

Revisiting the Profitability of Market Timing with Moving Averages*

Valeriy Zakamulin[†]

This revision: August 25, 2016

Abstract

In a recent empirical study by Glabadanidis (“Market Timing With Moving Averages” (2015), *International Review of Finance*, Volume 15, Number 13, Pages 387-425) the author reports striking evidence of extraordinary good performance of the moving average trading strategy. In this paper we demonstrate that “too good to be true” reported performance of the moving average strategy is due to simulating the trading with look-ahead bias. We perform the simulations without look-ahead bias and report the true performance of the moving average strategy. We find that at best the performance of the moving average strategy is only marginally better than that of the corresponding buy-and-hold strategy. In statistical terms, the performance of the moving average strategy is indistinguishable from the performance of the buy-and-hold strategy.

Key words: technical analysis, market timing, moving averages, performance evaluation

JEL classification: G11, G17.

1 Introduction

To time the market, traders often employ moving averages of prices (10-month simple moving average is particularly popular). A common belief is that one can identify the market trend by comparing the moving average of prices and the recent price. Specifically, the price above (below) the moving average signals the bullish (bearish) trend. However, whereas market timing with moving averages has been extensively employed by practitioners for more than half a century, academics had long been skeptical about its usefulness. The study by Brock, Lakonishok, and LeBaron (1992) marked the onset of change in the academics’ attitude towards technical analysis because this study tends to suggest that one should not dismiss the value

*The author is grateful to an anonymous referee and Steen Koekebakker for their comments and to Geirmund Glendrange and Sondre Tveiten for double-checking the author’s results. The usual disclaimer applies.

[†]a.k.a. Valeri Zakamouline, School of Business and Law, University of Agder, Service Box 422, 4604 Kristiansand, Norway, Tel.: (+47) 38 14 10 39, E-mail: Valeri.Zakamouline@uia.no

of market timing. Still, before the decade of 2000s, on the academic side there was common agreement that market timing does not work (see, for example, Sullivan, Timmermann, and White (1999) and Bauer and Dahlquist (2001)). Moving average trading strategies has become increasingly popular in the aftermath of the two recent severe stock market crashes: the Dot-Com bubble crash of 2000-01 and the Global financial crisis of 2007-08. This interest developed because backtests of many technical trading rules over the decade of 2000s reveal that these rules outperform the market by a large margin. The advantages of the moving average trading strategies in backtests are documented in a series of papers, among others by Okunev and White (2003), Faber (2007), Gwilym, Clare, Seaton, and Thomas (2010), Kilgallen (2012), Moskowitz, Ooi, and Pedersen (2012), Clare, Seaton, Smith, and Thomas (2013), Pätäri and Vilska (2014), and Glabadanidis (2015). A more skeptical view on the performance of the market timing strategies is presented by Zakamulin (2014) who argues that in the majority of published studies the backtests are implemented with data-mining bias and ignoring important market frictions.

Whereas the data-mining bias and ignoring the market impact and frictions are the two most common problems with backtests, a less common but still quite typical problem is look-ahead bias. The goal of this paper is to reconsider the results of the recent empirical study by Glabadanidis (2015) where the author reports striking evidence of extraordinary good performance of the moving average trading strategies. In particular, he finds the performance of the moving average trading strategies to be much higher than the performance reported in previous studies. This is especially surprising given the fact that superior performance was generated for a very broad range of the moving averaging window lengths, ranging from 6 months to 60 months. In this paper we demonstrate that “too good to be true” reported performance of the moving average strategy is due to simulating the trading with look-ahead bias. Specifically, in our empirical study we investigate the performances of the same trading strategies using the same datasets and sample period as in Glabadanidis (2015). First of all, we replicate the empirical results in the study by Glabadanidis (2015) by simulating moving average strategies with look-ahead bias. Second, we perform the simulations without look-ahead bias and report the true performance of moving average strategies.¹ We find that at

¹The interested readers can reproduce the results reported in this paper by downloading the R code of the program that simulates the trading, with and without look-ahead bias, and the relevant Ken French’s data from the author’s web-site vzakamulin.weebly.com.

best the performance of the moving average strategy is only marginally better than that of the corresponding buy-and-hold strategy. In statistical terms, the performance of the moving average strategy is indistinguishable from the performance of the corresponding buy-and-hold strategy.

2 Data

The data for this study are monthly value-weighted returns of sets of 10 portfolios sorted by size, book-to-market, and momentum. Additional data include monthly returns on a broad market index, the risk-free rate of return (proxied by one-month Treasury bill rate), the returns on the SMB (Small Minus Big) and HML (High Minus Low) Fama-French factors (Fama and French (1993)), and the returns on the MOM (Momentum) factor (Carhart (1997)). All data come from the data library of Kenneth French.² As in Glabadanidis (2015), our sample period starts in January 1960 and ends in December 2011.

3 Backtesting the Moving Average Strategy

Backtesting is the process of simulating a trading strategy using relevant historical data with the goal to evaluate its past performance. The returns to the moving average trading strategy are simulated as follows. Let (P_0, P_1, \dots, P_T) be the observations of the monthly (dividend-adjusted) closing prices of a portfolio. An L -month (simple) Moving Average (MA) at month-end t is computed as

$$MA_t(L) = \frac{P_t + P_{t-1} + \dots + P_{t-k+1}}{L}. \quad (1)$$

The trading signal for month $t + 1$ is generated at month-end t according to the following rule

$$\text{Signal}_{t+1} = \begin{cases} \text{Buy} & \text{if } P_t > MA_t(L), \\ \text{Sell} & \text{if } P_t \leq MA_t(L). \end{cases} \quad (2)$$

Let (R_1, R_2, \dots, R_T) be the monthly returns on a portfolio, where $R_{t+1} = (P_{t+1} - P_t)/P_t$, and let $(r_{f1}, r_{f2}, \dots, r_{fT})$ be the monthly risk-free rates of return over the same sample period. We suppose that buying and selling stocks is costly, whereas buying and selling Treasury bills

²http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

is costless. Denoting by τ the one-way transaction costs, the return to the market timing strategy over month $t + 1$ is given by

$$r_{t+1} = \begin{cases} R_{t+1} & \text{if } (\text{Signal}_{t+1} = \text{Buy}) \text{ and } (\text{Signal}_t = \text{Buy}), \\ R_{t+1} - \tau & \text{if } (\text{Signal}_{t+1} = \text{Buy}) \text{ and } (\text{Signal}_t = \text{Sell}), \\ r_{ft+1} & \text{if } (\text{Signal}_{t+1} = \text{Sell}) \text{ and } (\text{Signal}_t = \text{Sell}), \\ r_{ft+1} - \tau & \text{if } (\text{Signal}_{t+1} = \text{Sell}) \text{ and } (\text{Signal}_t = \text{Buy}). \end{cases} \quad (3)$$

It is worth noting that the moving average strategy is a switching strategy between cash and risky stocks. As in Glabadanidis (2015), we assume that one-way transaction costs amount to 50 basis points (0.5%), that is, $\tau = 0.005$.

4 Backtesting with Look-Ahead Bias

Simulation of a trading strategy with look-ahead bias is a common and insidious mistake in backtesting. Look-ahead bias occurs when backtest is conducted using data that was not, in reality, available to the trader at the time the backtest assumes. The empirical results reported in Glabadanidis (2015) can be replicated only if one, by mistake, simulates the moving average strategy with the following look-ahead bias. For the sake of the simplicity of exposition, in this section we assume that there are no transaction costs. Under this assumption, the correct simulation of the returns to the moving average trading strategy, given by equation (3), reduces to

$$r_{t+1} = \begin{cases} R_{t+1} & \text{if } P_t > MA_t(L), \\ r_{ft+1} & \text{if } P_t \leq MA_t(L). \end{cases} \quad (4)$$

In particular, at month-end t a trader observes the closing price P_t and computes the moving average and the trading signal for the subsequent month $t + 1$. If according to the new trading signal a trader has to switch the portfolio position, the trading occurs at the current closing price. It is important to note that at month-end t , when the trading signal is generated, the next month closing price P_{t+1} is unknown.

A quite typical mistake in backtesting is to simulate the same trading strategy with look-

ahead bias. In this case the simulation goes like this

$$r_{t+1} = \begin{cases} R_{t+1} & \text{if } P_{t+1} > MA_{t+1}(L), \\ r_{ft+1} & \text{if } P_{t+1} \leq MA_{t+1}(L). \end{cases} \quad (5)$$

With look-ahead bias, the trading strategy is simulated as though the trader has a perfect foresight of the next month closing price. Specifically, to earn the return R_{t+1} over month $t+1$, a Buy signal must be generated at month-end t . With look-ahead bias the trading signal at month-end t for the subsequent month $t+1$ is computed using the next month closing price P_{t+1} . However, in reality, at month-end t the next month closing price P_{t+1} is not available!

One can argue that since the moving average is computed using a window of L months and with, say $L = 24$, the advantage of allowing a trader to peek a little bit into the future seems to be negligible. However, even such a slight look-ahead bias translates into extraordinary good (and false) performance.

5 Empirical Results

Similarly to Glabadanidis (2015), we measure the performance by the Sharpe ratio and alpha in the Fama-French-Carhart 4-factor model. For the Sharpe ratio of each market timing strategy (denoted by SR_{MA}) we report the p-value of testing the null hypothesis that it is equal to the Sharpe ratio of the corresponding buy-and-hold portfolio (denoted by SR_{BH}). More formally, we test the hypothesis $H_0 : SR_{MA} = SR_{BH}$. For this purpose we apply the Jobson and Korkie (1981) test with the Memmel (2003) correction.

Table 1 reports the summary statistics and the performance of the buy-and-hold strategies (BH) and the moving average strategies MA(24) (the baseline case in Glabadanidis (2015)) and MA(10) (the standard case in the market timing literature) simulated **with look-ahead bias**. The results for BH and MA(24) strategies in Table 1 are virtually the same as those in Glabadanidis (2015).³ And these results are really very “intriguing”. Specifically, the average returns of the MA strategies are substantially higher than the average returns of the corresponding BH strategies. At the same time, the standard deviation of returns of the MA

³Very small differences can be attributed to the fact that Kenneth French revises periodically his datasets because of the revisions in the data series provided by the Center for Research in Security Prices (CRSP).

strategies is substantially lower than the standard deviation of returns of the corresponding BH strategies. As a result, the risk-return trade-off is improved substantially resulting in much higher Sharpe ratios of the MA strategies when compared to the Sharpe ratios of the BH strategies. In particular, the average Sharpe ratio of the MA(24) strategy is almost double as high as that of the BH strategy, whereas the average Sharpe ratio of the MA(10) strategy is almost triple as high as that of the BH strategy. The Sharpe ratios of all MA strategies are not only economically significantly higher, but also statistically significantly higher. As an extra advantage, for the majority of portfolios, the BH strategy has a negative return skewness while the MA strategy in most cases exhibits positive skewness. This feature makes the MA strategy very attractive to investors because apparently the BH strategy has higher variation in the domains of losses, whereas the corresponding MA strategy has higher variation in the domain of gains. Last but not least, whereas the alphas of the BH strategies are virtually zero, the alphas of the MA strategies are both economically and statistically significantly positive. Specifically, the average alpha of the MA(10) strategy amounts to about 11% on the annual basis.

[Insert Table 1 about here]

Table 2 reports the summary statistics and the performance of the BH strategies and the moving average strategies simulated **without look-ahead bias**. Apparently, the true performance of the MA strategies is not “intriguing” at all, especially when it comes to the performance of the MA(24) strategy. Specifically, whereas the standard deviation of returns of the MA strategies is still substantially lower than the standard deviation of returns of the respective BH strategies, the average returns of the MA strategies are also lower than the average returns of the respective BH strategies. The average Sharpe ratio of the MA(24) strategy is lower than the average Sharpe ratio of the corresponding BH strategy. The average Sharpe ratio of the MA(10) strategy is only marginally higher than the average Sharpe ratio of the BH strategy. Thus, the risk-return trade-off is slightly improved for the MA(10) strategy only. In statistical terms, the Sharpe ratios of the MA strategies are not statistically significantly different from the Sharpe ratios of the corresponding BH strategies. In addition, for the most of the MA strategies, the return skewness is more negative than the return skewness of the BH

strategies. This feature makes the MA strategy less attractive to investors who have a preference for skewness. The average alpha of the MA strategies is negative because the returns to the MA strategy have a large positive loading on the Momentum factor. A few alphas are also statistically significantly negative.

[Insert Table 2 about here]

6 Conclusions

In this paper we demonstrated that the sole “driver of abnormal performance” of the moving average strategies, reported in the empirical study by Glabadanidis (2015), is look-ahead bias. We performed the correct simulation of the same strategies using the same datasets and sample period as in the study by Glabadanidis (2015). We found that at best the performance of the moving average strategy is only marginally better than that of the corresponding buy-and-hold strategy in terms of the Sharpe ratio. In contrast, in terms of alpha, the performance of the moving average strategy is worse than that of the corresponding buy-and-hold strategy. In statistical terms, most of the time the performance of the moving average strategy is indistinguishable from the performance of the buy-and-hold strategy. Overall, the conclusions reached in this paper agree with the conclusions in Zakamulin (2014): the performance of moving average strategies is highly overstated to say the least.

References

- Bauer, Richard J., J. and Dahlquist, J. R. (2001). “Market Timing and Roulette Wheels”, *Financial Analysts Journal*, 57(1), 28–40.
- Brock, W., Lakonishok, J., and LeBaron, B. (1992). “Simple Technical Trading Rules and the Stochastic Properties of Stock Returns”, *Journal of Finance*, 47(5), 1731–1764.
- Carhart, M. M. (1997). “On Persistence in Mutual Fund Performance”, *Journal of Finance*, 52(1), 57–82.
- Clare, A., Seaton, J., Smith, P. N., and Thomas, S. (2013). “Breaking Into the Blackbox: Trend Following, Stop losses and the Frequency of Trading - The Case of the S&P500”, *Journal of Asset Management*, 14(3), 182–194.
- Faber, M. T. (2007). “A Quantitative Approach to Tactical Asset Allocation”, *Journal of Wealth Management*, 9(4), 69–79.

- Fama, E. F. and French, K. R. (1993). “Common Risk Factors in the Returns on Stocks and Bonds”, *Journal of Financial Economics*, 33(1), 3–56.
- Glabadanidis, P. (2015). “Market Timing With Moving Averages”, *International Review of Finance*, 15(3), 387–425.
- Gwilym, O., Clare, A., Seaton, J., and Thomas, S. (2010). “Price and Momentum as Robust Tactical Approaches to Global Equity Investing”, *Journal of Investing*, 19(3), 80–91.
- Jobson, J. D. and Korkie, B. M. (1981). “Performance Hypothesis Testing with the Sharpe and Treynor Measures”, *Journal of Finance*, 36(4), 889–908.
- Kilgallen, T. (2012). “Testing the Simple Moving Average across Commodities, Global Stock Indices, and Currencies”, *Journal of Wealth Management*, 15(1), 82–100.
- Memmel, C. (2003). “Performance Hypothesis Testing with the Sharpe Ratio”, *Finance Letters*, 1, 21–23.
- Moskowitz, T. J., Ooi, Y. H., and Pedersen, L. H. (2012). “Time Series Momentum”, *Journal of Financial Economics*, 104(2), 228–250.
- Okunev, J. and White, D. (2003). “Do Momentum-Based Strategies Still Work in Foreign Currency Markets?”, *Journal of Financial and Quantitative Analysis*, 38(2), 425–447.
- Pätäri, E. and Vilska, M. (2014). “Performance of Moving Average Trading Strategies over Varying Stock Market Conditions: the Finnish Evidence”, *Applied Economics*, 46(24), 2851–2872.
- Sullivan, R., Timmermann, A., and White, H. (1999). “Data-Snooping, Technical Trading Rule Performance, and the Bootstrap”, *Journal of Finance*, 54(5), 1647–1691.
- Zakamulin, V. (2014). “The Real-Life Performance of Market Timing with Moving Average and Time-Series Momentum Rules”, *Journal of Asset Management*, 15(4), 261–278.

Table 1: Performance of moving average strategies simulated with look-ahead bias

Portfolio	BH Portfolios					MA(24) Portfolios					MA(10) Portfolios				
	μ	σ	s	SR	α	p-val	μ	σ	s	SR	p-val	α	p-val	s	SR
Panel A: Size-sorted portfolios															
Low	13.5	22.4	-0.13	0.37	-0.78	(0.40)	17.9	17.0	0.35	0.75	(0.00)	5.25	(0.00)	1.24	1.32
2	12.9	22.3	-0.22	0.35	-1.19	(0.03)	17.9	16.8	0.27	0.76	(0.00)	5.66	(0.00)	1.26	1.28
3	13.6	21.3	-0.40	0.40	0.03	(0.95)	17.6	16.2	0.04	0.77	(0.00)	5.43	(0.00)	0.94	1.34
4	12.9	20.5	-0.46	0.38	-0.48	(0.34)	17.5	15.2	0.05	0.81	(0.00)	5.69	(0.00)	0.87	1.31
5	13.3	19.8	-0.47	0.41	0.45	(0.39)	17.4	14.6	-0.08	0.84	(0.00)	5.43	(0.00)	0.88	1.36
6	12.4	18.6	-0.49	0.39	0.14	(0.82)	16.5	13.7	0.08	0.83	(0.00)	5.24	(0.00)	0.79	1.32
7	12.5	18.3	-0.45	0.40	0.41	(0.47)	16.4	13.5	0.17	0.83	(0.00)	5.61	(0.00)	0.96	1.37
8	11.8	17.8	-0.42	0.38	0.25	(0.65)	15.8	13.2	0.15	0.81	(0.00)	5.44	(0.00)	0.77	1.31
9	11.2	16.3	-0.39	0.37	0.22	(0.67)	15.1	12.0	0.21	0.83	(0.00)	5.39	(0.00)	0.68	1.28
High	9.5	15.0	-0.31	0.29	0.52	(0.03)	13.1	11.7	-0.20	0.68	(0.00)	3.88	(0.00)	0.79	1.20
Panel B: Book-to-market-sorted portfolios															
Low	9.0	18.1	-0.18	0.21	1.62	(0.02)	14.1	13.3	0.28	0.67	(0.00)	5.91	(0.00)	0.82	1.19
2	10.4	16.6	-0.43	0.32	1.06	(0.12)	14.4	12.7	0.13	0.73	(0.00)	5.74	(0.00)	0.61	1.27
3	10.9	16.2	-0.46	0.36	0.80	(0.28)	15.7	12.0	0.27	0.88	(0.00)	6.87	(0.00)	0.72	1.29
4	10.7	16.7	-0.44	0.34	-0.65	(0.43)	14.8	12.1	0.42	0.80	(0.00)	5.37	(0.00)	0.84	1.23
5	10.6	15.7	-0.40	0.35	-0.95	(0.26)	13.9	11.8	0.19	0.74	(0.00)	4.03	(0.00)	0.87	1.26
6	11.7	15.8	-0.40	0.41	0.00	(1.00)	15.2	12.1	0.34	0.83	(0.00)	5.06	(0.00)	0.80	1.25
7	12.4	15.6	-0.09	0.47	-0.13	(0.87)	15.7	12.8	0.25	0.83	(0.00)	4.08	(0.00)	1.16	1.35
8	13.0	16.0	-0.44	0.49	-0.61	(0.35)	15.6	12.4	0.14	0.85	(0.00)	4.07	(0.00)	1.01	1.35
9	13.9	16.9	-0.29	0.52	0.02	(0.98)	18.0	13.0	0.22	0.99	(0.00)	6.04	(0.00)	0.99	1.38
High	15.2	20.6	0.08	0.49	-0.73	(0.50)	19.2	16.0	0.55	0.88	(0.00)	5.11	(0.00)	1.46	1.43
Panel C: Momentum-sorted portfolios															
Low	1.3	28.0	0.66	-0.14	-2.80	(0.04)	11.9	13.6	1.10	0.50	(0.00)	4.70	(0.01)	3.00	0.88
2	7.8	21.9	0.25	0.12	2.52	(0.00)	13.3	14.2	0.62	0.58	(0.00)	7.30	(0.00)	2.32	1.09
3	9.4	18.8	0.32	0.23	3.12	(0.00)	14.1	12.3	0.59	0.73	(0.00)	6.39	(0.00)	2.15	1.10
4	10.0	16.9	-0.11	0.29	2.21	(0.01)	13.8	11.6	0.51	0.75	(0.00)	6.39	(0.00)	0.92	1.13
5	9.0	15.7	-0.25	0.24	-0.27	(0.73)	13.2	10.9	0.44	0.75	(0.00)	5.00	(0.00)	1.06	1.14
6	10.1	15.9	-0.36	0.31	-0.16	(0.85)	14.2	11.6	0.55	0.79	(0.00)	4.99	(0.00)	1.04	1.18
7	10.4	15.4	-0.47	0.34	-0.81	(0.33)	14.3	12.0	0.13	0.76	(0.00)	4.42	(0.00)	0.79	1.28
8	12.4	15.8	-0.29	0.46	-0.35	(0.64)	15.1	13.1	-0.08	0.76	(0.00)	3.69	(0.00)	0.46	1.29
9	13.2	17.0	-0.51	0.47	-0.92	(0.24)	16.3	14.3	-0.10	0.78	(0.00)	4.33	(0.00)	0.47	1.32
High	17.5	21.8	-0.39	0.57	0.98	(0.30)	21.5	18.7	-0.06	0.87	(0.00)	6.91	(0.00)	0.47	1.46

Summary statistics for the respective buy-and-hold (BH) portfolio returns and the moving average (MA) strategy portfolio returns with the length of the moving average window of 24 and 10 months (these strategies are denoted by MA(24) and MA(10) respectively). The sample period covers January 1960 to December 2011. A one-way transaction cost of 0.5% has been imposed in the computation of the MA returns. μ is the annualized average return, σ is the annualized standard deviation of returns, s is the skewness, SR is the annualized Sharpe ratio, α is the alpha in the Fama-French-Carhart 4-factor model, and $p\text{-val}$ is the p-value. μ , σ , and α are reported in percentages. For the Sharpe ratio of the MA strategy, we test the hypothesis $H_0 : SR_{MA} = SR_{BH}$. For each alpha, we test the hypothesis $H_0 : \alpha = 0$. Bold text indicate values that are statistically significant at the 5% level.

Table 2: Performance of moving average strategies correctly simulated without look-ahead bias

Portfolio	BH Portfolios				MA(24) Portfolios				MA(10) Portfolios			
	μ	σ	s	SR	α	p-val	μ	σ	s	SR	α	p-val
Panel A: Size-sorted portfolios												
Low	13.5	22.4	-0.13	0.37	-0.78	(0.40)	11.3	17.8	-0.25	0.35	(0.75)	
2	12.9	22.3	-0.22	0.35	-1.19	(0.03)	10.7	18.1	-0.35	0.31	(0.63)	
3	13.6	21.3	-0.40	0.40	0.03	(0.95)	10.6	17.4	-0.56	0.32	(0.34)	
4	12.9	20.5	-0.46	0.38	-0.48	(0.34)	10.2	16.3	-0.53	0.31	(0.45)	
5	13.3	19.8	-0.47	0.41	0.45	(0.39)	10.6	15.9	-0.74	0.35	(0.46)	
6	12.4	18.6	-0.49	0.39	0.14	(0.82)	10.3	14.9	-0.69	0.35	(0.63)	
7	12.5	18.3	-0.45	0.40	0.41	(0.47)	11.1	14.5	-0.58	0.41	(0.90)	
8	11.8	17.8	-0.42	0.38	0.25	(0.65)	10.0	14.0	-0.50	0.35	(0.72)	
9	11.2	16.3	-0.39	0.37	0.22	(0.67)	9.6	12.8	-0.48	0.35	(0.84)	
High	9.5	15.0	-0.31	0.29	0.52	(0.03)	8.8	12.0	-0.34	0.30	(0.87)	
Panel B: Book-to-market-sorted portfolios												
Low	9.0	18.1	-0.18	0.21	1.62	(0.02)	8.6	13.9	-0.29	0.25	(0.73)	
2	10.4	16.6	-0.43	0.32	1.06	(0.12)	9.0	13.5	-0.51	0.29	(0.75)	
3	10.9	16.2	-0.46	0.36	0.80	(0.28)	9.2	13.2	-0.67	0.31	(0.61)	
4	10.7	16.7	-0.44	0.34	-0.65	(0.43)	9.4	13.4	-0.47	0.32	(0.86)	
5	10.6	15.7	-0.40	0.35	-0.95	(0.26)	9.6	12.7	-0.62	0.36	(0.96)	
6	11.7	15.8	-0.40	0.41	0.00	(1.00)	9.7	12.9	-0.54	0.36	(0.52)	
7	12.4	15.6	-0.09	0.47	-0.13	(0.87)	11.5	12.8	-0.13	0.50	(0.73)	
8	13.0	16.0	-0.44	0.49	-0.61	(0.35)	11.3	13.1	-0.24	0.47	(0.81)	
9	13.9	16.9	-0.29	0.52	0.02	(0.98)	11.7	13.8	-0.40	0.48	(0.61)	
High	15.2	20.6	0.08	0.49	-0.73	(0.50)	13.9	15.9	-0.15	0.55	(0.53)	
Panel C: Momentum-sorted portfolios												
Low	1.3	28.0	0.66	-0.14	-2.80	(0.04)	1.8	13.1	-0.51	-0.26	(0.42)	
2	7.8	21.9	0.25	0.12	2.52	(0.00)	6.2	14.0	0.05	0.08	(0.72)	
3	9.4	18.8	0.32	0.23	3.12	(0.00)	8.7	12.1	0.29	0.29	(0.57)	
4	10.0	16.9	-0.11	0.29	2.21	(0.01)	8.3	12.1	-0.14	0.27	(0.85)	
5	9.0	15.7	-0.25	0.24	-0.27	(0.73)	5.8	12.0	-0.67	0.06	(0.05)	
6	10.1	15.9	-0.36	0.31	-0.16	(0.85)	8.6	12.7	-0.53	0.27	(0.62)	
7	10.4	15.4	-0.47	0.34	-0.81	(0.33)	8.9	13.1	-0.61	0.28	(0.45)	
8	12.4	15.8	-0.29	0.46	-0.35	(0.64)	11.1	13.7	-0.32	0.44	(0.75)	
9	13.2	17.0	-0.51	0.47	-0.92	(0.24)	12.3	15.0	-0.47	0.48	(0.94)	
High	17.5	21.8	-0.39	0.57	0.98	(0.30)	15.5	20.0	-0.38	0.52	(0.42)	

Summary statistics for the respective buy-and-hold (BH) portfolio returns and the moving average (MA) strategy portfolio returns with the length of the moving average window of 24 and 10 months (these strategies are denoted by MA(24) and MA(10) respectively). The sample period covers January 1960 to December 2011. A one-way transaction cost of 0.5% has been imposed in the computation of the MA returns. μ is the annualized average return, σ is the annualized standard deviation of returns, s is the skewness, SR is the annualized Sharpe ratio, α is the alpha in the Fama-French-Carhart 4-factor model, and $p\text{-val}$ is the p-value. μ , σ , and α are reported in percentages. For the Sharpe ratio of the MA strategy, we test the hypothesis $H_0 : SR_{MA} = SR_{BH}$. For each alpha, we test the hypothesis $H_0 : \alpha = 0$. Bold text indicate values that are statistically significant at the 5% level.