Buy and sell signals on Bucharest Stock Exchange

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Abstract: Trading rules of the technical analysis are widely used in investing on the capital markets. However, prediction of the financial markets movements based on their past evolutions is in contradiction with the principles of the Efficient Market Hypothesis. In case of the emerging markets, the impact of the development markets evolutions could also be taken into consideration in establishing the trading rules. In this paper we investigate the efficiency of three simple trading rules on Romanian capital market. Two of them, Variable-Length Moving Average and Bollinger Bands, belong to the technical analysis methods, while the third is based on the impact of the shocks from New York Stock Exchange. The results indicate some significant differences between these methods of shocks' identification.

Keywords: Capital markets; Technical Analysis; Emerging Market Integration

JEL: *F30, G14, G15.*

1. INTRODUCTION

The technical analysis emploment in investing on the stock market is one of the most controversial subjects of the financial literature. Traders on the capital markets use widely the past evolutions of the markets to predict their future movements (e.g. Brorsen & Irwin, 1987; Park & Irwin, 2004). Such methods could be employed to identify buy and sell signals used in the investment decisions. A buy signal indicates favorable conditions to obtain profits by purchasing stocks. By contrary, a sell signal reveals the appropriate circumstances to sell stocks.

While the technical analysis is praised by most of the practitioners, there are many academics which are skeptics about it, especially the followers of Fama's (1970) Efficient Market Hypothesis. This theory, which stipulates that all the available information is included in current prices, is opposed to the methods of prediction based on the past evolution. However, other financial theories admitted the possibility of the technical analysis having a in revealing some characteristics of the capital markets evolution such as the impact of the psychological factors (e.g. Alexander, 1961; Borch, 1964; Jensen & Benington, 1970; Neftci & Policano, 1984; Treynor & Ferguson, 1985; Brown & Jennings, 1989; Froot et al., 1990; Blume et al., 1994; Gencay, 1998; Lo & MacKinlay, 1999; Lo et al., 2000).

The profitability of the investment strategies based on the technical analysis was investigated in numerous researches which led to mixed results (e.g. Donchian, 1960; Cootner, 1962; Fama & Blume, 1966; Brock et al., 1992; Knez & Ready, 1996; Parisi & Vasquez, 2000; Gunasekarage & Power, 2001; Hsu & Kuan, 2004; Kidd et al., 2004; Loh, 2004; Marshall et al., 2008; Metghalchi et al., 2008; Shefrin, 2008; Park & Heaton, 2014). In the last decades the efficiency of the technical analysis was improved by using in combination with other methods of investment in the financial markets (e.g. Brown & Jennings, 1989; Murphy, 1999; Lo et al., 2000; Leigh et al., 2002; Chavarnakul & Enke, 2008).

The financial globalization strengthened the linkages among the international capital markets (e.g. Chowdhury, 1994; Bekaert & Harvey, 1995; Dungey & Martin, 2007; Sharma & Seth, 2012). These linkages could be taken into consideration in the investment decision on the stock markets.

In this paper we approach the efficiency of the trading rules for investment on Bucharest Stock Exchange (BSE) using buy and sell signals. After Romania's adhesion to European Union BSE's integration in the world financial markets intensified. In these circumstances, the evolutions of the share prices could be significantly influenced by the international markets. We investigate the profitability of investment decisions based on three types of methods to identify buy and sell signals. Two of them belong to the technical analysis: Variable-Length Moving Average (VMA) and Bollinger Bands (BB). The third method is based on the impact of shocks from New York Stock Exchange (NYSE). The BSE evolution is expressed by five main indexes, while the shocks from NYSE are identified by employing the values of the S&P 500 index.

The rest of the paper is organized as it follows: the second part describes the data and methodology employed to identify buy and sell signals on BSE, the third part presents the empirical results and the fourth part concludes.

2. DATA AND METHODOLOGY

In this investigation about the simple trading rules on Romanian capital market we employ daily closing values of six indexes: five from BSE (BET, BET-C, BET-FI, BET-XT and BET-NG) and one from United States (the well known S&P 500).

Tab.1 The five indexes from BSE employed in the investigation

Index	Constituents (as presented by Bucharest Stock Exchange)	Period of time
BET	Most liquid 10 companies listed on the BSE regulated market	January 2007 – July 2015
BET-C	All the big companies listed on BSE, excepting the investment funds (SIFs)	January 2007 – June 2014
BET-FI	The five investment funds (SIFs)	January 2007 – July 2015
BET-XT	The most liquid 25 shares traded on BSE, including SIFs	January 2007 – July 2015
BET-NG	The companies which have the main business activity located in the energy sector and the related utilities	January 2007 – July 2015

As sources of data we use BSE, for the five Romanian indexes, and Yahoo! Finance for S&P 500. The sample of data covers the period January 2007 - July 2015, excepting BET-C which was not calculated anymore by BSE since July 2014. The composition of the five indexes from Romanian capital market is presented in the Table 1.

For all the five indexes from BSE we identify the buy and sell signals using three methods:

a. Variable-Length Moving Average;

b. Bollinger Bands;

c. NYSE shocks.

a. **The Variable-Length Moving Average** (VMA) method finds such signals by comparisons between short moving average (SMA) and long moving averages (LMA) of the prices. In order to eliminate unreliable signals, lower and the upper bands, around the LMA could be introduced (Brock et al., 1992). In the VMA trading rules these bands could be expressed by the percentage difference between the upper and lower band, called the Bandwith (BW).

A buy signal (b_t^{VMA}) occurs when SMA is above the LMA by an amount larger than the half of the BW. Similarly, a sell signal (s_t^{VMA}) is generated when SMA is below the LMA by more than the half of the BW. If the SMA is between the two bands no signal occurs (Brock et al., 1992). These trading rules could be transposed in the formulas:

$$\begin{cases} b_t^{VMA} : SMA_t > (1+0,5\times BW)\times LMA_t \\ s_t^{VMA} : SMA_t < (1-0,5\times BW)\times LMA_t \end{cases} \quad (1)$$

In practice, various form of VMA could be applied, with different periods of time for SMA and LMA. In this paper we employ a (1 – 50) VMA rule that means the period for SMA is one day and the period for LMA is 50 days. We also used a BW of 2 percent.

b. **The Bollinger Bands** (BB) analyzed the prices evolution using their trend and their volatility (Bollinger, 1992). It uses three bands: middle, upper and lower. The middle band, which indicates a trend of prices evolution, is determined through the moving average of a period of N days. The upper band is above the middle band by a number (k) of the standard deviation of the period of N days, while the lower band is below the middle band by the same number (k) of the standard deviation.

$$\begin{cases} M_t^{BB} = MA_t \\ U_t^{BB} = M_t^{BB} + k\times\sigma_t \\ L_t^{BB} = M_t^{BB} - k\times\sigma_t \end{cases} \quad (2)$$

We identify the buy and sell signals by the Volatility Breakout, one of the main applications of BB. A buy signal (b_t^{BB}) occurs when the price is higher than the upper band, while a sell signal (s_t^{BB}) is generated when the price is smaller than the lower band. Between the upper and lower bands no signal occurs. The conditions to identify buy and sell signals could be transposed into the relations:

$$\begin{cases} b_t^{BB} : P_t > U_t^{BB} \\ s_t^{BB} : P_t < L_t^{BB} \end{cases} \tag{3}$$

In this paper we employ a (20, 2) BB rule which means that N=20 and k=2.

c. **The NYSE shocks** method identifies the buy and sell signals by the impact on BSE of the evolution of S&P 500. A positive shock on NYSE, meaning that S&P 500 increased with more than 1 percent, generates a buy signal (b_t^{SP}) on BSE. Instead, a negative shock on NYSE, meaning that S&P 500 decreased with more than 1 percent, generates a sell signal (s_t^{SP}) on Romanian capital market. These trading rules could be transposed into relations:

$$\begin{cases} b_t^{SP} : SP_t > 1{,}1 \times SP_{t-1} \\ s_t^{SP} : SP_t < 0.9 \times SP_{t-1} \end{cases} \tag{4}$$

We analyze the reliability of the buy and sell signals identified by the three methods using the methodology of Cumby & Modest (1987) methodology. We calculate, for each of the five indexes of BSE, the logarithmic returns ($r_{i,t}$) as:

$$r_{i,t} = [\ln(P_{i,t}) - \ln(P_{i,t-1})] * 100 \tag{5}$$

where P_t and P_{t-1} are the closing prices of the index i on the days t and t-1, respectively.

We investigate the stationarity of the BSE indexes by employing the Augmented Dickey – Fuller (ADF) tests (Dickey & Fuller, 1979) using the intercept as deterministic term and choosing the numbers of lags by Akaike Information Criteria (Akaike, 1973).

The performances of the investment strategies based on the exploiting of buy signal are analyzed by the regression:

$$r_{i,t} = \alpha^B + \beta^B \times D_{t-1}^{Buy} + \varepsilon_t \tag{6}$$

where: D_{t-1}^{Buy} is a dummy variable that equals one when a buy signal occurs and zero otherwise; ε_t is the residual term.

The coefficient α^B expresses the average of the returns from the days when no buy signal occurs, while the coefficient β^B reflects the difference between the average of returns from the days when a buy signal is generated and the returns from the other days. A significant positive value of β^B indicates the reliability of the investment based on the buy signals.

The profitability of the investment strategies based on the sell signals is investigated by the regression:

$$r_{i,t} = \alpha^S + \beta^S \times D_{t-1}^{Sell} + \varepsilon_t \tag{7}$$

where D_{t-1}^{Sell} is a dummy variable that equals one when a sell signal occurs and zero otherwise.

The coefficient α^S indicates the average of the returns from the days when no sell signal occurs, while the coefficient β^S measures the difference between the average of returns from the days when a sell signal is generated and the returns from the other days. A significant negative value of β^S indicates the investments based on the sell signals are profitable.

For both regressions we investigate the significance of the coefficients by t tests. When heteroskedasticity is detected we apply the White's (1980) standard errors to the regressions parameters. In case of autocorrelation we apply Newey – West (1987) corrections.

3. EMPIRICAL RESULTS

The Table 2 reports the numbers of buy and sell signals identified by the three methods. Comparing to VMA, BB generated a much less number of trading signals. For both methods, the buy signals are more numerous than the sell signals. Obviously, the NYSE shocks method generated the same trading signals for all BSE indexes, excepting BET-C which covers a shorter period of time.

Tab.2 Numbers of buy and sell signals identified by the three methods

Index	**VMA**		**BB**		**NYSE shocks**	
	Buy	Sell	Buy	Sell	Buy	Sell
BET	859	706	280	200	307	307
BET-C	744	682	236	187	279	283
BET-FI	923	864	280	238	307	307
BET-XT	860	752	290	222	307	307
BET-NG	825	730	273	209	307	307

We analyze the stationarity of BSE indexes returns by employing ADF tests. The results, presented in the Table 3, rejected, for all indexes, the null hypothesis of unit root.

Tab.3 Results of ADF tests for the returns

Index	**Number of lags**	**Test statistics**
BET	19	-8.3292***
BET-C	21	-7.5579***
BET-FI	19	-9.1530***
BET-XT	19	-8.4014**
BET-NG	19	-9.0379***

Note: *** means significant at 0.01 level.

We continue by performing Cumby & Modest (1987) regressions for the buy and sell signals identified by the three methods. The parameters of these regressions for the VMA buy and sell signals are presented in the Table 4. For all the indexes we obtained significant positive values of the β^B_{VMA} coefficient. The maximum value of this coefficient corresponds to BET-FI index. The results of the regression for sell signals indicate significant negative values of the coefficient β^S_{VMA} for all the indexes excepting BET-NG. The larger negative value of this coefficient corresponds, again, to BET-FI index.

Tab.4 Results of Cumby & Modest (1987) regressions for the VMA method

Index	Buy signals regression			Sell signals regression		
	α_{VMA}^{B}	β_{VMA}^{B}	F test	α_{VMA}^{S}	β_{VMA}^{S}	F test
BET	−0.056 (0.047)	0.125* (0.074)	2.86*	0.062* (0.036)	−0.206** (0.090)	5.28**
BET-C	−0.103** (0.049)	0.199** (0.077)	6.63**	0.076* (0.041)	−0.279*** (0.084)	10.90***
BET-FI	−0.190*** (0.070)	0.364*** (0.103)	12.54***	0.107* (0.056)	−0.345*** (0.112)	9.45***
BET-XT	−0.092* (0.052)	0.180** (0.078)	5.35**	0.072* (0.038)	−0.261*** (0.094)	7.70***
BET-NG	−0.096** (0.048)	0.193** (0.080)	5.89**	0.021 (0.038)	−0.123 (0.088)	1.95

Notes: Standard Errors are within round brackets;
***, **, * mean significant at 0.01, 0.05 and 0.1 levels, respectively.

The Table 5 presents the results of the trading signals regressions for the BB method. For buy signals we obtained significant positive values of the β_{BB}^{B} coefficient for all indexes except BET-NG. The larger values of this coefficient correspond to BET – C and BET – FI. For the sell signals the results indicate significant negative values of β_{BB}^{S} only for BET - FI and BET – XT.

Tab.5 Results of Cumby & Modest (1987) regressions for the BB method

Index	Buy signals regression			Sell signals regression		
	α_{BB}^{B}	β_{BB}^{B}	F test	α_{BB}^{S}	β_{BB}^{S}	F test
BET	−0.031 (0.039)	0.193* (0.107)	3.24*	0.004 (0.035	−0.111 (0.177)	0.39
BET-C	−0.076* (0.041)	0.396*** (0.116)	11.62***	−0.006 (0.037)	−0.195 (0.171)	1.31
BET-FI	−0.083 (0.055)	0.383** (0.156)	6.00**	0.015 (0.051)	−0.431* (0.226)	3.64*
BET-XT	−0.067 (0.042)	0.347*** (0.106)	10.72***	0.022 (0.037)	−0.408** (0.186)	4.85**
BET-NG	−0.029 (0.041)	0.065 (0.111)	0.34	−0.011 (0.038)	−0.102 (0.159)	0.41

Notes: Standard Errors are within round brackets;
***, **, * mean significant at 0.01, 0.05 and 0.1 levels, respectively.

The results of the trading signals regressions for the NYSE method are reported in the Table 6. For the buy signals regressions we obtained, for all the five indexes, significant positive values of the β_{NY}^{B} coefficient, with the maximum value for BET – FI index. The regressions for the sell signals indicate significant negative values of the coefficient β_{NY}^{S} for all the indexes, with the largest values for BET-C and BET – FI.

Tab.6 Results of Cumby & Modest (1987) regressions for NYSE shocks method

Index	Buy signals regression			Sell signals regression		
	α_{NY}^{B}	β_{NY}^{B}	F test	α_{NY}^{S}	β_{NY}^{S}	F test

BET	−0.121*** (0.037)	0.833*** (0.128)	42.08***	0.153*** (0.035)	−1.092*** (0.136)	64.76***
BET-C	−0.147*** (0.039)	0.855*** (0.122)	49.26***	0.151*** (0.036)	−1.138*** (0.136)	69.96***
BET-FI	−0.181*** (0.052)	1.052*** (0.184)	32.59***	0.168*** (0.048)	−1.400*** (0.229)	37.46***
BET-XT	−0.145*** (0.039)	0.896*** (0.132)	46.12***	0.151*** (0.037)	−1.180*** (0.157)	56.23***
BET-NG	−0.123*** (0.038)	0.749*** (0.145)	26.79***	0.141*** (0.036)	−1.107*** (0.146)	57.28***

Notes: Standard Errors are within round brackets; *** means significant at 0.01 level.

4. CONCLUSIONS

In this paper we investigated the reliability of three types of investment strategies based on buy and sell signals from BSE: VMA, BB and NYSE shocks. The results of Cumby & Modest (1987) methodology revealed some significant differences between the three methods of shocks' identification and also some differences about the compatibility of the BSE indexes to investment strategies based on buy and sell signals.

In the case of buy signals, VMA and NYSE shocks methods led to profitable investment strategies for all five BSE indexes, while BB method only for four indexes. When it was applied to identify sell signals, the NYSE shocks method generated profitable investment strategies for all five BSE indexes, while the VMA method for four indexes and the BB method only for two indexes. These results confirmed the significant impact of the NYSE evolution on BSE (Dumitriu and Stefanescu, 2015; Stefanescu and Dumitriu, 2015). However, VMA method generated a much larger number of trading signals than NYSE shocks and this is an important aspect of such investment strategies. In these circumstances, it could be useful to combine the NYSE shocks method with some classical methods of the technical analysis.

From the five BSE indexes, the results of the Cumby & Modest (1987) methodology suggest that BET – FI is the most compatible with the investment strategies based on trading signals, while BET – NG is the less compatible. BET – FI, which incorporates the share prices of the investment funds, could be very sensitive to the short – term expectations and to the influence of the NYSE evolution (Dumitriu and Stefanescu, 2015). Instead, BET – NG, which incorporates the share prices of the companies which have the main business activity located in the energy sector and the related utilities, seems to be sensitive to other kind of stimuli, such as the oil price (Stefanescu and Dumitriu, 2013).

This investigation could be extended by studying the reliability of the three methods for the capital markets from other countries. Such analyze could also take into consideration the capacity of the shocks from other types of financial markets to generate buy and sell signals.

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