Emerging Markets Finance & Trade, 52:2434–2450, 2016

ISSN: 1540-496X print/1558-0938 online
DOI: 10.1080/1540496X.2015.1087785

Performance of Moving Average Trading Rules in a Volatile Stock Market: The Russian Evidence

Pasi Luukka[1], Eero Pätäri[1], Elena Fedorova[1], and Tatiana Garanina[2]

[1]*School of Business and Management, Lappeenranta University of Technology, Lappeenranta, Finland;* [2]*St. Petersburg University, Graduate School of Management, St. Petersburg, Russia*

ABSTRACT: This article examines the profitability of dual moving average crossover (DMAC) trading strategies in the Russian stock market over the 2003–12 period. It contributes to the existing technical analysis (TA) literature by testing, for the first time, the applicability of ordered weighted moving averages (OWMA) as an alternative calculation basis for determining DMACs. In addition, this article provides the first comprehensive performance comparison of DMAC trading rules in the stock market that is known as one of the most volatile markets in the world. The results show that the best trading strategies of the in-sample period can also outperform their benchmark portfolio during the subsequent out-of-sample period. Moreover, the outperformance of the best DMAC strategies is mostly attributable to their superior performance during bearish periods and, particularly, during stock market crashes.

KEY WORDS: market efficiency, moving average, ordered weighted average, portfolio performance, quantifier guided aggregation, technical analysis, trading rules

Introduction

The literature on the profitability of technical trading rules is abundant (e.g., see Allen and Karjalainen 1999; Lo, Mamaysky, and Wang 2000; Park and Irwin 2007; Bajgrowicz and Scaillet 2012). However, the results of the related studies are diverse and highly dependent on sample period, asset class being examined, technical trading rules and methodology employed. Generally, technical analysis (henceforth TA) is based on either the price history or the trading volume history of the underlying asset(s) or both. The majority of trading rules based on technical analysis assume that prices move in trends determined by the changing attitudes of traders toward various economic, political, and psychological forces. One of the most popular trend-determining techniques, known as the dual moving average crossover (henceforth DMAC) rule, is based on the crossing of two moving averages (henceforth MA) of prices. MA trading rules have been found to be the most profitable in many previous stock market studies (e.g., Brock, Lakonishok, and LeBaron 1992; Ratner and Leal 1999; Sullivan, Timmermann, and White 1999; Taylor 2000; Cheung, Lam, and Yeung 2011; Mitra 2011; Shynkevich 2012). However, the great majority of studies on the performance of MA trading rules in stock markets have focused on stock market index data (for few exceptions, see Szakmary, Davidson, and Schwarz 1999; Taylor 2000; Fong and Yong 2005; Pätäri and Vilska 2014).

To contribute to the existing literature, we examine, for the first time in TA literature, the applicability of ordered weighted moving averages (henceforth OWMA) for determining DMACs and compare the performance of OWMA-based trading rules to that of their simple moving average (SMA) and exponentially weighted moving average (EWMA) based counterparts, as well as to the performance of the passive buy-and-hold (henceforth B&H) benchmark portfolio.[1] The Russian stock market provides an interesting target for a profitability analysis of DMAC trading rules since it is one of the most volatile stock markets in the world. During the ten-year sample period from the beginning of 2003

Address correspondence to Eero Pätäri, Lappeenranta University of Technology, P.O. BOX 20, FI - 53851 Lappeenranta, Finland. E-mail: eero.patari@lut.fi

Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/MREE.

to the end of 2012, the average annual volatility of the Russian stock market has been as high as 29.86 percent[2], to say nothing about the volatilities of individual stocks that are, on average, more volatile than stock market indices. This may offer more profit opportunities for technical trading strategies, provided that they can exploit the greater volatility. For example, Gençay (1998) documents an enhancement in the relative performance of moving average rules during the volatile years for DJIA (Dow Jones Industrial Average) index data. Recently, Kim, Shamsuddin, and Lim (2011) have also found evidence that return predictability is associated with the stock market volatility. On the other hand, the higher volatility may cause spurious trading signals, as noted by Fong and Yong (2005) and Shynkevich (2012).

Our results show that the best trading strategies of the in-sample period can also outperform their B&H benchmark portfolio during the subsequent out-of-sample period in the Russian stock market. We also find evidence of the benefits of using DMAC combinations that are much longer than those employed in previous TA literature. However, the best DMAC rules of the out-of-sample period cannot be identified *ex ante* on the basis of the in-sample performance. In addition, the relative performance of the best past trading rules that are based on different DMAC variants vary over time.

The structure of the article is as follows: the next section describes the data and the methodology employed. The third section reports the results for both in-sample and out-of-sample periods by focusing on the comparison of those DMAC trading strategies that performed best during the in-sample period based on each DMAC variant examined. The final section concludes and summarizes the findings of the article.

Data and Methodology

The analysis of DMAC strategies uses dividend- and split-adjusted closing prices of the stocks included in the MICEX index that consists of the most liquid stocks of the Moscow Exchange. Both the stock price data and the index data are from Datastream. Prior to 2012, the index was permitted to include several stock series from the same issuer. However, to restrict the weights of individual companies and to maintain a higher degree of diversification in trading portfolios, we include only one stock series of each issuer (i.e., the most liquid one) in our sample. We compare the performance of DMAC trading portfolios to that of the corresponding B&H portfolio updated according to the changes of companies included in MICEX at each content checkpoint of the index. Our sample period ranges from the beginning of January 2003 to the end of December 2012. In addition, historical daily quotes prior to January 2003 are used to enable the calculation of moving averages from the beginning of the sample period.[3] The sample period is limited to ten years since before 2002, only a few Russian stocks were liquid enough for technical trading purposes.[4] The number of companies included in MICEX increases during the sample period, from twelve in the beginning of 2003 to forty-four by the end of 2012. To alleviate data-snooping bias and to avoid look-ahead bias, we divide our sample period into two five-year sub-periods and test the performance of the best DMAC strategies of the first sub-period (i.e., January 2003 to December 2007) during the subsequent sub-period (i.e., from January 2008 to December 2012).

DMAC rules are employed to generate buy and sell signals for each stock. In contrast to most previous studies, we do not set any pre-fixed maximum (minimum) lengths for short-term (long-term) moving averages, but allow them to vary so that the ratio of the short-term MA to the long-term MA cannot exceed two-thirds. However, we set the maximum length of long-term MA to 200 days, which implies that the maximum length for short-term MA in this particular case is 133 days, but shorter in all the other cases. Within such ranges, we get 13,333 DMAC combinations for each of the DMAC variants which are introduced later in this section and in the following subsection. Consistent with many previous studies (e.g., Brock, Lakonishok, and LeBaron 1992; Ready 2002; How, Ling, and Verhoeven 2010; Pätäri and Vilska 2014), we assume that a trader can have either a long position (buy days) or no position (sell days) in each stock. A buy (sell) signal is generated when the shorter moving average rises above (or falls below) the longer moving average.[5] Parallel to the majority of previous peer-group studies (e.g., McKenzie 2007; Metghalchi, Marcucci, and Chang 2012) we assume that a DMAC trader can observe the prices a few minutes prior to the day's closing and make the potential transactions at the closing prices of the same day.[6]

We maintain the long position after the buy signal for the particular stock until we get the sell signal. In other words, we do not cash or rebalance long positions at checkpoints of the content of the index, except in cases where a DMAC rule gives a simultaneous sell signal. The cash inflows from sold positions are invested in risk-free asset. We use the Russia Interbank ninety-day interest rate (from Datastream) as a proxy for the risk-free rate of return. Every time a new buy signal is received, the proportion of cash assets invested in a new stock series is determined on the basis of both the total amount of stocks with a sell signal and the total sum of cash assets. For example, assume that at a certain time point we have n stocks with sell signals. When one of those stocks gets a buy signal, $1/n$ of the cash assets is allocated to that particular stock.

Dividends are accounted for in our analysis by reinvesting the paid-out dividends in the same stock on the payout day unless the sell signal is received between the ex-dividend day and the payout day. In the latter case, the cash inflows from paid-out dividends, as well as those from the sales of underlying stocks, are added into the cash assets. Our sample is free of survivorship bias because no constituent stocks have been delisted during the 2003–12 period.

For consistency reasons, the weights of stocks in the B&H benchmark portfolio are neither rebalanced at the checkpoints of the content of the index. In cases where a new company is added to the index, the initial portfolio weight for that company is $1/N$, in which N refers to the total number of companies included in the B&H benchmark portfolio after taking account of all the added and removed stock series at the latest checkpoint. For the sake of comparability, the new entrants are included in the B&H benchmark portfolio only after the 200-day trading history in the Moscow Exchange. Where the total price required for the purchase(s) of new stock series into the B&H benchmark portfolio exceeds that obtained from selling the stocks excluded from the index at the latest checkpoint, the deficit is financed by selling a part of the long positions on each of the existing B&H portfolio stocks, so that the relative weights of the old portfolio stocks remain the same. In the reverse case, the surplus is invested in the existing B&H portfolio stocks by following the same principle. Thus, the stock weight of the B&H portfolio remains 100 percent all the time, except in those cases where the new entrants do not have a long enough trading history (ie., 200 days) to be included in active trading portfolios at the content checkpoint in which it is included in MICEX. In such cases, the temporary cash assets are invested at a risk-free rate until the criterion for the minimum length of trading history is fulfilled.

For the real-world performance comparison of trading portfolios, we form time-series for each portfolio by taking account of both the weight changes caused by price fluctuations of the stocks in the trading portfolios and the transaction costs incurred from the purchases and sales of the stocks. We use three different variants to calculate moving averages in DMACs. The first variant is based on simple moving averages (SMA), while the second relies on exponentially weighted moving averages (EWMA).[7] The last one is based on OWMAs, which, to our best knowledge, have not been employed before for the determination of trading signals in the context of TA. For each of the three variants, we report the proportions of the strategies that have outperformed their B&H counterparts in terms of both absolute returns and the skewness- and kurtosis-adjusted Sharpe ratios (henceforth SKASR) during both in-sample and out-of-sample periods.[8] We also document the detailed performance statistics from both sub-periods for those strategies that have performed best in terms of either absolute returns, the standard Sharpe ratio, or the SKASR during the first five-year (i.e., in-sample) period. All the performance statistics are calculated from the viewpoint of an institutional investor who is not liable to the taxation of dividends and capital gains. We assume that the average transaction costs are 1 percent per trade.[9]

To find out whether the relative performance of the trading strategies against B&H strategies depends on general stock market conditions, we divide the sample period into bull and bear market periods according to turning points of the Russian stock market. We then calculate cumulative returns for each bullish and bearish sub-period and make comparisons between DMAC variants.

Ordered Weighted Averages and Their Applications in the DMAC Context

Ordered weighted averaging (OWA) operators were first introduced by Yager (1988). This subsection shortly introduces the OWA operator and the weight generation scheme employed in our empirical tests. An OWA operator F is a mapping $F{:}R^n \to R$ with following components: a weighting vector $W = (w_1, w_2, \cdots, w_n)^T$ given by $w_i \in [0, 1]$; $\sum_{i=1}^{n} w_i = 1$ and an aggregation function defined by

$$F(a_1, a_2, \cdots, a_n) = \sum_{i=1}^{n} w_i b_i \tag{1}$$

where n refers to the length of the particular moving average, $A = (a_1, a_2, \cdots, a_n)$ is the set of elements (i.e., daily quotes of the stock prices in this context) being averaged and b_i is the ith highest quote within the set $a_1, a_2, \cdots, a_n$. The key characteristic of this operator relies on the vector $B = (b_1, b_2, \cdots, b_n)$ that represents a decreasing order of the components of A. As noted by Yager (1988), the OWA weights are associated with a particular ordered position rather than a particular attribute. In other words, each w_i of W weights the counterpart element b_i of B, but without considering either the current alternative or the attribute from which this position comes. For example, w_1 is the weight associated withb_1, the highest quote of A; w_2 is the weight associated withb_2, the second-highest quote of A, and so on.

One of the most central issues in the theory of OWA operators is the generation of the associated weights for the weighting vector W. The quantifier guided aggregation for this purpose is introduced by Yager (1991), who divides quantifiers into three categories: Regular Increasing Monotone (RIM), Regular Decreasing Monotone (RDM), and Regular UniModal (RUM) quantifiers, according to their properties. The RIM quantifier must satisfy the following three properties: $Q(0) = 0$, $Q(1) = 1$, and $Q(x) \geq Q(y), x \geq y$. In this article, we apply one of the most commonly-used RIM quantifiers for the weight generation as follows:

$$Q(x) = x^p,\ p \geq 0. \tag{2}$$

A procedure for generating weights from the quantifier varies depending on the type of quantifier employed. In the case of the RIM quantifier, the weights are generated as follows:

$$w_i = Q\left(\frac{i}{n}\right) - Q\left(\frac{i-1}{n}\right), for\ i = 1, \ldots, n. \tag{3}$$

The OWA operator aggregates the values between minimum and maximum (e.g., see Yager 1991). The RIM quantifier can generate different values within this interval by changing the parameter p value in Equation (2). For $p = 1$, we get the standard arithmetic mean as special case (similarly as $p \to \infty, OWA \to min$, and $p \to 0, OWA \to max$). When applying ordered weighted averaging to the calculation of DMACs, we refer to the related trading strategies simply as ordered weighted moving averages (OWMA).

Table 1 demonstrates the number of the buy and sell signals created by the same DMAC combination for each of the three DMAC variants employed in this article.[10] It also illustrates the impact of changing the weights in OWA by means of parameter p value on trading signal sensitivity. The higher values of p induce more trading signals. In contrast to EWMAs, which reduce the weights of observations exponentially when moving back through time, OWMAs for $p > 1$ reduce the weights of the observations with high values and thus smooth their impact on

Table 1. The number of trading signals for each DMAC(18,78) variant during the first sub-period

DMAC variant	Trading signals
SMA	11
EWMA	32
OWMA(p = 0.5)	8
OWMA(p = 2)	46
OWMA(p = 3)	54
OWMA(p = 4)	70
OWMA(p = 5)	88
OWMA(p = 6)	110
OWMA(p = 7)	120
OWMA(p = 8)	124
OWMA(p = 9)	132
OWMA(p = 10)	142

Notes: The table shows the number of trading signals given by each DMAC variant named in the first column for one trading asset over the 2003–7 period.

the calculation of MAs while increasing the weights of the observations with low values. Correspondingly, OWMAs for $p < 1$ work conversely. We tested ten different p values shown in Table 1 to find out which one of them is the best in terms of performance of the related DMAC strategies. During the in-sample period, $p = 8$ resulted in the best performance among all OWMA-based trading portfolios. Therefore, all the reported results of OWMA trading strategies are henceforth based on this particular p value.

Test Procedures for Performance Comparisons

The performance comparison between the portfolios is made on the basis of three performance metrics: the average return, the Sharpe ratio (Sharpe 1966, 1994), and the skewness- and kurtosis-adjusted Sharpe ratio (SKASR) developed by Pätäri (2011)[11]. We employ SKASR as an alternative and complementary risk-adjusted performance metric because the return distributions of technical trading portfolios are not consistent with the normality assumption related to the use of standard deviation as a risk proxy, like in the standard Sharpe ratio. Since we assume the daily return for sell days to equal the risk-free rate of return there is an asymmetry in return generation. This may induce leptokurtosis that consequently can bias the standard Sharpe ratio comparisons. Moreover, returns of technical trading strategies can be assumed to be positively skewed since the strategies are designed to follow the axiom "*cut your losses and let your profits run*," as stated by Bookstaber (1985). Although the above-described sources of measurement biases are partially alleviated by our choice of using monthly returns instead of daily returns as a basis of performance comparisons, it is justified and reasonable to take the potential impacts of violations of the normality assumption into account in performance comparisons. The inclusion of higher moments of return distributions in the performance evaluation of equity portfolios is also motivated by numerous recent studies (e.g., see Opdyke 2007; Ledoit and Wolf 2008; Zakamouline and Koekebakker 2009; Homm and Pigorsch 2012). For this particular sample data, the comparison between the results based on the standard Sharpe ratio and those based on the SKASR show that the shapes of the return distributions of the trading portfolios being examined in this study deviate from normality to the extent that the performance rank orders do change in many cases when taking account of skewness and kurtosis dimensions. In order to avoid validity problems stemming from the negative excess returns in the context of the Sharpe ratio comparisons, we use a refined version of the Sharpe ratio introduced by Israelsen (2005) as follows:

$$SR = \frac{r_i - r_f}{\sigma_i^{(ER/|ER|)}} \tag{4}$$

where r_i = the average monthly return of a portfolio i
r_f = the average monthly risk free rate of the return
σ_i = the standard deviation of the monthly excess returns of a portfolio i
ER = the average excess return of portfolio i.
Analogously, we use similar refinement to the SKASR as follows:

$$SKASR = \frac{r_i - r_f}{SKAD_i^{(ER/|ER|)}} \tag{5}$$

where $SKAD_i$ = skewness- and kurtosis-adjusted standard deviation of the monthly excess returns of a portfolio i (see Pätäri 2011 for details of the calculation of $SKAD_i$).

The statistical significances of the differences between comparable pairs of the Sharpe ratios are given by the p-values of the Ledoit-Wolf test[12], which is based on the circular block bootstrap method.

Results

Descriptive Statistics

Panel A in Table 2 presents summary statistics for the data of the individual stocks, while Panel B does the same for the B&H benchmark portfolio. The daily arithmetic average return of the B&H portfolio is higher than that of the individual stocks during the full sample period, particularly during the first five-year sub-period, whereas the reverse holds for the latter sub-period. The last-mentioned finding is

Table 2. Summary statistics for daily returns

	Full sample	1st sub-period	2nd sub-period
Panel A: Data on individual stocks			
N	49,056	16,688	32,368
Mean	0.075%	0.163%	0.029%
Maximum	70.09%	70.09%	66.61%
Minimum	–51.66%	–51.66%	–43.05%
Standard deviation	3.24%	2.84%	3.43%
Skewness	0.97	1.02	0.95
Kurtosis	32.94	49.92	27.75
Panel B: Data on B&H benchmark portfolio			
N	2,437	1,198	1,239
Mean	0.089%	0.173%	–0.000%
Maximum	23.52%	15.65%	23.52%
Minimum	–16.91%	–15.33%	–16.91%
Standard deviation	2.09%	1.87%	2.29%
Skewness	0.13	–0.34	0.42
Kurtosis	15.50	10.30	16.92

Notes: The results based on daily arithmetic average returns are presented for the full sample period (January 2003–January 2012) and two nonoverlapping sub-periods (January 2003–December 2007 and January 2008–January 2012). Panel A presents the results for the data of individual stocks and Panel B for the data of B&H benchmark portfolio. N refers to the total number of daily return observations included in each sample period. Skewness is sample skewness and kurtosis is sample excess kurtosis.

explained by the fact that the number of companies included in MICEX has increased most rapidly during the latter sub-period and particularly, toward the end of this period. Because the end of the latter five-year period was bullish, such new entrants bias the cross-sample average return of individual stocks upward as the weight of positive daily returns is higher than it is for the sample of companies that have the full-length return time-series for the same period. The difference in the daily arithmetic average return between the sample of individual stocks and the B&H benchmark portfolio during the latter sub-period is also emphasized due to more positive skewness and higher leptokurtosis of the daily return distribution of individual stocks.

Performance Comparisons

For each DMAC variant, we calculate the cumulative returns for all 13,333 MA length combinations and report the numbers and the proportions of such DMAC strategies that have generated a higher return or a higher SKASR than the corresponding B&H portfolio[13] (in Tables 3 and 5). We also document the detailed performance statistics as well as return accumulation from both sub-periods for those strategies that have performed best during the first five-year (i.e., in-sample) period (in Figures 1 and 2, and Tables 4 and 6).

In-Sample Results

Table 3 shows the numbers and the proportions of such DMAC rules (among 13,333 DMAC combinations) that have generated a higher return or a higher SKASR than the corresponding B&H

Table 3. Relative performance of the 13,333 DMAC strategies during the in-sample period

DMAC variant	Return	SKASR
OWMA	508 (3.81%)	4,716 (35.37%)
SMA	47 (.35%)	4,576 (34.32%)
EWMA	0 (0)	4,976 (37.32%)

Notes: For each of the three DMAC variants named in the first column, the table reports the numbers and the proportions of such DMAC strategies that have generated a higher return and/or a higher SKASR than the corresponding B&H portfolio during the 2003–7 period.

Table 4. Performance of the best DMAC strategies during the 2003–7 (in-sample) period

DMAC rule	Return	Volatility	Skewness	Kurtosis	SR	SKASR	sign.
OWMA(94,182)	59.76%	28.38%	2.026	10.033	.416	.724	0.17**
OWMA(104,181)	53.63%	23.05%	.814	2.640	.461	.547	4.23*
SMA(60,185)	45.96%	19.58%	–.171	–.341	.464	.444	12.46
SMA(69,198)	45.70%	18.98%	–.128	–.468	.475	.472	9.42
EWMA(6,184)	39.52%	20.51%	.034	–.175	.378	.385	75.66
EWMA(6,156)	40.04%	21.50%	–.009	–.174	.365	.363	92.94
Benchmark (B&H)	45.21%	23.50%	–.257	–.566	.381	.368	

Note: ** (*) Significant at 1 percent(5 percent) risk level. The table reports the annualized geometric return, volatility, sample skewness, sample excess kurtosis, Sharpe ratio (SR), and SKASR for the best DMAC strategies of the first sub-period and the B&H benchmark portfolio. Statistical significance of the performance differences between the DMAC strategies and the corresponding benchmark portfolio is evaluated by the Ledoit-Wolf test in the last column (only significance levels in percentage points are reported).

Table 5. Relative performance of the 13,333 DMAC strategies during the out-of-sample period

DMAC variant	Return	SKASR
OWMA	13,234 (99.26%)	13,294 (99.71%)
SMA	13,237 (99.28%)	13,285 (99.64%)
EWMA	13,304 (99.78%)	13,325 (99.94%)

Notes: For each of the three DMAC variants named in the first column, the table reports the numbers and the proportions of such DMAC strategies that have generated a higher return and/or a higher SKASR than the corresponding B&H portfolio during the 2008–12 period.

Table 6. Performance of the best DMAC strategies during the 2008–12 (out-of-sample) period

DMAC rule	Return	Volatility	Skewness	Kurtosis	SR	SKASR	sign.
OWMA(94,182)	9.74%	15.79%	.441	.743	.027	.030	5.16
OWMA(104,181)	11.36%	14.86%	.525	.663	.058	.066	2.19*
SMA(60,185)	8.20%	17.03%	.743	2.251	.001	.001	10.01
SMA(69,198)	10.29%	15.11%	.247	.962	.038	.039	6.09
EWMA(6,184)	10.19%	8.74%	–.265	1.918	.063	.057	1.78*
EWMA(6,156)	11.26%	9.84%	.100	1.619	.085	.084	1.24*
Benchmark (B&H)	–4.36%	32.14%	–.887	1.804	–.96	–.16	

Note: *Significant at 5 percent risk level. The table reports annualized geometric return, volatility, sample skewness, sample excess kurtosis, Sharpe ratio (SR), and SKASR for the best DMAC strategies of the first sub-period (insample period) and for the B&H benchmark portfolio. Statistical significance of the performance differences between the DMAC strategies and the benchmark portfolio is evaluated by the Ledoit-Wolf test in the last column (only significance levels in percentage points are reported). Please note that the negative Sharpe ratios and SKASRs documented for the B&H benchmark portfolio are given as thousandths for the sake of accuracy.

portfolio during the in-sample period from 2003 to 2007 for each of the three DMAC variants examined. In terms of absolute returns, only very few of the DMAC trading rules have been able to outperform the B&H benchmark portfolio. The highest percentages are documented for OWMA-based DMAC rules of which 3.81 percent have yielded better than their benchmark. The worst-performing DMAC variant during this period that can be described as heavily bullish at the overall level is based on EWMA for which none of the 13,333 trading rules have exceeded the comparable benchmark return. Instead, in terms of the SKASR, the outperformer rates are clearly higher as more than one-third of the active trading rules have generated a higher SKASR than that of the corresponding B&H portfolio regardless of what DMAC variant is employed.

However, based on the Ledoit-Wolf test, only two of the best past DMAC trading strategies have been able to significantly outperform the B&H portfolio during these heavily bullish conditions. Both of them are OWMA-based trading rules (see Table 4). The best performance in terms of both absolute returns and the SKASR is documented for OWMA(94,182), which generates 59.76 percent average annual return with 28.38 percent annual volatility, whereas the corresponding B&H return is 45.21 percent p.a. with 23.50 percent volatility.

The comparison of MA length combinations on which the best trading rules within each DMAC variant are based reveals that in almost all cases, the longer MA is close to its maximum employed in this study, whereas there is clearly more variability in the lengths of shorter MAs. For the best EWMA-based DMAC rules, the shorter MAs are remarkably shorter than for their SMA- and OWMA-based counterparts.

Out-of-Sample Results

Table 5 shows the outperformer rates for the out-of-sample period from 2008 to 2012 corresponding to those reported for the in-sample period in Table 3. The results are dramatically different since almost all the DMAC trading rules examined have outperformed their passive benchmark portfolio during the latter period in terms of both absolute returns and SKASR regardless of the DMAC variant employed. For this period, the highest outperformer rates are documented for EWMA-based DMAC variants, while the reverse holds for the preceding in-sample period in terms of absolute returns. This seemingly contradicting finding is explained by the differences between sub-periods: The first one is heavily bullish, including only one three-month bearish period during which the cumulative loss of MICEX was 29.64 percent. In contrast, the latter sub-period includes the financial crisis period during which MICEX lost as much as 73.57 percent of it before-crisis value in six months. Moreover, the latter period also includes another bearish period during which MICEX depreciated by one-third, approximately, during the thirteen-month period. During these two stock market crashes, almost all DMAC trading portfolios have lost far less of their value than their passive benchmarks, since they have managed to either cut their losses at a relatively early stage of the declining markets or to avoid the whole crash thanks to the right timing of sell signals. However, in spite of high outperformer rates, very few of the best past DMAC trading portfolios chosen for closer examination have been able to significantly outperform their B&H portfolio in a statistical sense on the basis of the Ledoit-Wolf test during the latter sub-period. The proportions of statistically significant outperformers are also drastically lower within all the 13,333 DMAC combinations for all three DMAC variants than the proportions reported in Table 5.

The results reported in Table 6 show that all the best trading rules from the in-sample period have outperformed the corresponding B&H portfolio during the out-of-sample period (see also Figure 2 for cumulative return graphs). The best risk-adjusted performance among the best past trading rules is reported for EWMA(6,156) that generates 11.26 percent annual return coupled with only 9.84 percent annual volatility which, compared to the corresponding return and volatility of the corresponding B&H portfolio (−4.36 percent p.a. and 32.14 percent, respectively), indicates significant outperformance at the 1.24 percent level.[14] EWMA(6,184), that is the best EWMA-based trading rule in terms of both standard Sharpe ratio and SKASR during the in-sample period, also significantly outperforms the B&H portfolio (at the 1.78 percent level). In addition, OWMA(104,181) also outperforms the benchmark portfolio at the 5 percent level, whereas OWMA(94,182) and SMA(69, 198) do that at the 10 percent level. The significance of outperformance of these strategies is for the most part explained by the fact that their risk is at its highest approximately only half of that of the corresponding B&H portfolio.

Our overall results show that the best calculation basis for DMAC signals varies over time and is nonpredictable. On the other hand, all the best past trading strategies have dominated the B&H benchmark portfolio in the mean-risk framework (i.e., they have earned higher return with lower risk than their benchmark) during the subsequent out-of-sample period, which speaks for the usefulness of the DMAC trading rules in the Russian stock market. In addition, most of the best past trading strategies have also significantly outperformed their passive benchmark portfolio during the same period. Instead, during the in-sample period, only two of them have managed to do that on the basis of the Ledoit-Wolf test. However, the abnormal return of the best trading rule (that is OWMA(94,182)) over the B&H portfolio is 14.55 percent p.a., which generates a remarkable return difference during the five-year in-sample period (see Figure 1). In addition, the corresponding return difference during the following out-of-sample period of the same length is almost of the same size (i.e., 14.10 percent p.a.) for the same strategy, which indicates performance persistence for this particular trading strategy in terms of absolute returns (see Figure 2).

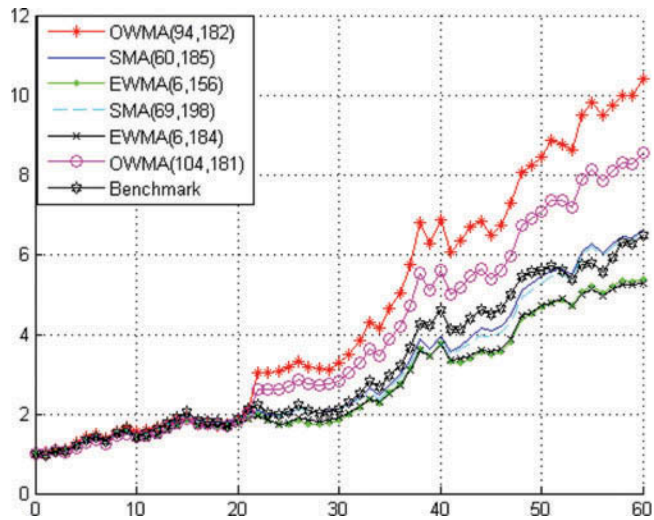

Figure 1. Cumulative returns on the best DMAC trading portfolios during the 2003–7 period. The curves depict the return accumulation of the first sub-period's best DMAC strategies and that of the corresponding B&H benchmark portfolio (the starting points of all graphs are scaled to one index point on the last trading day of December 2002). The timespan depicted in the horizontal axis is in months.

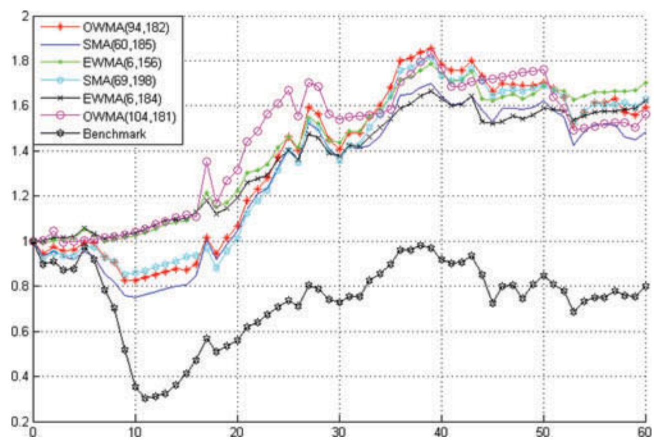

Figure 2. Cumulative returns on the best past DMAC trading portfolios during the 2008–12 period. The curves depict the return accumulation of the first sub-period's best DMAC strategies determined for each of the three DMAC variants examined and that of the corresponding B&H benchmark portfolio (the starting points of all graphs are scaled to one index point on the last trading day of December 2007). The timespan depicted in the horizontal axis is in months.

Performance Decomposition Based on Bull and Bear Market Periods

The previous results from the out-of-sample period show that following the best past DMAC rules would have paid off in the Russian stock market. In order to trace whether their relative performance depends on the general stock market cycle, we perform an additional test by dividing the sample period into bull and bear market periods according to the turning points of the Russian stock market. Based on the MICEX index statistics, we define four separate bullish and three bearish periods within the ten-year sample period. The division is done similarly to Edwards, Biscarri, and Pérez de Gracia (2003), who use a 20 percent return (loss) from the previous trough (peak) to the subsequent peak (trough) in the demarcation of bullish (bearish) periods. Furthermore, the minimum length for bullish and bearish sub-periods is set to one month in order to distinguish primary trends from short-run movements of stock prices. As a result, we get an aggregate bull market period that includes 1,954 daily returns and consists of four distinct bullish periods.[15] The aggregate bear market period is constructed from the remaining days of the full sample period (483 trading days in total) including three distinct bearish periods. The date ranges for each sub-period are specified in Table 7 that shows the returns of the best past trading strategies and the corresponding B&H returns for each of the seven above-mentioned sub-periods. Figures 3 and 4 illustrate the aggregate log-scale returns of the same trading strategies during the aggregate bullish and bearish sub-periods, respectively.[16]

Decomposition of portfolio performance based on bull and bear market periods confirms the previous finding that the outperformance of the best DMAC rules against their benchmark portfolio is mostly attributable to the fact that the best past DMAC trading portfolios lose far less of their value during bearish periods than their passive B&H benchmark portfolio (see Table 7, Panel B and Figure 3). The phenomenon is clearly discernible during the stock market crash caused by the financial crisis period. Within the half-year period from May 19, 2008 to November 21, 2008 the B&H benchmark portfolio lost 73.87 percent of its value, whereas the greatest loss for the best past trading strategies was 13.52 percent for OWMA(94,182). By contrast, the smallest drops during the same sub-period among the best past trading portfolios are reported for EWMA-based trading strategies for which the corresponding losses are only around 5 percent. Altogether, all the best past trading strategies have pulled through this particular crash period without major losses regardless of what DMAC variant they are based on.

The results from the three different bearish sub-periods show that the best past trading strategy as well as the best DMAC variant differ over time. Among the best past trading rules, the EWMA-based DMAC strategies would generally have offered the best protection against the stock market declines.

Table 7. Decomposition of the performance of DMAC strategies

DMAC rule	03-01-08–04-04-12	04-07-29–08-05-19	08-11-24–11-04-08	12-05-24–12-12-28	Total bull
Panel A: Cumulative returns during bullish periods					
OWMA(94,182)	103.95%	525.16%	127.24%	7.31%	3 009.2%
OWMA(104,181)	99.03%	400.14%	125.60%	9.15%	2351.2%
SMA(60,185)	106.73%	255.96%	116.27%	7.24%	1606.7%
SMA(69,198)	106.12%	259.76%	114.09%	8.05%	1615.3%
EWMA(6,184)	96.19%	220.86%	61.60%	6.05%	978.8%
EWMA(6,156)	94.78%	222.74%	75.85%	5.12%	1061.4%
Benchmark (B&H)	117.12%	301.80%	288.81%	19.00%	3936.4%

DMAC rule	04-04-13–04-07-28	08-05-20–08-11-21	11-04-11–12-05-23	Total bear
Panel B: Cumulative returns during bearish periods				
OWMA(94,182)	−20.58%	−13.52%	−21.53%	−46.1%
OWMA(104,181)	−17.42%	−10.34%	−21.08%	−41.6%
SMA(60,185)	−14.89%	−12.67%	−18.15%	−39.2%
SMA(69,198)	−15.90%	−13.40%	−18.33%	−40.5%
EWMA(6,184)	−16.51%	−5.50%	−9.36%	−28.5%
EWMA(6,156)	−15.61%	−4.73%	−10.60%	−28.1%
Benchmark (B&H)	−26.81%	−73.87%	−34.30%	−87.4%

Notes: The table reports the cumulative returns of the first sub-period's best DMAC strategies for the observed bull and bear market periods separately for each of the best past DMAC strategies. The corresponding statistics are also shown for the benchmark portfolio. The results for the bullish (bearish) periods are in adjacent columns. Panel A (B) indicates the returns during the bullish (bearish) periods. The date ranges for the sub-periods are denoted as yy-mm-dd.

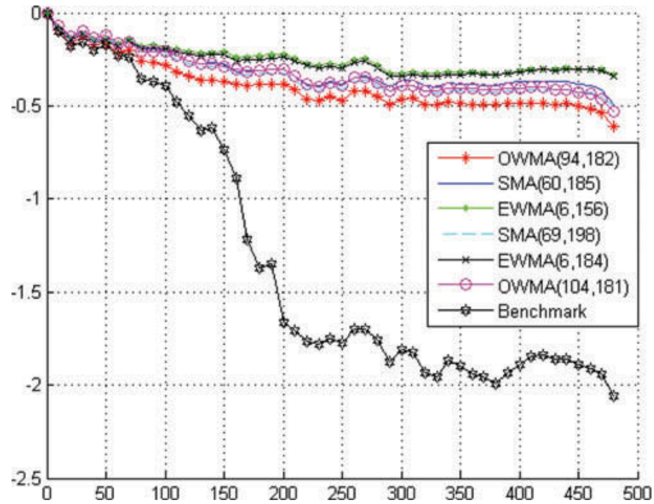

Figure 3. Return accumulation of the best past DMAC strategies during the bear market periods. The figure illustrates the logarithmic return accumulation of the first sub-period's best DMAC strategies and the corresponding B&H benchmark return during the bearish periods. The timespan depicted in the horizontal axis is in days.

Their total loss would have been approximately 28 percent if all the bearish periods had appeared without any bullish periods in between times. By contrast, the corresponding loss in the case of passive B&H benchmark portfolio would have been 87.4 percent.

During the bullish periods, all six active trading strategies examined lose, on average, compared to the B&H benchmark portfolio, although during the isolated bullish periods, some of them are able to beat the benchmark occasionally. In bullish conditions, the best overall performance among the best past active trading strategies in terms of absolute returns is documented for OWMA (94,182). Despite that all the best past DMAC rules underperform in terms of cumulative returns against the benchmark portfolio during the bullish periods (Table 7, Panel A and Figure 4), the return difference during the half-year crash period caused by the financial crisis is big enough in favor of DMAC strategies to the extent that most of the best past DMAC strategies outperform their benchmark portfolio during the five-year out-of-sample period. Thus, based on the results from the Russian stock market, the best past DMAC rules would have partially hedged a long-term equity investor against stock market crashes, though they would have not made her immune to the crashes.

Altogether, our overall findings on the relative performance of active trading strategies against the B&H strategy during bullish and bearish periods are consistent with Fong and Yong (2005), Andrada-Félix and Fernández-Rodríguez (2008), and Pätäri and Vilska (2014), who also find outperformance of technical trading strategies during bearish periods. Instead, our results contrast with Fong and Ho (2001) and Chang, Lima, and Tabak (2004), who report particularly significant abnormal returns over and above the B&H strategy during bullish periods. Our overall results are also in line with Yen and Hsu (2010), who find that significant outperformance of active trading strategies is more frequent in bearish than in bullish periods in the three stock index futures markets (i.e., LIFFE FTSE 100, EUREX DJ Euro Stoxx 50, and SIMEX MSCI Taiwan Index futures markets). In contrast, Chang, Lima, and Tabak (2004) conclude that for a sample of thirteen stock market indices (eleven from emerging markets and two from developed markets), technical trading rules seem to perform much better in bullish than in bearish periods.

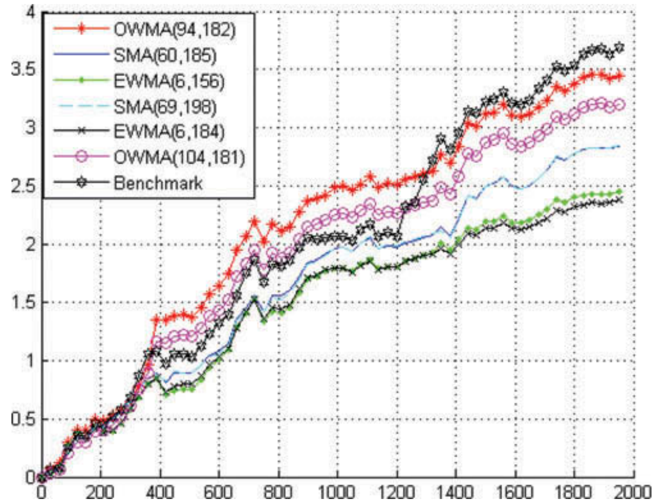

Figure 4. Return accumulation of the best past DMAC strategies during the bull market periods. The figure illustrates the logarithmic return accumulation of the first sub-period's best DMAC strategies and the corresponding B&H benchmark return during the bullish periods. The timespan depicted in the horizontal axis is in days.

Discussion

We find evidence of the benefits of using DMAC combinations that are much longer than those tested in previous TA literature. Therefore, it is possible that the results of the previous studies have suffered from the limits set in the maximum length for the shorter MA. Because shorter DMAC combinations generate more trading signals than their longer counterparts, the underperformance of the trading strategies based on the former type of DMACs against the latter type of DMACs indicates that shorter DMAC combinations have also generated false trading signals to the extent that the shorter DMAC rules have underperformed against their longer counterparts in the long term. Therefore, the limits may have biased the aggregate results of DMAC performance studies to look worse than they would have been without such restrictions.

When considering the robustness of the results, one should note that the sample period employed is not very long, and therefore our results may be specific to this particular sample period. However, the Russian sample data would not have enabled a valid comparison between trading strategies if older sample data had been included, because the Russian stock market has not been liquid enough for this kind of examination until the 2000s. In the near future, it might be worthwhile to replicate the research design by using such a sample data in which both in-sample and out-of-sample periods extend over the full economic cycle. On the other hand, both survivorship bias and look-ahead bias have been taken into account in the research design. An interesting extension would also be to examine whether the combined strategies that merge DMACs and conventional time series forecasts in the spirit of Fang and Xu (2003) would further enhance the performance of trading portfolios. This, however, we leave for future research.

We test a large number of DMAC variants and combinations. The great majority of the trading rules examined underperform against the comparable B&H strategy during the five-year in-sample period from 2003 to 2007. However, the best trading rules of that period outperform their passive benchmarks during the subsequent out-of-sample period, though these rules are not among the best ones during the latter period. On the other hand, the best trading rules of that period do not significantly outperform the best past trading rules during the out-of-sample period.

Our results show further that the performance gap between the best past trading strategies and their passive benchmark portfolio has not narrowed over time in the Russian stock market. In this sense, our results somewhat contradict such previous findings according to which the prediction power of trading strategies fades over time (e.g., see Hsu, Hsu, and Kuan 2010 and Shynkevich 2012). Instead, our evidence is consistent with the adaptive markets hypothesis of Lo (2004), who states that market efficiency may not follow a systematic trend toward greater efficiency, as claimed by proponents of the efficient markets hypothesis, but can be "highly context dependent and dynamic."

Conclusions

This article examines the performance of trading strategies that are based on several DMAC variants in the Russian stock market over the 2003–12 period. It contributes to the existing technical analysis literature by examining for the first time the performance of OWMA-based DMAC trading rules and by comparing it to that of the standard and EWMA-based DMAC rules. We test the performance of trading portfolios formed on the basis of 159,996 trading rules based on several DMAC variants. The majority of the trading rules underperformed against the comparable B&H strategy during the in-sample period, but the best trading rules of that period outperformed their passive benchmark portfolio during the subsequent out-of-sample period. Instead, during the in-sample period which was heavily bullish, only the best OWMA-based DMAC combinations were capable of significantly outperforming the passive benchmark portfolio. Moreover, our results indicate that at least for this particular sample, it would have been beneficial to extend the shorter MA employed in DMAC trading rules far longer than done commonly in TA literature, since for most of the best DMAC combinations documented in this study, the optimal length for the shorter MA is far beyond the commonly-used maximum of twenty days. As an additional contribution to TA literature, we decompose the full-sample-period performance into separate bull- and bear-period performance. The decomposition shows clearly that for this particular sample data, the benefits of following DMAC strategies are mostly attributable to bearish periods, and particularly, to stock market crashes.

Notes

1. The profitability of technical trading rules in emerging stock markets has been examined by Ojah and Karemera (1999); Ratner and Leal (1999); Chang, Lima, and Tabak (2004); MacKenzie (2007); Fifield, Power, and Knipe (2008); Krausz, Lee, and Nam (2009); and Moosa and Li (2011), but the Russian market is not included in any of these studies. To our knowledge, the only exceptions are Chong, Cheng, and Wong (2010) and Ni, Lee, and Liao (2013), who both briefly examine the profitability of only a few technical trading rules as a basis of index trading in the BRIC (Brazil, Russia, India, and China) stock markets. The former study compares the annual returns of nine technical trading rules which do not include any DMAC strategies to the buy and hold returns of the corresponding indices. The latter focuses on only yhree DMAC combinations that, according to the authors, are often employed by practitioners. Moreover, the results of Ni, Lee, and Liao (2013) are restricted to average holding period returns obtained by following buy/sell signals, and the significance of the results is benchmarked against zero return instead of the B&H return as done commonly in TA literature (e.g., see Brock, Lakonishok, and LeBaron 1992; Hsu and Kuan 2005; Cheung, Lam, and Yeung 2011). Moreover, neither of the above-mentioned closest peer-group studies takes transaction costs into account. In addition, they use another stock index as a proxy for the Russian stock market (i.e. the RTS index) instead of MICEX. However, we prefer MICEX in our study for several reasons: The overall liquidity of MICEX companies has been higher than that of RTS companies due to the higher turnover in MICEX, although there is a significant overlap in the constituents of these two indices (e.g., see Grigoriev and Valitova 2002; Roschkow, Marsh, and Todorovic 2009 for details). The higher liquidity implies a better pricing efficiency, which supports the use of MICEX for our purposes. Second, the constituent list of the MICEX index has been updated on a regular basis from the beginning of its calculation, unlike that of RTS, which enables the calculation of a passive B&H benchmark return for the trading portfolios of constituent stocks. Third, unlike RTS data, MICEX data is available in the original currency (i.e., in rubles) throughout the 2003–12 sample period.

2. Throughout the study, we report the annualized volatilities calculated from the monthly returns. The reader should note that the annualized volatilities calculated from daily returns are generally much higher. For example, in this case, the corresponding volatility is as high as 37.28 percent p.a. based on daily returns.

3. As the longest moving average employed in our study is 200, the maximum number of preceding daily quotes required is 200.

4. Over the sample period, we also set an additional filter rule according to which stocks included in the analysis were not allowed to have more than fifteen equal prices in two subsequent trading days during the year preceding the investment period. If this rule was violated, we excluded such stocks from our sample until the above-mentioned condition was satisfied. The previous year price history was employed for this purpose to avoid look-ahead bias.

5. To eliminate "whiplash" signals in cases when shorter and longer MAs are close to each other, we test all DMAC rules with a 1 percent band, which requires that the shorter MA must exceed the longer MA by o1 percent before a buy signal is implemented. Correspondingly, the shorter MA must go below the longer MA by 1 percent to trigger a sell signal.

6. An alternative method is to calculate technical trading returns with one-day lag by beginning with the closing quote one day after a technical signal is initiated, consistently with e.g., Bessembinder and Chan (1998), Fong and Yong (2005), and Pätäri and Vilska (2014). However, this method also includes a trade-off because the trader would lose the one-day return if the timing of the buy signal is right. Correspondingly, in the case of the right timing of the sell signal, he/she would cut his/her losses one day later than when using the more commonly-used assumption employed in this article. We also calculated trading returns with one-day lag as a robustness check. Consistent with McKenzie (2007), the results were very similar for both calculation variations. Therefore, and for the sake of brevity, we only report the results based on the first-introduced assumption.

7. Many different weighting schemes are used for exponential weighting (e.g., see Gardner Jr., 1985, 2006). In this article, we use a widely-used variant as follows: $w_i = 2/(i + n)$, where i refers to the serial number of the freshness indicator of the price quote within the timespan over which a moving average is calculated and n is the length of the particular moving average. Thus, the lowest weight within the timespan (i.e., $1/n$) is given to the oldest quote, while the newest gets the highest weight (i.e. $2/(1 + n)$. We use this simple weighting scheme because it takes into account the wide range of MA lengths employed in our empirical tests.

8. The performance metrics are calculated on the basis of monthly returns in order to avoid some nondesirable characteristics of daily return distributions (e.g., high kurtosis and higher autocorrelation). In addition, the reader should note that the trading strategies chosen for closer examination are not the top three strategies among the all trading strategies examined, but instead, the best strategies among those that are based on three different DMAC variants employed (i.e., SMA, EWMA, and OWMA).

9. The percentage of transaction costs is based on the estimate given by the Moscow Exchange. We use equal proportional transaction costs throughout the full sample period, though in the real world, the transaction costs would have been higher during the first five-year sub-period. This approach was chosen for two main reasons: First, if an investor had liked to follow the best strategies of the first sub-period during the second sub-period, he/she would have paid the transaction costs according to the cost level of the second sub-period, not according to that of the first sub-period. Therefore, it is justified to also take into account the decrease in transaction costs in the calculation of returns of the DMAC strategies during the out-of-sample period (i.e., during the first sub-period). Second, we would like to keep our programming code as simple as possible, because in any case, we can only have an estimate of the real transaction costs.

10. The choice of DMAC combination used for comparison and demonstration purposes is arbitrary, and it is not the best-performing DMAC combination based on any of them being compared. We also made similar comparisons for other length combination of DMACs between the three DMAC variants examined and ended up with similar results according to which OWMA-based strategies with high p values generated the greatest number of trading signals, whereas the corresponding number was lowest for OWMA-based strategies with $p = 0.5$.

11. Pätäri and Tolvanen (2009) employed SKASR in their hedge fund study under the name of "adjusted Sharpe ratio," which by its content was exactly equal to the SKASR used in this study. The name SKASR was adopted by Pätäri (2011) to avoid confusions with the other closely-related definition for "adjusted Sharpe ratio" introduced by Pézier (2004).

12. The Ledoit-Wolf test can take account of asymmetries in return distributions being compared, as well as the impact of autocorrelation in return time-series, which is particularly important to control when using the emerging market data (eg., see Harvey 1995; Kinnunen 2013). Because of the complexity of the test procedure and space limitations we do not describe the Ledoit-Wolf test in more detail here, but recommend the interested reader to see the original article (Ledoit and Wolf 2008. The corresponding programming code is freely available at: http://www.econ.uzh.ch/faculty/wolf/publications.html).

13. This implies that we get the results for 12 × 13,333 = 159,996 active trading strategies. Due to the abundance of the results and the fact that the great majority of the trading strategies underperform against their passive benchmark portfolio during the in-sample period, we only report for each DMAC variant the proportion of those strategies that have generated higher returns than their passive benchmark portfolio to the total number of

MA length combinations (which is always 13,333 for each DMAC variant). The corresponding proportions are also reported on the basis of SKASRs.

14. The reader should note that the reported results are for those DMAC strategies that were the best within each DMAC variant during the in-sample period. None of those DMAC combinations were the best during the subsequent out-of-sample period. However, the results for the best strategies during the latter period are not reported in detail, because it would have been impossible to identify such DMAC strategies beforehand. The variability of the best rules over time is consistent with the earlier literature (e.g., see Sullivan, Timmermann, and White 1999; Ready 2002; Szakmary, Shen, and Sharma 2010; Pätäri and Vilska 2014).

15. The last sub-period from of May 24, 2012 to the end of December 2012 is classified as bullish despite the fact that the cumulative return of the MICEX index from the previous trough does not exceed 20 percent by the end of 2012. However, the rising trend continued until January 2013, when the cumulative return of 20 percent from the previous trough was exceeded before the trend turned down again.

16. The reader should note that the aggregate log-scale returns are used only to demonstrate the dependency of the relative performance of DMAC trading portfolios compared to the B&H portfolio on the general stock market trend. Thus, they are not real-world returns due to the discontinuity of the time span depicted.

References

Allen, F., and R. Karjalainen. 1999. Using genetic algorithms to find technical trading rules. *Journal of Financial Economics* 51 (2):245–71. doi:10.1016/S0304-405X(98)00052-X.

Andrada-Félix, J., and F. Fernández-Rodríguez. 2008. Improving moving average trading rules with boosting and statistical learning methods. *Journal of Forecasting* 27 (5):433–49. doi:10.1002/for.v27:5.

Bajgrowicz, P., and O. Scaillet. 2012. Technical trading revisited: False discoveries, persistence tests, and transaction costs. *Journal of Financial Economics* 106 (3):473–91. doi:10.1016/j.jfineco.2012.06.001.

Bessembinder, H., and K. Chan. 1998. Market efficiency and the returns to technical analysis. *Financial Management* 27 (2):5–17. doi:10.2307/3666289.

Bookstaber, R. 1985. *The complete investment book: Trading stocks, bonds, and options with computer applications*. Glenview, IL: Scott Foresman and Co.

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. doi:10.1111/j.1540-6261.1992.tb04681.x.

Chang, E. J., E. J. A. Lima, and B. M. Tabak. 2004. Testing for predictability in emerging equity markets. *Emerging Markets Review* 5 (3):295–316. doi:10.1016/j.ememar.2004.03.005.

Cheung, W., K. S. K. Lam, and H. Yeung. 2011. Intertemporal profitability and the stability of technical analysis: Evidences from the Hong Kong stock exchange. *Applied Economics* 43 (15):1945–63. doi:10.1080/00036840902817805.

Chong, T. T.-L., -S. H.-S. Cheng, and E. N.-Y. Wong. 2010. A comparison of stock market efficiency of the BRIC countries. *Technology and Investment* 1 (4):235–38. doi:10.4236/ti.2010.14029.

Edwards, S., J. G. Biscarri, and F. Pérez de Gracia. 2003. Stock market cycles, financial liberalization and volatility. *Journal of International Money and Finance* 22 (7):925–55. doi:10.1016/j.jimonfin.2003.09.011.

Fang, Y., and D. Xu. 2003. The predictability of asset returns: An approach combining technical analysis and time series forecasts. *International Journal of Forecasting* 19 (3):369–85. doi:10.1016/S0169-2070(02)00013-4.

Fifield, S. G. M., D. M. Power, and D. G. S. Knipe. 2008. The performance of moving average rules in emerging stock markets. *Applied Financial Economics* 18 (19):1515–32. doi:10.1080/09603100701720302.

Fong, W. M., and Y. W. Ho. 2001. Simple trading rules and the market for internet stocks. *International Review of Finance* 2 (4):247–68. doi:10.1111/irfi.2001.2.issue-4.

Fong, W. M., and L. H. M. Yong. 2005. Chasing trends: Recursive moving average trading rules and internet stocks. *Journal of Empirical Finance* 12 (1):43–76. doi:10.1016/j.jempfin.2003.07.002.

Gardner, E. S., Jr. 1985. Exponential smoothing: The state of the art. *Journal of Forecasting* 4 (1):1–28. doi:10.1002/(ISSN)1099-131X.

Gardner, E. S., Jr. 2006. Exponential smoothing: The state of the art – part II. *International Journal of Forecasting* 22 (4):637–66. doi:10.1016/j.ijforecast.2006.03.005.

Gençay, R. 1998. The predictability of security returns with simple technical trading rules. *Journal of Empirical Finance* 5 (4):347–59. doi:10.1016/S0927-5398(97)00022-4.

Grigoriev, L., and L. Valitova. 2002. Two Russian stock exchanges: Analysis of relationships. *Russian Economic Trends* 11 (3):44–53. doi:10.1111/ruet.2002.11.issue-3.

Harvey, C. 1995. The cross-section of volatility and autocorrelation in emerging markets. *Finanzmarkt Und Portfolio Management* 9 (1):12–34.

Homm, U., and C. Pigorsch. 2012. Beyond the sharpe ratio: An application of the aumann-serrano index to performance measurement. *Journal of Banking & Finance* 36 (8):2274–84. doi:10.1016/j.jbankfin.2012.04.005.

How, J., M. Ling, and P. Verhoeven. 2010. Does size matter? A genetic programming approach to technical trading. *Quantitative Finance* 10 (2):131–40. doi:10.1080/14697680902773629.

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):471–84. doi:10.1016/j.jempfin.2010.01.001.

Hsu, P.-H., and C.-M. Kuan. 2005. Reexamining the profitability of technical analysis with data snooping checks. *Journal of Financial Econometrics* 3 (4):606–28. doi:10.1093/jjfinec/nbi026.

Israelsen, C. L. 2005. A refinement to the sharpe ratio and information ratio. *Journal of Asset Management* 5 (6):423–27. doi:10.1057/palgrave.jam.2240158.

Kim, J. H., A. Shamsuddin, and K.-P. Lim. 2011. Stock return predictability and the adaptive markets hypothesis: Evidence from century-long U.S data. *Journal of Empirical Finance* 18 (5):868–79. doi:10.1016/j.jempfin.2011.08.002.

Kinnunen, J. 2013. Dynamic return predictability in the Russian stock market. *Emerging Markets Review* 15 (1):107–21. doi:10.1016/j.ememar.2012.12.001.

Krausz, J., S.-Y. Lee, and K. Nam. 2009. Profitability of nonlinear dynamics under technical trading rules: Evidence from pacific basin stock markets. *Emerging Markets Finance and Trade* 45 (4):13–35. doi:10.2753/REE1540-496X450402.

Ledoit, O., and M. Wolf. 2008. Robust performance hypothesis testing with the sharpe ratio. *Journal of Empirical Finance* 15 (5):850–59. doi:10.1016/j.jempfin.2008.03.002.

Lo, A. W. 2004. The adaptive markets hypothesis. Market efficiency from an evolutionary perspective. *Journal of Portfolio Management* 30 (5):15–29. doi:10.3905/jpm.2004.442611.

Lo, A. W., H. Mamaysky, and J. Wang. 2000. Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation. *Journal of Finance* 55 (4):1705–70. doi:10.1111/jofi.2000.55.issue-4.

McKenzie, M. D. 2007. Technical trading rules in emerging markets and the 1997 Asian currency crises. *Emerging Markets Finance and Trade* 43 (4):46–73. doi:10.2753/REE1540-496X430403.

Metghalchi, M., J. Marcucci, and Y.-H. Chang. 2012. Are moving average trading rules profitable? Evidence from the European stock markets. *Applied Economics* 44 (12):1539–59.

Mitra, S. K. 2011. How rewarding is technical analysis in the Indian stock market? *Quantitative Finance* 11 (2):287–97. doi:10.1080/14697680903493581.

Moosa, I., and L. Li. 2011. Technical and fundamental trading in the Chinese stock market: Evidence based on time-series and panel data. *Emerging Markets Finance and Trade* 47 Supplement (1):23–31. doi:10.2753/REE1540-496X4701S103.

Ni, Y.-S., J.-T. Lee, and Y.-C. Liao. 2013. Do variable length moving average trading rules matter during a financial crisis period? *Applied Economics Letters* 20 (2):135–41. doi:10.1080/13504851.2012.684784.

Ojah, K., and D. Karemera. 1999. Random walks and market efficiency tests of Latin American emerging equity markets: A revisit. *Financial Review* 34 (2):57–72. doi:10.1111/fire.1999.34.issue-2.

Opdyke, J. D. 2007. Comparing sharpe ratios: So where are the p-values? *Journal of Asset Management* 8 (5):308–36. doi:10.1057/palgrave.jam.2250084.

Park, C.-H., and S. H. Irwin. 2007. What do we know about the profitability of technical analysis? *Journal of Economic Surveys* 21 (4):786–826. doi:10.1111/joes.2007.21.issue-4.

Pätäri, E. J. 2011. Does the risk-adjustment method matter at all in hedge fund rankings? *International Research Journal of Finance and Economics* 6 (75):69–99.

Pätäri, E. J., and J. T. Tolvanen. 2009. Chasing performance persistence of hedge funds—Comparative analysis of evaluation techniques. *Journal of Derivatives & Hedge Funds* 15 (3):223–40. doi:10.1057/jdhf.2009.11.

Pätäri, E. J., and M. Vilska. 2014. Performance of moving average trading strategies over varying stock market conditions: The Finnish evidence. *Applied Economics* 46 (24):2851–72. doi:10.1080/00036846.2014.914145.

Pézier, J. 2004. Risk and risk aversion. In *The professional risk managers' handbook*, ed. C. Alexander and E. Sheedy, vol. I. Wilmington, DE: PRMIA Publications.

Ratner, M., and R. Leal. 1999. Tests of technical trading strategies in the emerging equity markets of Latin America and Asia. *Journal of Banking & Finance* 23 (12):1887–905. doi:10.1016/S0378-4266(99)00042-4.

Ready, M. J. 2002. Profits from technical trading rules. *Financial Management* 31 (3):43–61. doi:10.2307/3666314.

Roschkow, S. V., I. Marsh, and N. Todorovic. 2009. *MICEX vs RTS. battle of exchanges: Who wins the order flow supremacy?* Working paper, Cass Business School, London, UK.

Sharpe, W. F. 1966. Mutual fund performance. *Journal of Business* 39 (S1):119–38. doi:10.1086/jb.1966.39.issue-S1.

Sharpe, W. F. 1994. The Sharpe ratio. *Journal of Portfolio Management* 21 (1):49–58. doi:10.3905/jpm.1994.409501.

Shynkevich, A. 2012. Performance of technical analysis in growth and small cap segments of the US equity market. *Journal of Banking & Finance* 36 (1):193–208. doi:10.1016/j.jbankfin.2011.07.001.

Sullivan, R., A. Timmermann, and H. White. 1999. Data-snooping, technical trading rule performance, and the bootstrap. *Journal of Finance* 54 (5):1647–91. doi:10.1111/jofi.1999.54.issue-5.

Szakmary, A. C., W. N. Davidson, and T. V. Schwarz. 1999. Filter tests in Nasdaq stocks. *Financial Review* 34 (1):45–70. doi:10.1111/fire.1999.34.issue-1.

Szakmary, A. C., Q. Shen, and S. C. Sharma. 2010. Trend-following trading strategies in commodity futures: A re-examination. *Journal of Banking & Finance* 34 (2):409–26. doi:10.1016/j.jbankfin.2009.08.004.

Taylor, S. J. 2000. Stock index and price dynamics in the UK and the US: New evidence from a trading rule and statistical analysis. *European Journal of Finance* 6 (1):39–69. doi:10.1080/135184700336955.

Yager, R. R. 1988. On ordered weighted averaging aggregation operators in multicriteria decisionmaking. *IEEE Transactions on Systems, Man, and Cybernetics* 18 (1):183–90. doi:10.1109/21.87068.

Yager, R. R. 1991. Connectives and quantifiers in fuzzy sets. *Fuzzy Sets and Systems* 40 (1):39–75. doi:10.1016/0165-0114(91)90046-S.

Yen, S. M.-F., and Y.-L. Hsu. 2010. Profitability of technical analysis in financial and commodity futures markets—A reality check. *Decision Support Systems* 50 (1):128–39. doi:10.1016/j.dss.2010.07.008.

Zakamouline, V., and S. Koekebakker. 2009. Portfolio performance evaluation with generalized sharpe ratios: Beyond the mean and variance. *Journal of Banking & Finance* 33 (7):1242–54. doi:10.1016/j.jbankfin.2009.01.005.