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The anatomy of returns from moving average trading rules in the Russian stock market

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ABSTRACT

This paper examines the profitability of index trading strategies that are based on dual moving average crossover (DMAC) rules in the Russian stock market over the 2003–2012 period. It contributes to the existing technical analysis (TA) literature by comparing for the first time in emerging markets the relative performance of individual stocks' trading portfolios with that of trading strategies for the index that consists of the same stocks (i.e., the most liquid stocks of the Moscow Exchange). The results show that the best trading strategies of the in-sample period can outperform buy-and-hold strategy during the subsequent out-of-sample period, although with low statistical significance. In addition, we document the benefits of using DMAC combinations that are much longer than those employed in previous TA literature. Moreover, the decomposition of the full-sample-period performance into separate bull- and bear-period performances shows that the outperformance of the best past index trading strategies over is mostly attributable to the fact that they managed to stay mostly out of the stock market during a dramatic crash caused by the global financial crisis.

KEYWORDS
Technical analysis; moving average; ordered weighted average; trading rules; index trading; market efficiency

JEL CLASSIFICATION
G11; G14; G17

I. Introduction

The profitability of technical trading rules in emerging stock markets has been examined by Ratner and Leal (1999), Chang, Lima and Tabak (2004), McKenzie (2007), Fifield, Power and Knipe (2008), Krausz, Lee and Nam (2009), Moosa and Li (2011) and Dbouk, Jamali and Soufani (2014), among others, but the Russian market is included in only few such studies. To the best of our knowledge, the only exceptions are Chong, Cheng and Wong (2010), Ni, Lee and Liao (2013), Aye et al. (2014) and Luukka et al. (forthcoming), the first three of which briefly examine the profitability of only few technical trading rules as a basis of index trading in the Brazil, Russia, India and China (BRIC) stock markets.[1] By contrast, Luukka et al. (forthcoming) compare the performance of a large number of trading rules that are all based on dual moving average crossover (DMAC) approach. Their sample data consists of individual MICEX constituent stocks of which they form trading portfolios. However, Luukka et al. (forthcoming) do not compare the relative performance of individual stocks' trading portfolios to that of trading strategies for a comparable index, which, to our best knowledge, has only been done before by Pätäri and Vilska (2014) in the Finnish market. Our paper is an extension to Luukka et al. (forthcoming) in that it reports the results of index trading strategies for the same time period (i.e., 2003–2012) and for the same DMAC combinations and compares, for the first time in emerging markets, the performance of index trading with that of the portfolio formed on the individual constituent stocks of the underlying index.

II. Data and methodology

The MICEX index data is from Datastream. The 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 (MA) from the beginning of the sample period. To alleviate data-snooping bias and to avoid look-ahead bias, we divide our sample period into two 5-year sub-periods and test

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[1]Beside the BRIC countries, the sample data of Aye et al. (2014) also includes the South African stock market.

the performance of the best DMAC strategies of the first sub-period (from Jan 2003 to Dec 2007) during the subsequent sub-period (from Jan 2008 to Dec 2012). In contrast to most previous studies but similarly to Luukka et al. (forthcoming), we do not set any pre-fixed maximum (minimum) lengths for short-term (long-term) MAs, but allow them to vary so that the ratio of the short-term MA to the long-term MA does not exceed 2/3. However, the maximum length of the long-term MA is set to 200 days, which implies that the maximum length for the short-term MA in this particular case is 133 days, but shorter in all other cases. Within such ranges, we form 13 333 DMAC combinations for each of the DMAC variants, which are based on simple MAs (SMA), exponentially weighted MAs[2] (EWMA) and ordered weighted MAs[3] (OWMA), similarly to Luukka et al. (forthcom-forthcoming). Consistent with many previous studies (e.g., Brock, Lakonishok and LeBaron 1992; 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 the index.[4] A buy (sell) signal is generated when the shorter MA rises above (or falls below) the longer MA.[5] In line with 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. We maintain the long position after the buy signal until we receive the sell signal. The cash inflows from sold positions are invested in the risk-free asset. The Russia Interbank 90-day interest rate (from Datastream) is used as a proxy for the risk-free rate of return.

For the real-world performance comparison of trading portfolios, we form daily time series for each trading portfolio. For each of the three DMAC variants, we report the proportions of the strategies that outperformed their buy-and-hold (B&H) counterparts in terms of both raw returns and the skewness- and kurtosis-adjusted Sharpe ratios[6] (henceforth SKASR) during both in-sample and out-of-sample periods.[7] We also document the detailed performance statistics from both sub-periods for those DMAC rules that have performed best within each DMAC variant during the first 5-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 capital gains. We assume that the average transaction costs are 1% per trade.[8] To find out whether the relative performance of the trading strategies against B&H strategies depends on general stock market

[2]Many different weighting schemes have been used for exponential weighting in TA literature (e.g., see Gardner 2006). In this paper, 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 MA is calculated and n is the length of the particular MA. We use this simple weighting scheme as it fairly takes account of the wide range of MA lengths employed in this study.

[3]In contrast to EWMAs, which reduce the weights of observations exponentially when moving back through time, the weights of the observations for OWMAs are determined on the basis of their order of magnitude (see Luukka et al. forthcoming for details).

[4]Because of the emerging status of the Russian stock market, we do not include the use of short positions in our analyses for two main reasons: During a part of the sample period, the Russian regulators banned short sales (see Kudrov et al. 2012, for details). In addition, even if short sales had been allowed, their transaction costs would most probably have been high enough to nullify their benefits, particularly during the out-of-sample period when the short selling ban was set. We tested this by assuming that short selling would have been permissible throughout the out-of-sample period using the average of short selling costs of 18 Russian brokers documented in Kudrov et al. (2012) as an estimate of short selling costs. The results showed that after the inclusion of transaction costs, the strategies also allowing short selling would have been outperformed by the long-only strategies even if short selling had been permissible throughout the out-of-sample period, which was not the case.

[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% band, which requires that the shorter MA must exceed (fall below) the longer MA by 1% before a buy (sell) signal is implemented (we also repeated the tests without a band filter. Generally, the results did not change much, and due to space limitations, we report only the results for the DMAC rules with a 1% filter).

[6]The adjustment for skewness and kurtosis is made by multiplying the standard deviation in the denominator of the standard Sharpe ratio by the ratio Z_{CF}/Z_c, where Z_c is the critical value of the probability based on the standard normal distribution (set to – 1.96 to correspond to the 95% probability level) and Z_{CF} is the corresponding skewness- and kurtosis-adjusted value calculated on the basis of the fourth-order Cornish–Fisher expansion as follows:

$$Z_{CF} = Z_C + (Z_C^2 - 1)S/6 + (Z_C^3 - 3Z_C)K/24 - (2Z_C^3 - 5Z_C)S^2/36,$$

where S refers to Fisher's skewness and K to excess kurtosis (see Pätäri 2011, for the introduction of the SKASR and the related risk metrics *skewness- and kurtosis-adjusted deviation* (SKAD).

[7]All 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).

[8]The percentage is based on the updated estimates of explicit (i.e., commissions and other fees) and implicit (represented for the most part by the price impact of the trades) trading costs for emerging market countries (documented in Domowitz, Glen and Madhavan 2001; Chong, Cheng and Wong 2010), allowing for the fact that the proportion of implicit trading costs to total transaction costs is remarkably lower in the case of index trading than in the case of trading on individual stocks. Given that the brokerage fees of Russian exchange traded funds are remarkably lower than the trading cost estimate employed in this study and that the transaction costs are generally clearly lower for institutional investors than for retail traders, the estimate employed in our study is on the safe side in the sense that the true after-costs returns would be downward rather than upward biased.

Table 1. Summary statistics for daily returns of the MICEX index.

	Full-sample period	1st sub-period	2nd sub-period
N	2,437	1,198	1,239
Mean	0.091%	0.17%	0.016%
Maximum	28.69%	10.68%	28.69%
Minimum	−18.66%	−10.00%	−18.66%
Standard deviation	2.38%	1.98%	2.71%
Sample skewness	0.41	−0.50	0.78
Sample excess kurtosis	20.43	6.61	22.2

The results based on daily returns are presented for the full sample period (Jan 2003–Jan 2012) and two nonoverlapping sub-periods (Jan 2003–Dec 2007 and Jan 2008–Jan 2012). N refers to the total number of daily return observations included in each sample period.

Table 2. Relative performance of the 13 333 DMAC strategies during the 2003–2007 period.

DMAC variant	Return	SKASR
OWMA	332 (2.49%)	2182 (16.37%)
SMA	46 (.35%)	1537 (11.53%)
EWMA	0 (0)	0(0)

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 generated a higher return or a higher SKASR than the B&H portfolio during the in-sample period.

conditions, we further divide the sample period into bull and bear market periods according to turning points of the MICEX index. We then calculate cumulative returns for each bullish and bearish sub-period and make comparisons between the best past DMAC strategies.

The performance comparison of the trading portfolios is based on the average return, the Sharpe ratio (Sharpe 1966) and the SKASR. To avoid validity problems stemming from the negative excess returns in risk-adjusted performance comparisons, we use refined versions introduced by Israelsen (2005)[9] for both types of Sharpe ratios. The statistical significances of the differences between comparable pairs of the Sharpe ratios are given by the *p*-values of the Ledoit–Wolf test,[10] which is based on the circular block bootstrap method. Table 1 presents summary statistics for the MICEX Index data.

III. Results

In-sample results

Table 2 shows the number and the proportion of such DMAC rules (among 13 333 DMAC combinations) that generated a higher return or a higher SKASR than the corresponding B&H portfolio during the in-sample period from 2003 to 2007 for each of the three DMAC variants examined. In terms of raw returns, only a few of the DMAC trading rules were able to outperform their passive benchmark: The highest percentages are documented for the OWMA-based DMAC rules of which 2.49% generate a higher return than their benchmark. Based on the SKASR, the corresponding outperformance percentage is 16.37%. In this sense, our results are in line with Luukka et al. (forthcoming) who also reported much higher outperformer rates for the DMAC trading portfolios formed on individual stocks in terms of the SKASR than in terms of raw returns. However, they reported very even as well as remarkably higher outperformer rates based on the SKASR for all three DMAC variants (ranging from 34.32% to 37.32%), whereas our results indicate much more variability among them: the worst-performing DMAC variant during this period is that based on the EWMA, for which none of the 13 333 trading rules outperform the B&H portfolio in terms of either raw returns or SKASRs. The differences between the outperformance rates are explained by the differences in signal sensitivities among the DMAC variants. On average, the EWMA-based rules generate more sell signals as well as more false signals than their OWMA- and SMA-based counterparts.

The comparison of the best DMAC combinations within each of the three DMAC variants reveals that the best EWMA rule is also dominated by OWMA- and SMA-based counterparts in both mean-risk frameworks (i.e., in the mean-variance as well as in the mean-SKAD framework, implying that it generates remarkably lower return at slightly higher risk level (see Table 3)). The highest SKASR (0.363) is reported for OWMA(113,200), whereas the lowest (0.268) is for EWMA(1,178). Based on the Ledoit–Wolf test, the former outperforms the latter at the 5% significance level. With respect to the rank order of the best trading rules within the three DMAC variants, Luukka et al. (forthcoming) reported parallel results for the best trading portfolios of

[9]Israelsen (2005) suggests to multiply the excess return by its volatility in cases when negative excess return is negative in order to maintain the interpretation of the Sharpe ratios consistent throughout the distribution of the ratios (see the original article for details).

[10]See the original article for details (Ledoit and Wolf 2008. The corresponding programming code is freely available at: http://www.econ.uzh.ch/faculty/wolf/publications.html).

Table 3. Performance of the best DMAC strategies during the 2003–2007 period.

DMAC rule	Return	Volatility	Skewness	Kurtosis	SR	SKASR	Sign
OWMA(113,200)	47.49%	24.41%	−.519	−.228	.384	.363	9.34
SMA(132,199)	44.77%	24.74%	−.411	−.295	.357	.344	46.36
EWMA(1,178)	36.12%	25.52%	−.368	−.559	.274	.268	43.34
MICEX (B&H)	42.72%	26.11%	−.392	−.669	.322	.305	

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 MICEX index portfolio. Statistical significance (in percentages) of the performance differences between the DMAC strategies and the corresponding benchmark portfolio is shown in the last column. The first (second) number in parentheses indicates the length of the shorter (longer) MA (in days).

individual stocks in the same market and for the same sample period, except that the average annual returns of such portfolios were at their best more than 10% points higher (i.e., 59.76% p.a. for OWMA (94,182) rule) than those of the best index trading portfolios examined in this paper. Based on the Ledoit–Wolf test, the outperformance of the best DMAC rule (i.e., OWMA(113,200)) against B&H portfolio is significant at the 10% level, but not at the 5% level, though both OWMA(113,200) and SMA(132,199) rules have higher returns and lower risk than the B&H portfolio. The significance levels of outperformance are generally lower than those reported by Luukka et al. (forthcoming) for the best portfolios of individual stocks.

The comparison of MA length combinations among the best trading rules within each DMAC variant reveals that although the longer MA is close or equal to the maximum employed in this study for all variants, there is a huge difference in the lengths of the shorter MAs between the best EWMA-based rule and its SMA- and OWMA-based counterparts. This difference strongly affects the signal sensitivity; as EWMA(1,178) generates 13 signals (either buy or sell) during the in-sample period, the corresponding numbers for OWMA(113,200) and SMA(132,199) are only 4 and 6, respectively. Based on the return difference between the three best DMAC variants, it is easy to infer that many of the EWMA(1,178) signals are false. In contrast, all the four signals generated by OWMA(113,200) are correct.[11] Figure 1 illustrates the cumulative returns of the best index trading strategies during the in-sample period.

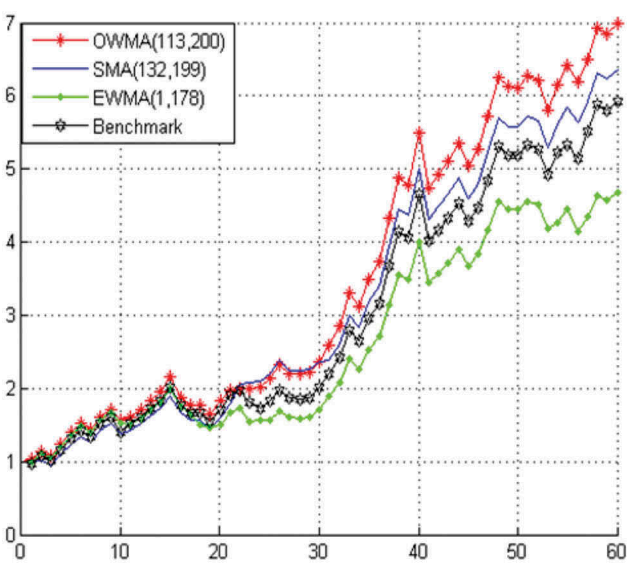

Figure 1. Cumulative returns on the best strategies during the 2003–2007 period. The curves depict the monthly return accumulation of the first sub-period's best index trading strategies and that of the B&H index portfolio.

Out-of-sample results

Table 4 shows the outperformer rates for the out-of-sample period from 2008 to 2012, correspondingly to those reported for the in-sample period in Table 2. The rates are dramatically different to their in-sample counterparts since almost all the DMAC trading rules examined outperform their benchmark portfolio during the latter period in terms of both raw returns and SKASR, regardless of the DMAC variant employed. The highest outperformer rates within this time span are documented for the EWMA-based DMAC var-

Table 4. Relative performance of the 13 333 DMAC strategies during the 2008–2012 period.

DMAC variant	Return	SKASR
OWMA	13 054 (97.91%)	13 253 (99.40%)
SMA	13 035 (97.76%)	13 159 (98.70%)
EWMA	13 298 (99.74%)	13 308 (99.81%)

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 generated a higher return or a higher SKASR than the B&H portfolio during the out-of-sample period.

[11] In this particular case, a sell (buy) signal is considered correct if the underlying index return has been negative (positive) when the signal has been 'on'.

Table 5. Performance of the best DMAC strategies during the 2008–2012 period.

DMAC rule	Return	Volatility	Skewness	Kurtosis	SR	SKASR	Sign
OWMA(113,200)	5.13%	16.64%	−1.22	2.855	−.11*	−.14*	42.58
SMA(132,199)	11.51%	13.21%	−0.63	2.166	.069	0.060	9.07
EWMA(1,178)	1.26%	19.31%	−0.01	3.627	−.31*	−.31*	74.41
MICEX (B&H)	−4.83%	32.22%	−.536	1.197	−1.00*	−1.15*	

* x 10^{-3}

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 (in-sample period) and for the B&H benchmark portfolio. Statistical significance (in percentages) of the performance differences between the DMAC strategies and the benchmark portfolio is shown in the last column).

iants, but as for the in-sample period, the performance of the best past EWMA rule is inferior to that of its OWMA- and SMA-based counterparts.

The best performance is documented for SMA (132,199), which is the only one among the best past trading rules for which the average return is above the risk-free return (see Table 5). However, all these trading rules outperform their passive benchmark portfolio, but only the outperformance of SMA (132,199) is significant at the 10% level, but not at the 5% level, despite its average annual return being 16.34% points higher than that of the MICEX index portfolio and its total risk being less than half of that of MICEX.

Again, the significances of outperformance are generally lower than those reported by Luukka et al. (forthcoming) for the best portfolios of individual stocks, even though for this sub-period, the return of the best index trading portfolio is marginally higher than that of the corresponding trading portfolio of the MICEX constituent stocks (11.51% vs. 11.36% p.a.), unlike during the first sub-period. In this sense, our results support the findings of Pätäri and Vilska (2014) on the time variability in relative performance between trading portfolios individual stocks and index trading. Figure 2 illustrates the cumulative returns of the best past index trading strategies during the out-of-sample period.

During this more volatile sub-period, the difference in the signal sensitivity between the best past EWMA rule and its OWMA- and SMA-based counterparts become emphasized. While the former generates 24 signals, the corresponding number for the latter two is only 8. In all cases, the signals of SMA (132,199) somewhat lag those of OWMA(113,200), but for this sub-period, the lags, on average, are beneficial particularly due to better-timed buy signal following the crash period. The market decline following the pre-crisis sell signal of SMA(132,199) is – 46.36%, whereas it is – 37.78% for the corresponding signal of OWMA(113,200). The avoidance of the corresponding levels of loss results in the outperformance of SMA(132,199) over OWMA(113,200) during this sub-period.[12]

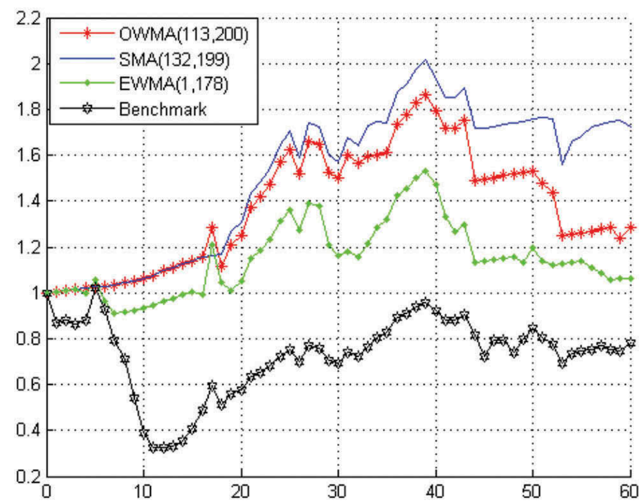

Figure 2. Cumulative returns on the best trading strategies during the 2008–2012 period. The curves depict the monthly return accumulation of the first sub-period's best DMAC strategies determined for each of the three DMAC variants examined and that of the B&H index portfolio.

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

[12]Although the outperformance of SMA(132,199) over OWMA(113,200) is not statistically significant, the former dominates the latter in the mean-variance framework (i.e., the return of SMA(132,199) is higher, whereas its volatility is lower). The dominance also holds in the mean-SKAD framework. In addition to the better timing of the buy signal following the financial crisis period, the better performance of SMA(132,199) is also explained by the smaller average losses stemming from false signals (the number of which is equal to both of these two trading rules during this period).

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 10-year sample period. We follow Edwards, Biscarri and Pérez De Gracia (2003) in using a 20% 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 obtain an aggregate bull market period that includes 1954 daily returns and consists of four distinct bullish periods.[13] 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 6, which also shows the returns of the best past trading strategies and the corresponding B&H returns for each of the seven sub-periods.

Table 6 shows that the outperformance of the best past DMAC portfolios is mostly attributable to the fact that such portfolios lost far less of their value during the financial crisis than the B&H index portfolio. Within the half-year period from May to November 2008, the MICEX index lost 73.57% of its value, whereas the greatest loss among the best past index trading strategies was 12.46% for the EWMA(1,178). The best past trading strategy OWMA(113,200) managed to stay out of the stock market throughout the crash period, and therefore generated a positive return of 4.66% due to the risk-free return earned. However, the best past trading strategies were not as successful during the other two bearish periods, since they then experienced a similar decline as the MICEX index.

During the bullish periods, all the best past trading strategies lost, on average, to their benchmark, although during the isolated bullish periods, the two best strategies were able to occasionally beat the MICEX index. However, the return difference during the bull market conditions in favour of the B&H portfolio increases drastically during the 30-month bullish period from November 2008 to April 2011, since all the best past trading strategies generate at least one false sell signal within that time span. The false sell signals in the middle of a bullish period explain the difficulties of the DMAC rules to outperform in such conditions, since being out-of-the-market in heavily bullish conditions even for a short time period is hard to compensate with other timing decisions, particularly when the MA trading rules are always late in identifying the turning points of the stock markets. Altogether, our results are in this sense consistent with Fong and Yong (2005), Andrada-Félix and Fernández-Rodríguez (2008), Yen and Hsu (2010), Pätäri and Vilska (2014) and Luukka et al. (forthcoming), who all documented outperformance of technical trading strategies during bearish periods; however, our results contrast with those of Fong and Ho (2001) and Chang,

Table 6. Decomposition of the performance of DMAC strategies.

		Panel A: Bullish periods			
Rules	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
OWMA(113,200)	128.79%	273.11%	77.79%	4.75%	1489.7%
SMA(132,199)	102.37%	362.61%	92.59%	14.84%	1970.5%
EWMA(1,178)	112.47%	198.00%	66.43%	−5.32%	897.7%
MICEX (B&H)	115.44%	304.67%	259.04%	17.36%	3573.7%
		Panel B: Bearish periods			
	04-04-13–04-07-28	08-05-20–08-11-21	11-04-11–12-05-23		Total bear
OWMA(113,200)	−29.64%	4.66%	−36.66%		−53.4%
SMA(132,199)	−29.64%	−3.68%	−27.15%		−50.6%
EWMA(1,178)	−31.04%	−12.46%	−28.20%		−56.7%
MICEX (B&H)	−29.64%	−73.57%	−32.30%		−87.4%

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*.

[13]The last sub-period from 24 May 2012 to the end of December 2012 is classified as bullish despite the cumulative return of the MICEX index from the previous trough not exceeding 20% by the end of 2012. However, the rising trend continued until January 2013, when the cumulative return of 20% from the previous trough was exceeded before the next declining trend.

Lima and Tabak (2004), who report particularly significant abnormal returns over and above the B&H portfolio during bullish periods.

IV. Conclusions

This paper examines the performance of index trading strategies that are based on several DMAC variants in the Russian stock market over the 2003–2012 period. It contributes to the existing TA literature by examining for the first time the performance of OWMA-based DMAC trading rules on index trading and by comparing it to that of the SMA- and EWMA-based DMAC rules. This is also the first time when the relative performance of individual stocks' trading portfolios in emerging markets (relying partially on the recent results of Luukka et al. forthcoming) is compared to that of trading strategies for an index that consists of the same stocks included in the trading portfolios (i.e., the most liquid stocks of the Moscow Exchange).

The great majority of the trading rules underperformed against the comparable B&H strategy during the in-sample period, but the best trading rules of the in-sample period outperformed their passive benchmarks during the subsequent out-of-sample period, although with low statistical significance. Consistent with the results of Luukka et al. (forthcoming) for the trading portfolios of individual stocks, the benefits of extending the shorter MA employed in the DMAC trading rules far longer than commonly done in TA literature are also evident in the case of index trading strategies. This finding has also significant practical implications since the use of standard upper limits for the length of the shorter MA would have ruled out the best DMAC combinations. Therefore, in highly volatile stock markets, like in Russia, the use of sufficiently long short-term MAs in the DMAC rules is particularly important.

The decomposition of the 10-year performance into separate bull- and bear-period performances shows that the benefits of following the best past DMAC strategies are principally because they managed to stay, for the most part, out of the stock market during a huge crash caused by the global financial crisis. However, the same does not hold for the two other smaller crashes included in the 10-year sample period. This finding somewhat diverges from the results of Luukka et al. (forthcoming) who find some evidence of market timing ability among the best past trading portfolios of individual stocks during all three bearish periods. Hence, for the Russian sample data, DMAC trading on individual stocks has been somewhat safer than the comparable index trading, at least during this particular sample period, given that the trading rules would have been chosen on the basis of their historical (i.e., in-sample) performance. This result is explained by the characteristic difference between the trading strategies on the index and the trading portfolios of its constituent stocks. While the former is either an 'all-in' or 'all-out' strategy, the market exposure of the latter is very seldom either 0% or 100%, but for most of the time, somewhere between these two extremes. To our best knowledge, this fundamental difference has not been discussed in earlier TA literature. It has also important practical implications for investors; if the DMAC rules, on average, could generate abnormal returns, the negative impact of unavoidable false signals on overall performance would better even out when there are several trading assets instead of only one.

Disclosure statement

No potential conflict of interest was reported by the authors.

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