4: SPA results

	Without costs		With costs	
Asset	Upper p-value	Lower p-value	Upper p-value	Lower p-value
Panel A : Indexes				
S&P 500	0.236	0.229	0.499	0.461
FTSE 100	0.045^{**}	0.041^{**}	0.192	0.156
DAX 30	0.074^{*}	0.053^{*}	0.132	0.092^{*}
EURO STOXX 50	0.023^{**}	0.023^{**}	0.066^{*}	0.056^{*}
NIKKEI 225	0.026^{**}	0.023^{**}	0.045^{**}	0.036^{**}
HANG SENG	0.266	0.161	0.421	0.235
IBOVESPA	0.155	0.116	0.241	0.173
SSE COMP	0.323	0.206	0.361	0.225
BSE SENSEX	0.666	0.435	0.692	0.462
MICEX	0.544	0.37	0.598	0.398
Panel B : Exchange Rates				
EUR/USD	0.73	0.673	0.99	0.942
EUR/JPY	0.392	0.354	0.569	0.427
USD/JPY	0.308	0.257	0.682	0.479

Panel A, B, and C refer to indexes and exchange rates, respectively. The stars denote significance: $*$ denotes significance at 10% while $**$ indicates significance at 5%.

Table 5: SSPA test : Significant strategies without costs

Asset	Significance	Strategies
FTSE 100	5%	133
FTSE 100	10%	133
DAX 30	5%	None
DAX 30	10%	3, 103, 13, 43 and 23
EURO STOXX 50	5%	125 and 175
EURO STOXX 50	10%	125, 175, 126 and 124
NIKKEI 225	5%	53 and 13
NIKKEI 225	10%	53, 13, 43 and 103

This tables identifies the outperforming strategies for each underlying asset, that were significant in the SPA test. The numbers refer to the strategies presented in Table 2.

We only have 5 significant strategies at the 5% significance level (strategies 13, 53, 125, 133, and 175). There are 6 more strategies outperforming the benchmark at the a 10% significance level. Only three active strategies (i.e. 13, 43, and 103) lead to abnormal profits (before costs) on two different markets (i.e. DAX and NIKKEI).

When costs and luck are correctly discounted, the overall empirical results show that contrarian investors are very unlikely to generate abnormal profits above those provided by a passive buy-and-hold strategy

5 Conclusion

Although the efficient market hypothesis is widely regarded as a cornerstone of modern finance, the search for market-beating returns is still very much alive.[4] This quest for the Holy Grail in finance often consists in designing active strategies with the goal of taking advantage of behavioral biases such as bounded rationality, self-attribution, overconfidence, or overreaction.

The main purpose of this study is to test whether a contrarian investor who is fully aware of these behavioral biases is able to 'beat the market'. We therefore investigate the predictive power of reversal signals based on significant market variations and control for transaction costs, borrowing costs, and randomness. For instance, overselling a stock moves the market price away from its fundamental value. Contrarian investors benefit from this shock as long as informed value traders react by pushing the price back towards the fundamental value.

Testing the added value of active strategies is no easy task. Such testing is indeed plagued by a very serious issue: data mining. When thousands of researchers and practitioners test thousands of trading strategies on the same time series, the null hypothesis of no abnormal profit is indeed very likely to be rejected at a given level of confidence because of pure luck only. Basic procedures of statistical hypothesis testing on single time series could therefore lead to wrong statistical decisions. We therefore apply the Superior Predictive Ability (SPA) test and its stepwise extension (SSPA) that correct for the presence of data snooping bias and control for the luck factor. These methods are more powerful than traditional bootstrap approaches. We construct contrarian strategies based on predetermined daily market variations (from ±1% to ±10%). We also use various percentiles in the tails of the return distribution and apply a 5-year rolling window to update the buy and sell signals. Two different cash management approaches are proposed and four different double-or-out options are introduced. Overall, we

[4] After being wiped out in one of the many stock market crashes of his era, Isaac Newton already wrote in 1768: 'I can calculate the motions of the heavenly bodies but not the movements of the stock market'.

test 200 contrarian strategies for each underlying asset. The dataset includes 10 different stock indexes (including emerging markets) and three exchange rates.

After adjusting for data-snooping bias, only a few strategies beat the buy-and-hold benchmark strategy, which suggests that contrarian strategies are overall not successful. For some indexes (NIKKEI, EURO STOXX, FTSE, and DAX), there is nevertheless some evidence of predictability. The level of predictability is lower after the inclusion of transaction costs but the change remains limited, pointing to the failure of contrarian strategies to generate abnormal gross profits.

Foolish are the conservatives who still defend the idea that markets are always efficient. Equally devoid of any good sense are the behavioral fundamentalists who claim that markets are sufficiently inefficient to design robust, long-lasting, and profitable actively-managed strategies. Such is the main conclusion of this empirical study.

References

Barber, B. M. and T. Odean (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies 21*(2), 785–818.

Barberis, N. and A. Shleifer (2003). Style investing. *Journal of Financial Economics 68*(2), 161 – 199.

Barberis, N., A. Shleifer, and R. Vishny (1998). A model of investor sentiment. *Journal of Financial Economics 49*(3), 307 – 343.

Brock, W., J. Lakonishok, and B. LeBaron (1992). Simple technical trading rules and the stochastic properties of stock returns. *Journal of Finance 47*(5), 1731–64.

Chan, K. C. (1988). On the contrarian investment strategy. *The Journal of Business 61*(2), pp. 147–163.

Cooper, M. J., R. C. Gutierrez, and A. Hameed (2004). Market states and momentum. *The Journal of Finance 59*(3), 1345–1365.

Daniel, K. D., D. Hirshleifer, and A. Subrahmanyam (1998). Investor psychology and security market under- and over-reactions. *The Journal of Finance 53*(6), 1839–1886.

Daniel, K. D., D. Hirshleifer, and A. Subrahmanyam (2001). Overconfidence, arbitrage, and equilibrium asset pricing. *The Journal of Finance 56*(3), 921–965.

De Bondt, W. F. M. and R. Thaler (1985). Does the stock market overreact? *The Journal of Finance 40*(3), 793–805.

Dechow, P. M. and R. G. Sloan (1997). Returns to contrarian investment strategies: Tests of naive expectations hypotheses. *Journal of Financial Economics 43*(1), 3 – 27.

Duvinage, M., P. Mazza, and M. Petitjean (2013). The intraday performance of market timing strategies and trading systems based on Japanese candlesticks. *Quantitative Finance*, forthcoming.

Hansen, P. R. (2005). A test for superior predictive ability. *Journal of Business & Economic Statistics 23*, 365–380.

Hong, H., J. D. Kubik, and J. C. Stein (2005). Thy neighbor's portfolio: Word-of-mouth effects in the holdings and trades of money managers. *The Journal of Finance 60*(6), 2801–2824.

Hsu, P.-H., Y.-C. Hsu, and C.-M. Kuan (2010). Testing the predictive ability of technical analysis using a new stepwise test without data snooping bias. *Journal of Empirical Finance 17*(3), 471–484.

Huang, D. (2006). Market states and international momentum strategies. *The Quarterly Review of Economics and Finance 46*(3), 437 – 446.

Kahneman, D. (1973). *Attention and Effort*. Prentice-Hall series in experimental psychology. Prentice-Hall.

Kahneman, D. (2003). Maps of bounded rationality: Psychology for behavioral economics. *American Economic Review 93*(5), 1449–1475.

Kahneman, D. and D. Lovallo (1993). Timid choices and bold forecasts: A cognitive perspective on risk taking. *Management Science 39*(1), 17–31.

Kahneman, D. and A. Tversky (1972). Subjective probability: A judgment of representativeness. *Cognitive Psychology 3*(3), 430 – 454.

Kahneman, D. and A. Tversky (1973). On the psychology of prediction. *Psychological Review 80*(4), 237–251.

Lakonishok, J., A. Shleifer, and R. W. Vishny (1994). Contrarian investment, extrapolation,
1 and risk. *The Journal of Finance 49*(5), 1541–1578.

Lo, A. and A. MacKinlay (1990). When are contrarian profits due to stock market overreaction?
2 *Review of Financial Studies 3*(2), 175–205.

Loughran, T. (2012). On david dreman's contrarian investment strategies: The psychological
3 edge. *Journal of Behavioral Finance 13*(3), 163–163.

Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our
4 capacity for processing information. *Psychological Review 63*(2), 81–97.

5 Odean, T. (1999). Do investors trade too much? *American Economic Review 89*, 1279–1298.

Olson, D. (2004). Have trading rule profits in the currency markets declined over time? *Journal
6 of Banking and Finance 28*(1), 85–105.

Read, D., G. L. and M. Rabin (1999). Choice bracketing. *Journal of Risk and Uncer-
7 tainty 19*(1-3), 171–97.

Redelmeier, D. A. and A. Tversky (1992). On the framing of multiple prospects. *Psychological
8 Science 3*(3), 191–193.

Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Eco-
9 nomics 69*, pp. 99–118.

10 Simon, H. A. (1957). *Models of Man.* New–York.

Simon, H. A. (1959). Theories of decision making in economics and behavioral science. *Amer-
11 ican Economic Review 49*, pp. 223–83.

Simon, H. A. (1979). Rational decision making in business organizations. *American Economic
12 Review 69*(4), pp. 493–513.

Slovic, P. (1972). Psychological study of human judgment: Implications for investment decision
13 making. *The Journal of Finance 27*(4), 779–799.

Sullivan, R., A. Timmermann, and H. White (1999). Data-Snooping, Technical Trading Rule
14 Performance, and the Bootstrap. *Journal of Finance 5*, 1647–1691.

Tversky, A. and D. Kahneman (1974). Judgment under uncertainty: Heuristics and biases.
15 *Science 185*(4157), 1124–1131.

Tversky, A. and D. Kahneman (1981). The framing of decisions and the psychology of choice. *Science 211*(4481), 453–458.

Weinstein, N. D. (1980). Unrealistic optimism about future life events. *Journal of Personality and Social Psychology 39*(5), 806–820.

White, H. (2000). A reality check for data snooping. *Econometrica 68*(5), 1097–1126.