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Capabilities of Statistical Residual-Based Control Charts in Short- and Long-Term Stock Trading

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Abstract

The aim of this paper is to introduce and develop additional statistical tools to support the decision-making process in stock trading. The prices of CROBEX10 index stocks on the Zagreb Stock Exchange were used in the paper. The conducted trading simulations, based on the residual-based control charts, led to an investor's profit in 67.92% cases. In the short run, the residual-based cumulative sum (CUSUM) control chart led to the highest portfolio profits. In the long run, when average stock prices were used and 2-sigma control limits set, the residual-based exponential weighted moving average control chart had the highest portfolio profit. In all other cases in the long run, the CUSUM control chart appeared to be the best choice. The acknowledgment that the SPC methods can be successfully used in stock trading will, hopefully, increase their use in this field.

Key words: Zagreb Stock Exchange; investments; statistical process control; autocorrelation; residual-based control charts

1 Introduction

The stock market is recognized as a vital part of a country's economy, finances, and growth. Tachiwou (2010) considered the stock market as an indicator of an economy's financial health and as a base for economic growth in the short and long run. The positive effects of stock markets on economic growth have also been recognized by other authors (Caporale, Howells, & Soliman, 2004; Manas, 2005). In order to be capable of adopting the role of investors and being included in stock trading, individuals need to be financially literate (Almenberg & Dreber, 2012; Guiso, Sapienza, & Zingales, 2008, van Rooij, Lusardi, & Alessie, 2011) and have developed computer and Internet skills (Bogan, 2008).

The filter trading rules were introduced by Alexander (1961, 1964). Alexander's work on the filter trading rules presented one of the earliest academic works focused on the investigation of stock prices trends using statistical rules (Venkataramani, 2003). His work was followed by the works of Fama and Blume (1965) and Dryden (1969) and further developed by Sweeney (1988) and Corrado and Lee (1992). The filter-trading rule is defined as a sequence of buy and sell signals. These signals are given according to a mechanical rule. For instance, the buy signal is given if the daily closing price of an observed stock moves up at least F percent from a subsequent low. After the stock is bought, the investor holds the stock and awaits the sell signal. The sell signal is given when the closing prices drops at least F percent from a subsequent high. The

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subsequent lows and highs can be defined in different ways (Sullivan, Timmermann, & White, 1999) whereas the *F* value is the filter size for the trading rule and represents the minimally acceptable percentage change of the observed stock value for the investor.

The research question is this study is whether statistical control charts, as a statistical process control (SPC) method, could be useful in trading stocks—that is, whether control charts are capable of giving signals for buying, holding, and selling stocks. Control charts were introduced by Shewhart in 1924 (Best & Neuhauser, 2006). Over the years, control charts, and other statistical control process methods, have found their use in different fields not only in mass production. For instance, control charts could be used in the financial analysis also. Right before the appearance of filter trading rules, H. V. Roberts (1959) was one of the first to suggest the use of statistical quality control methods for the study of market price levels and changes. Hubbard (1967) studied Moody's Composite 200 Stock Average from 1950 to 1967 and used logarithmic monthly values in order to construct control charts, which he used to determine the price trend and compare it with gross national product and personal income trends. Most importantly, he identified ways to recognize signs for buying or holding stocks. According to Hubbard (1967), small price differences edging up and down the centre line have no recognizable pattern; consequently, such differences contain no useful information for helping an investor decide whether to buy or sell stocks. On the other hand, significant departures from the centre line signals stock price overvaluation or undervaluation.

Statistical control charts are rarely explored as a technique in stock trading and portfolio analysis (Gandy, 2012; Rebisz, 2015). According to McNeese and Wilson (2002), one of the main reasons for rarely using statistical control charts in financial analysis is managers' attitude that control charts are inappropriate for their kind of work. However, Kovarik and Sarga (2014) used cumulative sum (CUSUM) and exponentially weighted moving average (EWMA) control charts to deal with the corporate cash flow control. Meanwhile, Gandy (2012) used CUSUM control charts in credit portfolio analyses. Therefore, in all analyses the focus is on the analysis based on individual (I), exponentially weighted moving average (EWMA), and cumulative sum (CUSUM) control charts. These control charts are also chosen because their application is intuitive and not too complex for an average investor. Furthermore, what is also important is that the selected control charts can give immediate signals to an investor.

According to the above stated research questions and literature review, three research hypotheses are defined:

H1: Statistical control charts are useful for making decisions about stock trading.

H2: Stock trading based on the individual (I) control chart overall gives a portfolio profit that is higher than the profit achieved by using the exponentially weighted moving average (EWMA) control chart or the cumulative sum (CUSUM) control chart.

H3: Stock trading based on opening prices overall results in higher portfolio profit than the trading based on average prices.

In order to test these research hypotheses, data from the Zagreb Stock Exchange were used. Four parallel analyses were conducted. The analyses used open and average prices of stocks from the CROBEX10 market index in the short and long run. The observed data and used methods are explained in Section 2. The conducted short-run analysis is given in Section 3, whereas the long-run analysis is provided in Section 4. Section 5 compares and discusses the obtained results. Final conclusions and suggestions for further research are given in Section 6.

2 Data and Methodology

The Zagreb Stock Exchange (ZSE) is the only regulated modern stock exchange in the Republic of Croatia (Benić & Franić, 2008; Zagreb Stock Exchange, 2014b). In 2013, 208 stocks were listed (Zagreb Stock Exchange 2014a) as well as 9 stock (equity) indices (Zagreb Stock Exchange, 2014e). The analysis included only the CROBEX10 index, which includes 10 stocks with the highest free float market capitalization and turnover (Zagreb Stock Exchange, 2014d) and that are traded in more than 90% trading days (Zagreb Stock Exchange, 2014c). This approach ensured the use of appropriate and quality data series with enough data points for the analysis without long breaks. The CROBEX10 index composition is shown in Table 1.

It has to be emphasized that the CROBEX10 index has two regular revisions during a year: on the third Friday in March and in September (Zagreb Stock Exchange, 2014d). Thus, the CROBEX10 index composition can be considered very unstable and changeable, which has to be taken into account in the long-run analyses of the CROBEX10 index.

Selected stocks were observed through two different periods. The first period was from 1 January to 31 December 2012 while the second period includes the period from the stocks' initial listings on ZSE to 29 August 2014. The first period will show control charts' capabilities for stock trading in

Table 1. *CROBEX10 Index Stock Members on 1 September 2014 and the Number of Trading Days*

Stock symbol	Enterprise	Total number of trading days in 2012	Overall number of trading days*
ADPL-R-A	AD Plastik d.d.	248	2,147
ADRS-P-A	Adris grupa d.d.	240	2,761
ATGR-R-A	Atlantic Grupa d.d.	245	1,676
ERNT-R-A	Ericsson Nikola Tesla d.d.	250	3,817
HT-R-A	Hrvatski Telekom d.d.	250	1,740
INA-R-A	INA-industrija nafte d.d.	246	1,721
KORF-R-A	Valamar Adria Holding d.d.	250	2,809
LEDO-R-A	Ledo d.d.	237	2,117
PODR-R-A	Podravka d.d.	247	4,474
PTKM-R-A	Petrokemija d.d.	249	2,505

Source: Zagreb Stock Exchange (2014d).

Note: *Includes the period from the stocks' initial listings on ZSE to 29 August 2014.

the short run; the second period will show their capabilities in the long run. Because the observed stocks have different dates of their initial listings on ZSE, the overall number of trading days among them differs much more than in the short-run analysis. The stocks ATGR-R-A (1,676 trading days) and INA-R-A (1,721 trading days) have the lowest overall number of trading days. According to Table 1, the stock PODR-R-A, which was initially listed on ZSE in 1995, has the highest overall number of trading days (4,474 trading days). Because the stock PODR-R-A has the longest trading tradition, the analysis for this stock is shown in more detail than for the other observed stocks.

In the analysis, the research variables include the opening price and the average price. Both variables are given in Croatian kuna (HRK). The variable opening price was used in the analyses mainly because of an investor's ability to react fast to the control chart signals to buy or to sell stocks. Thus, the first assumption in the opening price analyses is that the investor can trade on the same day the trading signal was received. The second assumption is that the investor can react fast, thereby securing a price equal to the opening price of that trading day.

As in the opening price analyses, in the average price analyses it is also assumed that the investor can react on the same day the trading signal was received. But contrary to the opening price analyses, in the average price analyses there is no need for the investor to be very fast in trading. In the opening price analyses, the investor has to trade right after the first or the opening price is announced whereas in the average price analysis, the investor can choose when to trade throughout the whole trading day. However, it is assumed that the investor will wait until the trading day ends, which means that the trade will be at the average price level of that trading day. More precisely, here it is assumed that the investor has an opportunity to make the last transfer of the day.

In order to emphasize that the main goal is to earn only the difference between the buy and sell price, no additional payments are considered in the analysis. Thus, it is assumed that no additional pay outs (e.g., dividends) are made to investors. Similarly, it is assumed that there are no additional costs for investors, such as trade commissions.

From the many available statistical control charts (Montgomery, 2013; Montgomery & Runger, 2011), it can be determined that the following control charts are the most appropriate to use in this case: control chart for individual units (I), exponentially weighted moving average (EWMA) control chart, and cumulative sum (CUSUM) control chart. The main criteria for control chart selection were intuitive approach, straightforward analysis, and sensitivity to a drift in the process. The "forgetfulness" parameter in the EWMA control chart is set to 0.3 because that is the value usually used (NIST/SEMATECH, 2013). In general, the choice of the parameter value is somewhat arbitrary (Lucas & Saccucci, 1990). Although the moving range (MR) control chart is presented, but it plays only a supportive role. The characteristics of the mentioned control charts are well described in existing literature (Box, Luceno, & Paniagua-Quinones, 2009; del Castillo, 2002; Dumičić & Žmuk, 2011a, 2011b; Hunter, 1986; Kovarik & Klimek, 2012; Liu & Tien, 2011; Montgomery & Friedman, 1989; Montgomery, Jennings, & Pfund, 2011; Page, 1954; S. W. Roberts, 1959; Ryu, Wan, & Kim, 2010; Riaz, Abbas, & Does, 2011; SAS Institute, 2014; Wild & Seber, 1999).

Financial data are very sensitive to mean shifting, and strong autocorrelation appears very often (Kovarik & Klimek, 2012), resulting in the high probability that the observed stock price data are also autocorrelated. The autocorrelation can have a huge impact on decision making based on control charts through the increased false alarm rates (Schmid, 1995; Schmid & Schone, 1997; Vanbrackle & Reynolds, 1997). Therefore, attention was given to developing different procedures in those cases (Alwan, 1991; Harris & Ross, 1991; Lu & Reynolds, 1999a, 1999b, 2001). The autocorrelation problem can be resolved by skipping data, adjusting the control limits of the existing control charts, and using the residual-based control chart analysis (Vasipulos & Stamboulis, 1978; Woodall & Faltin, 1993). Usually, the residual-based control charts are used to deal with the autocorrelation problem (Alwan & Roberts, 1988; Moskowitz, Wardell, & Plante, 1994).

It has been shown that economic and financial data could be autocorrelated (Levich & Rizzo, 1998; Sewell, 2011). Consequently, it is expected that this would be valid for stock data as well (Lewellen, 2002; Lillo & Farmer, 2004; Tolvi, 2002). If autocorrelation is present in open and average stock prices, the Autoregressive Integrated Moving Average (ARIMA) model is used (Box & Jenkins, 1976).

3 Short-run Stock Trading Analysis Based on Open and Average Prices

For the purpose of this paper, a short period is defined as the period of one year. Therefore, in the short-run stock trading analysis, only data from 2012 were used. First, the opening prices of CROBEX10 stocks were analysed. Afterwards, analyses based on the average prices of CROBEX10 stocks were conducted.

Control charts are most effective when the data are uncorrelated and are illustrated with stationary behaviour (Montgomery, 2013). Thus, the presence of data autocorrelation at the opening prices of CROBEX10 stocks was investigated. The analysis demonstrated that all observed stocks had an autocorrelation coefficient close to 1. As a result, it was concluded that the autocorrelation problem has a significant impact on the control charts.

In order to solve the autocorrelation problem, the *ARIMA*(p,d,q) modelling approach was used. If the skip data procedure had been used, some trading days would not have been observed. This does not seem to be logical and surely is not acceptable for an investor. Thus, the skip data procedure was not considered. Similarly, adjusting the control limits of the existing control charts—another recommended technique for dealing with the autocorrelation problem in such cases—was not considered either because this technique assumes a low autocorrelation level, which was not the case here. Given the strong autocorrelation, significant adjustments of control limits would be required, which is not acceptable.

In order to determine the p and q levels, the auto-correlation function (ACF) and the partial auto-correlation function (PACF) were used. If the ACF cut-off after q and if at the same time the PACF showed infinite tails off dominated by damped exponential waves and cosine waves, the moving average model of order q or the model *ARIMA*(0,0,q) was chosen. If the ACF showed infinite tails off dominated by damped exponential waves and cosine waves and if the PACF cut off after p, the autoregressive model of order p or the model *ARIMA*(p,0,0) was chosen. If exponential waves and cosine waves were present in both the ACF and the PACF, then an appropriate *ARIMA*(p,0,q) model was chosen. Before determining the p and q levels, the presence of the polynomial trend was checked and the value of d was chosen accordingly.

In order to estimate parameters of the *ARIMA*(p,d,q) models for CROBEX10 stocks, the approximate maximum likelihood method introduced by McLeod and Sales (1983) was used. Once the parameters were estimated for the selected *ARIMA*(p,d,q) model, the adequacy of the selected model for the data was checked. If the fitted model was adequate, the residuals should be approximately white noise, which means they should have zero mean and be uncorrelated. The key instruments are the ACF and the PACF of the residuals. If the model is appropriate, most of the coefficients of the ACF and the PACF should be close to zero. If the coefficients of the ACF and the PACF were not close to zero, the new *ARIMA*(p,d,q) model was chosen and the adequacy procedure was repeated. In the process of finding the best appropriate *ARIMA*(p,d,q) model, the parsimony principle was used. In other words, if two *ARIMA*(p,d,q) models had similar statistical characteristics, the simpler model was chosen (Hyndman, 2001).

After the ACF and the PACF confirmed the selected *ARIMA*(p,d,q) model adequacy, the statistical significance of estimated parameters was checked. If all estimated parameters were statistically significant at the 5% level, the final decision was made to accept the selected *ARIMA*(p,d,q) model as adequate. When some statistically non-significant estimated parameters existed, a new *ARIMA*(p,d,q) model was chosen.

After identifying the initial *ARIMA*(p,d,q) model and estimation of its parameters, Noskievičová (2007) recommended identifying outliers, inspecting their causes, and realizing adequate corrective actions. Due to the simplification of the

Table 2. *Explorative Analysis of Opening Prices of CROBEX10 Stocks in HRK in 2012 and Chosen Adequate ARIMA(p,d,q) Models*

Share	k	Min.	Max.	Mean	Median	Std. dev.	Var. coef. (in %)	*ARIMA(p,d,q)* model
ADPL-R-A	248	100.99	128.94	111.52	108.73	7.42	6.66	(1,0,0)
ADRS-P-A	240	202.01	256.98	222.67	217.00	13.29	5.97	(2,0,0)
ATGR-R-A	245	454.00	550.00	492.05	492.02	19.77	4.02	(2,0,0)
ERNT-R-A	250	880.01	1,374.99	1,158.10	1,175.05	109.64	9.47	(1,1,0)
HT-R-A	250	193.00	244.40	211.00	205.99	13.89	6.58	(1,1,0)
INA-R-A	246	3,550.00	4,500.00	3,858.21	3,728.02	265.83	6.89	(1,1,0)
KORF-R-A	250	70.61	110.99	94.30	95.57	11.58	12.28	(1,0,0)
LEDO-R-A	237	4,900.00	7,720.00	5,836.94	5,701.04	660.84	11.32	(1,0,0)
PODR-R-A	247	206.01	276.50	239.94	242.99	19.73	8.22	(1,0,0)
PTKM-R-A	249	184.80	340.00	229.27	226.73	31.17	13.60	(7,2,0)

Source: Author's calculations.

procedure and the nature of the process, outliers were not further inspected in the analysis. Namely, investors are interested in having a simple and fast procedure for everyday use. In addition, omitting outliers or some other outlier corrective actions could have a significant impact on stocks' history and trade decisions. The selected adequate *ARIMA*(*p*,*d*,*q*) models for opening prices of CROBEX10 stocks in 2012 are summarized along with the basic explorative analysis results in Table 2.

After the adequate *ARIMA*(*p*,*d*,*q*) models were chosen and the models' parameters were estimated, residuals for each CROBEX10 stock were calculated. In the further analysis, the residual-based control chart approach was used (Montgomery, 2013). In this approach, instead of using the original data, the residuals are used in order to construct the control chart. Because of the use of residuals, the analysis results are less intuitive and interpretable than the results of the analysis in which the original data were used; however, these disadvantages of using residuals in the control chart analysis can be neglected because in this case the aim is not to interpret the results, but to observe whether a significant difference of a residual from the other residuals exists. If such a significant difference exists between real and model values from the other residual differences, the residual falls outside the control limits. In that case, if the residual is above the upper control limit, the real stock price is significantly higher than it was anticipated by the model incorporating all previous prices. This situation results in investors' motivation to sell stocks because they can achieve a significantly higher price than expected. On the other hand, investors are encouraged to buy stocks if the price is significantly lower than expected; in other words, this situation results in investors' motivation for buying. In this case, the residual is under the lower control limit.

After the selected residual-based control charts of opening prices were constructed for each CROBEX10 stock in 2012, investor trading was simulated according to the control charts' signals. In the trading simulations I, EWMA (with λ=0.3), and CUSUM control charts were used. The moving range (MR) control chart was omitted from the analysis because of its inability to provide buying signals—namely, by definition, a range cannot be negative. It is very likely that the lower control limit needs to be set at 0, and no data can have a value lower than that value. In this way, this case leads to an absence of buying signals. Furthermore, an investor's trading was simulated based on these three selected residual-based control charts with 2-sigma and 3-sigma control limits separately. Six trading simulations were conducted for each CROBEX10 stock.

It was assumed that an investor bought stocks at the very beginning of the year at the price equal to the first opening price in 2012. Similarly, it was assumed that the investor did not want to have any stocks at the end of the year. If investors had any stocks in their portfolios at the end of the year, they would have sold all stocks at the last opening price in 2012. All investors' transactions were made at the opening price level in HRK. In order to keep the analysis simple, no trade commission was considered. The investor bought only one stock for each buy signal. The buy signal was given when a residual fell below the lower control limit. On the other hand, if a residual was above the upper control limit, the sell signal was given. In that case, the investor sold all stocks in the portfolio. Table 3 provides the stock trade simulation results based on opening prices for all CROBEX10 stocks in 2012.

Table 3 shows the results of 60 stock trade simulations conducted based on opening prices for all CROBEX10 stocks in 2012. According to the results provided in Table 3, 51 stock trade simulations gave a positive investor score whereas 9

Table 3. *Trade Simulation of CROBEX10 Stocks Based on Opening Prices Using the Residual-based Control Chart for Individual Units (I), the Residual-based Exponentially Weighted Moving Average (EWMA) Control Chart (λ=0.3), and the Residual-based Cumulative Sum (CUSUM) Control Chart, 2012*

Stock	Control chart	Control limits: +/- 2 std.		Control limits: +/- 3 std.	
		Number of trades	Investor score, HRK	Number of trades	Investor score, HRK
ADPL-R-A	*I*	12	1.63	4*	7.62
	EWMA	8	6.11	2	13.50
	CUSUM	20	4.89	14	11.65
ADRS-P-A	*I*	13	97.63	4*	12.39
	EWMA	8*	54.37	2	17.51
	CUSUM	12	34.19	4*	20.19
ATGR-R-A	*I*	7	66.98	2	36.00
	EWMA	5	143.97	2	36.00
	CUSUM	15	276.37	6	106.00
ERNT-R-A	*I*	15	560.87	7	187.00
	EWMA	15	600.83	9	314.78
	CUSUM	40	2,510.96	34	1,750.19
HT-R-A	*I*	9	-29.76	5	-42.56
	EWMA	12	-54.16	7	-61.96
	CUSUM	31	-119.25	21	-120.64
INA-R-A	*I*	22*	523.70	10*	137.95
	EWMA	14*	1,013.96	10*	712.96
	CUSUM	45*	1,207.41	33*	2,010.20
KORF-R-A	*I*	9	3.80	2	25.54
	EWMA	7*	91.86	2	25.54
	CUSUM	11	31.06	6*	73.26
LEDO-R-A	*I*	12	3,576.52	2	1,840.00
	EWMA	4	1,347.78	2	1,840.00
	CUSUM	10	2,163.44	4	2,759.89
PODR-R-A	*I*	11*	-7.24	5*	2.93
	EWMA	11*	7.14	5*	19.05
	CUSUM	22*	0.39	10*	36.64
PTKM-R-A	*I*	14*	189.97	8	131.47
	EWMA	11*	-33.07	7*	-278.41
	CUSUM	38*	426.26	32*	276.81

Notes: The number of trades includes initial buying.

*The stocks were sold on the last trading day.

Source: Author's calculations.

trade simulations led to a negative score. Thus, using residual-based control charts based on opening prices and according to stated assumptions, an investor could achieve profit in 85% of the cases. Looking at the investor score according to the residual-based control charts, it can be concluded that the residual-based CUSUM control charts achieved the highest investor score in most cases. Of the 20 cases, the residual-based CUSUM control chart had the highest investor score in 12 cases, the residual-based EWMA control chart in 4 cases, and the residual-based I control chart also in 4 cases. Meanwhile, looking at the investor score according to different control limit levels, in most cases better scores were achieved when 2-sigma control limits were used. In 19 cases, higher investor scores were achieved with the use of

Table 4. *Explorative Analysis of Average Prices of CROBEX10 Stocks in HRK in 2012 and Chosen Adequate ARIMA(p,d,q) Models*

Stock	k	Min.	Max.	Mean	Median	Std. dev.	Var. coef. (in %)	*ARIMA*(*p*,*d*,*q*) model
ADPL-R-A	248	101.02	128.35	111.46	108.50	7.38	6.62	(2,1,2)
ADRS-P-A	240	203.37	253.57	222.71	216.50	13.32	5.98	(1,0,0)
ATGR-R-A	245	456.23	548.01	492.37	493.15	20.45	4.15	(1,0,0)
ERNT-R-A	250	880.09	1,378.76	1,159.19	1,175.19	109.83	9.47	(5,2,0)
HT-R-A	250	193.64	243.76	210.89	205.92	13.83	6.56	(1,0,0)
INA-R-A	246	3,550.00	4,499.37	3,867.06	3,747.93	266.97	6.90	(1,0,0)
KORF-R-A	250	71.00	110.85	94.33	95.36	11.51	12.20	(2,1,1)
LEDO-R-A	237	4,947.40	7,839.72	5,849.52	5,748.19	664.09	11.35	(7,2,0)
PODR-R-A	247	205.17	276.53	240.21	244.05	19.78	8.24	(1,0,0)
PTKM-R-A	249	185.07	354.87	228.98	226.46	31.21	13.63	(2,1,2)

Source: Author's calculations.

2-sigma control limits than with the use of 3-sigma control limits. On the other hand, the use of 3-sigma control limits, rather than 2-sigma control limits, resulted in higher investor scores in only 11 cases.

As with the opening price analysis, the average price analysis also highlighted the autocorrelation problem. The analysis indicated that the autocorrelation problem is present in all the observed stocks. In order to solve the autocorrelation problem, the *ARIMA*(*p*,*d*,*q*) modelling approach was used. The selected adequate *ARIMA*(*p*,*d*,*q*) models for average prices of CROBEX10 stocks in 2012 are given next to the explorative analysis results in Table 4. The *ARIMA*(*p*,*d*,*q*) modelling enabled estimating residuals for each CROBEX10 stock. In the next step, these residuals were used to form residual-based control charts (I, EWMA, and CUSUM), which enabled the introduction of the investor's CROBEX10 stock trade simulation. The investor scores based on the trade simulation of CROBEX10 stocks in 2012 can be obtained from the author upon request.

4 Long-run Stock Trading Analysis Based on Opening and Average Prices

In a long-run analysis, data are observed over a long period—namely, more than one year. In this long-run analysis, prices of CROBEX10 stocks were observed from their initial listings on ZSE to 31 August 2014. The prerequisite of being on ZSE for more than a year was fulfilled by all the observed stocks.

Table 5. *Explorative Analysis of Opening Prices of CROBEX10 Stocks in HRK in the Period from Stocks' Initial Listings to 31 August 2014 and Chosen Adequate ARIMA(p,d,q) Models*

Stock	k	Min.	Max.	Mean	Median	Std. dev.	Var. coef. (in %)	*ARIMA* (*p*,*d*,*q*) model
ADPL-R-A	2,147	32.00	284.89	125.05	118.00	51.34	41.05	(1,0,1)
ADRS-P-A	2,761	135.65	611.99	312.21	281.03	96.68	30.97	(9,4,1)
ATGR-R-A	1,676	320.00	1,060.00	653.47	682.26	135.34	20.71	(2,1,1)
ERNT-R-A	3,817	59.00	4,250.00	1,259.05	1,295.00	895.26	71.11	(9,4,2)
HT-R-A	1,740	141.60	402.00	237.49	230.02	51.37	21.63	(3,1,2)
INA-R-A	1,721	960.00	4,500.00	2,825.24	2,852.00	1,021.40	36.15	(2,0,1)
KORF-R-A	2,809	21.00	250.00	106.10	104.01	56.59	53.33	(1,1,0)
LEDO-R-A	2,117	100.00	20,800.00	6,789.39	6,000.00	3,539.97	52.14	(1,0,0)
PODR-R-A	4,474	60.00	639.00	253.23	245.00	109.23	43.13	(3,0,2)
PTKM-R-A	2,505	12.85	340.00	165.36	163.00	70.86	42.85	(2,0,1)

Source: Author's calculations.

Table 6. *Trade Simulation of CROBEX10 Stocks Based on Opening Prices Using the Residual-based Control Chart for Individual Units (I), the Residual-based Exponentially Weighted Moving Average (EWMA) Control Chart (λ=0.3), and the Residual-based Cumulative Sum (CUSUM) Control Chart, the Period from Stocks' Initial Listings to 31 August 2014*

Stock	Control chart	Control limits: +/- 2 std.		Control limits: +/- 3 std.	
		Number of trades	Investor score	Number of trades	Investor score
ADPL-R-A	*I*	131*	-20.08	61*	18.84
	EWMA	95	-165.19	42*	441.89
	CUSUM	359	-166.87	273*	-1,099.36
ADRS-P-A	*I*	162*	368.22	68	-229.54
	EWMA	79	-590.02	39*	6,298.52
	CUSUM	351	17,679.61	257	26,780.99
ATGR-R-A	*I*	77*	-1,494.22	39*	-1,007.04
	EWMA	73	612.43	34	-154.51
	CUSUM	189*	1,200.04	133*	1,385.55
ERNT-R-A	*I*	285*	10,528.37	136	8,673.67
	EWMA	233	12,610.56	120*	18,318.30
	CUSUM	697*	-20,773.40	548	-12,336.46
HT-R-A	*I*	102*	-147.13	62*	4.37
	EWMA	131	405.99	78*	-446.14
	CUSUM	347	1,044.53	310*	929.33
INA-R-A	*I*	120	26.02	49	2,904.31
	EWMA	80	-9,679.52	44	-3,755.11
	CUSUM	252	2,887.18	185	17,384.00
KORF-R-A	*I*	179	214.74	62*	13.03
	EWMA	129*	-266.56	62*	-83.73
	CUSUM	421*	252.28	305*	-296.70
LEDO-R-A	*I*	130	11,186.31	79	14,851.54
	EWMA	108	10,593.40	60	-18,205.58
	CUSUM	221*	62,296.22	187	60,163.02
PODR-R-A	*I*	282	1,792.96	109	1,093.27
	EWMA	189	-659.43	79*	25.95
	CUSUM	538	3,536.01	337	3,671.00
PTKM-R-A	*I*	138*	-565.05	44*	114.60
	EWMA	121*	-415.85	58*	689.78
	CUSUM	358*	2,650.81	266*	4,070.07

Notes: The number of trades includes initial buying.

*The stocks were sold on the last trading day.

Source: Author's calculations.

A long-run analysis based on opening prices was conducted first, followed by an analysis based on average prices. The long-run stock trading analysis based on opening prices began with an explorative analysis. According to results provided in Table 5, as opposed to the short-run analysis, the stocks show a higher variability level in the long run. The lowest coefficient of variation in the long run is roughly one-third higher than the highest coefficient of variation in the short run. In the long run, ATGR-R-A (20.71%) and HT-R-A (21.63%) had the lowest coefficient of variation of opening prices.

Despite different variability data levels, the autocorrelation problem was also present in the long run. In order to solve the autocorrelation problem, *ARIMA*(*p*,*d*,*q*) modelling was used again. The selection of *ARIMA*(*p*,*d*,*q*) models was

Table 7. *Explorative Analysis of Average Prices of CROBEX10 Stocks in HRK in the Period from Stocks' Initial Listings to 31 August 2014 and Chosen Adequate ARIMA(p,d,q) Models*

Stock	k	Min.	Max.	Mean	Median	Std. dev.	Var. coef. (in %)	*ARIMA* (*p*,*d*,*q*) model
ADPL-R-A	2,147	32.34	286.74	124.99	118.14	51.35	41.08	(1,1,1)
ADRS-P-A	2,761	134.84	613.55	312.12	281.53	96.58	30.94	(3,0,0)
ATGR-R-A	1,676	320.70	1,068.53	653.79	684.98	135.42	20.71	(1,1,0)
ERNT-R-A	3,817	59.01	4,278.96	1,259.07	1,287.90	894.20	71.02	(7,4,2)
HT-R-A	1,740	142.46	397.50	237.52	229.91	51.28	21.59	(2,1,0)
INA-R-A	1,721	965.22	4,499.37	2,829.47	2,851.01	1,025.32	36.24	(1,1,1)
KORF-R-A	2,809	21.15	248.54	106.22	104.15	56.73	53.41	(6,4,2)
LEDO-R-A	2,117	100.00	20,612.26	6,795.14	5,999.99	3,534.16	52.01	(5,4,2)
PODR-R-A	4,474	60.00	635.79	253.44	245.00	109.14	43.06	(1,1,1)
PTKM-R-A	2,505	12.85	354.87	165.16	162.51	70.73	42.82	(4,4,0)

Source: Author's calculations.

conducted in the same way as described earlier within the short-run analysis. The selected *ARIMA*(*p*,*d*,*q*) models are given in Table 6.

After the selection of *ARIMA*(*p*,*d*,*q*) models, the residuals were calculated and trade simulations were performed. The results of the conducted trade simulations for CROBEX10 stocks for the period from their initial listings to 31 August 2014 are given in Table 8. In addition to the investor score achieved using I, EWMA, and CUSUM control charts and 2-sigma and 3-sigma control limits, Table 8 also provides the number of trades. Out of 60 trade analyses conducted, the investor score was positive in 38 and negative in 22 cases. Consequently, it could be concluded that using residual-based control charts with opening prices and according to the trading simulation assumptions, an investor could achieve profit in 63.33% of the cases. Looking at the investor scores according to the used residual-based control charts, the use of the residual-based CUSUM control chart resulted in the highest investor score in most (i.e., 15) cases. The residual-based I control chart had the highest investor score in 2 cases, while the residual-based EWMA control chart had the highest in 3 cases. Looking at the investor score according to different control limits levels, in most cases better scores were achieved when 3-sigma control limits were used. In 19 cases, higher investor scores were achieved with the use of 3-sigma control limits than with the use of 2-sigma control limits. In 11 cases, the use of 2-sigma control limits resulted in a higher investor score than the use of 3-sigma control limits.

The basic explorative statistics of CROBEX10 stocks' average prices in the long run are very similar to the statistics of opening prices. Table 7 shows that only ATGR-R-A (20.71%) and HT-R-A (21.59%) had coefficients of variation under 30%.

The autocorrelation analysis of average prices revealed high autocorrelation presence for all CROBEX10 stocks. The autocorrelation problem was solved using the *ARIMA*(*p*,*d*,*q*) modelling. The selected *ARIMA*(*p*,*d*,*q*) models are given in Table 9. The *ARIMA*(*p*,*d*,*q*) models enabled the calculation of residuals used in the construction of residual-based I, EWMA, and CUSUM control charts. These residual-based control charts and different control limits levels (2-sigma and 3-sigma level) were the basis for conducting stock trading simulations. The trade simulation results can be obtained from the author upon request.

5 Discussion

This paper attempted to emphasize the ability of control charts to achieve profit rather than to quantify it. This ability was observed according to used residual-based control charts (I, EWMA, CUSUM), observed periods (short run, long run), and stock prices (opening price, average price). The numbers of positive and negative investor scores according to these three variables are given in Table 8.

Looking at prices of CROBEX10 stocks, the opening price analysis is more successful than the average price analysis. In the opening price analysis, 89 of 120 cases had a positive investor score. In other words, in 74.17% of the cases, the investor who used an opening price analysis profited. The profit rate obtained from the average price analysis was 61.67%, which is lower than the rate obtained from the opening price analysis, although still remarkably high.

The profit rate difference is more evident when, instead of stock prices, periods of different length are compared.

Table 8. *Positive (Profit) and Negative (Loss) Investor Scores Achieved in the Short-run and the Long-run Trade Simulation of CROBEX10 Stocks Based on Opening and Average Prices Using the Residual-based Control Chart for Individual Units (I), the Residual-based Exponentially Weighted Moving Average (EWMA) Control Chart (λ=0.3), and the Residual-based Cumulative Sum (CUSUM) Control Chart*

Observed stock price	Control chart	No of cases: Short-run*		No of cases: Long-run**		No of cases: Overall	
		Profit	Loss	Profit	Loss	Profit	Loss
Opening price	*I*	17	3	14	6	31	9
	EWMA	16	4	9	11	25	15
	CUSUM	18	2	15	5	33	7
	Total	51	9	38	22	89	31
Average price	*I*	16	4	10	10	26	14
	EWMA	14	6	11	9	25	15
	CUSUM	15	5	8	12	23	17
	Total	45	15	29	31	74	46
Overall	*I*	33	7	24	16	57	23
	EWMA	30	10	20	20	50	30
	CUSUM	33	7	23	17	56	24
	Total	96	24	67	53	163	77

* Short run includes the period from 1 January to 31 December 2012.

** Long run includes the period from stocks' initial listings to 31 August 2014.

Source: Author's calculations.

The control charts showed a considerably higher ability to achieve profit in the short run (80%) than in the long run (55.83%). In the context of stock trading, the I control chart has proven to be the most successful control chart in achieving profit with a profit rate of 71.25%, followed by the CUSUM control chart (70%) and the EWMA control chart (62.50%).

Examining the overall level, of 240 performed trade simulations, the investor achieved a profit in 163 and a loss in 77 cases, resulting in an overall profit rate of 67.92%. This rate is rather high, suggesting that the control charts provide a good quality basis for making decisions about trading on the stock market. The conducted statistical test confirmed the initial conclusion—namely, at the 5% significance level, $\alpha = 0.05$, the null hypothesis that control charts will be successful and result in a profit of 50% or less cases can be rejected (standard error = 0.0323, z-value = 5.55, p-value = 0.0000). Thus, the first research hypothesis was accepted.

In addition to examining trade simulation cases and whether profit or loss was realized, an investor would also be interested in the total portfolio profit and investment rates. Because each trade simulation began by buying stocks at the same initial price, only the total portfolio profit was examined. The portfolio profits for given residual-based control charts, observed periods, stock prices, and different control limit deviations are shown in Table 9.

In the short run, the highest portfolio profit was achieved by using the residual-based CUSUM control chart in all possible cases. On the other hand, regardless of the observed stock prices, if the 2-sigma control limits were used, the residual-based I achieved a higher portfolio profit than the residual-based EWMA control chart. But when the 3-sigma control limits were used, then in the short run, regardless of the observed stock prices, the residual-based EWMA control chart had a higher portfolio profit than the I control chart.

In the long-run, the supremacy of the residual-based CUSUM control chart was violated when trading stocks at average prices and using 2-sigma control limits. In all other cases the residual-based CUSUM control chart achieved the highest portfolio profit. The portfolio profit difference among the residual-based CUSUM control chart and the other two control charts used was especially noticeable if the stock trading was based on opening prices. As opposed to the short run, in the long run the difference between the residual-based I and the EWMA control charts is presented according to the observed stock prices and not according to different control limits levels. Thus, in the short run, the residual-based I control chart achieved a higher portfolio profit by using opening prices as basis for trade simulations than the residual-based EWMA control chart regardless of the control limits level. On the other hand, the residual-based EWMA control chart achieved a higher portfolio profit than the residual-based I control chart when the average price was used.

Table 9. *Portfolio Profits Achieved in the Short-run and the Long-run Trade Simulation of CROBEX10 Stocks Based on Open and Average Prices Using the Residual-based Control Chart for Individual Units (I), the Residual-based Exponentially Weighted Moving Average (EWMA) Control Chart (λ=0.3), and the Residual-based Cumulative Sum (CUSUM) Control Chart with Different Control Limit Deviations (2 and 3 standard deviations), in HRK*

Observed stock price	Control chart	Portfolio profit					
		Short-run*		Long-run**		Overall	
		+/-2 std.	+/- 3 std.	+/-2 std.	+/- 3 std.	+/-2 std.	+/- 3 std.
Opening price	*I*	4,984.10	2,338.34	21,890.14	26,437.05	26,874.24	28,775.39
	EWMA	3,178.79	2,638.97	12,445.81	3,129.37	15,624.60	5,768.34
	CUSUM	6,535.72	6,924.19	70,606.41	100,651.44	77,142.13	107,575.63
	Total	14,698.61	11,901.50	104,942.36	130,217.86	119,640.97	142,119.36
Average price	*I*	5,595.57	3,024.09	-25,289.59	-4,184.89	-19,694.02	-1,160.80
	EWMA	4,695.74	4,261.15	49,322.79	15,154.20	54,018.53	19,415.35
	CUSUM	6,838.92	7,527.93	-44,103.06	17,936.77	-37,264.14	25,464.70
	Total	17,130.23	14,813.17	-20,069.86	28,906.08	-2,939.63	43,719.25
Overall	*I*	10,579.67	5,362.43	-3,399.45	22,252.16	7,180.22	27,614.59
	EWMA	7,874.53	6,900.12	61,768.60	18,283.57	69,643.13	25,183.69
	CUSUM	13,374.64	14,452.12	26,503.35	118,588.21	39,877.99	133,040.33
	Total	31,828.84	26,714.67	84,872.50	159,123.94	116,701.34	185,838.61

* Short run includes the period from 1 January to 31 December 2012.

** Long run includes the period from stocks' initial listings to 31 August 2014.

Source: Author's calculations.

Table 10 lists residual-based control charts with which the highest portfolio profit was achieved according to observed stock prices, investment length, and different control limits deviations. If stocks' opening prices and 3-sigma control limits were used, the best choice was to use the residual-based CUSUM control chart in order to achieve the highest portfolio profit through stock trading. The residual-based CUSUM control chart was the best choice in short-run investments, but because of poor scores achieved in the long run when using the average price as the basis for stock trading and 2-sigma control limits as limits for trading signals, the residual-based CUSUM control chart cannot unambiguously be recommended for use in the stock trading process. The drastically bad results of the residual-based CUSUM control chart led to the choice of the residual-based EWMA control chart as the best one for achieving the highest portfolio profit when stocks' average prices were observed and 2-sigma control limits used. Furthermore, the residual-based EWMA control chart proved to be the best choice when 2-sigma control limits were used overall.

Table 10. *Recommended Residual-based Control Charts for Stock Trading According to Observed Stock Prices, Investment Length, and Different Control Limit Deviations*

Observed stocks' price	Short-run		Long-run		Overall	
	+/-2 std.	+/- 3 std.	+/-2 std.	+/- 3 std.	+/-2 std.	+/- 3 std.
Opening price	*CUSUM*	*CUSUM*	*CUSUM*	*CUSUM*	*CUSUM*	*CUSUM*
Average price	*CUSUM*	*CUSUM*	*EWMA*	*CUSUM*	*EWMA*	*CUSUM*
Overall	*CUSUM*	*CUSUM*	*EWMA*	*CUSUM*	*EWMA*	*CUSUM*

Source: Author's calculations.

The second research hypothesis assumed that the use of the I control chart would lead to higher portfolio profits compared to profits gained by the EWMA and the CUSUM control charts. The results in Tables 9 and 10 indicate that the I control chart was never the best choice; indeed, in most cases, it was the worst choice to use in stock trading. Therefore, research hypothesis H2 was rejected.

The results indicated that an investor should use the EWMA and/or the CUSUM control charts in the stock trading, whereas the I control chart should be omitted because of inferior results. Another consideration for investors is whether they should use opening or average prices as the starting point of the trade analysis. The portfolio profits gained by opening and average prices can be compared using data from Table 12. In the short run and when using the control chart and different control limit levels, stock trading based on average prices achieved higher portfolio profits overall and individually than stock trading based on opening

Table 11. *Comparison of "Pick-and-hold" Strategy and Control Charts Approach Portfolio Results, in HRK*

Observed stocks' price	Short-run		Long-run	
	Pick-and-hold	Control charts	Pick-and-hold	Control charts
Opening price	3,082.92	6,924.19	11,850.35	100,651.44
Average price	3,152.50	7,527.93	11,796.19	17,936.77

Source: Author's calculations.

prices. On the other hand, in the long run, stock trading based on opening prices achieved higher profits overall than the trading based on average prices. However, whereas the portfolio profits achieved in the short run favoured only one certain stock price, in the long run the portfolio profits of the I and the CUSUM control charts favoured the opening price analysis and the EWMA control chart favoured the analysis based on average prices.

If the portfolio profits in the short and long run are examined together, a significantly higher portfolio profit is achieved through the use of opening prices than the use of average prices. What played a crucial role in designating the opening price analysis better than the average prices analysis on the overall level was its far better performance in the long run. Consequently, the third research hypothesis was accepted.

Table 11 compares portfolio results for the "pick-and-hold" strategy and the control charts approach. In the "pick-and-hold" strategy, it is assumed that an investor bought stocks on 1 January 2012 (short run) or on the day of the initial stock's listing (long run) and kept them until 31 December 2012 or 29 August 2014, respectively. In order to compare the control charts, it was assumed that an investor bought only one share of each observed stock. For the portfolio results in the control charts approach, the scores for CUSUM control charts using three standard deviation limits were used because they were the best (see Table 9).

The results in Table 11 show that the control charts approach resulted in higher portfolio profits in all cases compared to the "pick-and-hold" strategy. However, in the control charts approach, costs like transaction and analysis costs were excluded.

6 Conclusions

The paper investigated the ability to use statistical control charts in stock portfolio analyses. The preliminary analyses showed the presence of the autocorrelation problem in relation to all opening and average prices of CROBEX10 stocks on which the analyses were based. In order to overcome the autocorrelation problem, the $ARIMA(p,d,q)$ modelling was applied. Consequently, residual-based control charts were used in the analysis. The analysed variables demonstrated the need to base the analysis on the residual-based I, EWMA (), and CUSUM control charts. Therefore, in order to research the statistical control charts' ability to ensure successful stock trading in periods of different lengths, two periods were introduced. The first, short-run, period covered from 1 January to 31 December 2012 whereas the second, long-run, period included the stocks' initial listings to 31 August 2014. The explorative analysis showed that the short-run data had significantly lower variability than the long-run data. Therefore, the short-run analysis also represented the low data variability case whereas the long-run analysis was the high data variability case.

Although the overall profit rate was 67.92%, which can be considered rather high and successful and led to the first research hypothesis being accepted, further developments of the procedure used are expected to lead to an even higher profit rate. Additional information about stocks, not included in the procedure, could significantly improve the profit rate. An investor is interested in achieving not only portfolio profit through stock trading, but also the highest portfolio profit possible. In the short run, the analysis based on the residual-based CUSUM control chart led to higher portfolio profits than analyses based on the residual-based I and EWMA control charts. In the long run, the highest portfolio profit, based on opening prices, was gained by the residual-based CUSUM control chart; if average prices were considered, then the highest portfolio profit was achieved by the residual-based EWMA control chart. Thus, the I control chart was not the most appropriate choice to use in the stock trading process. Consequently, the second research hypothesis was rejected. Despite lower portfolio profits in the short run, using the opening price instead of the average price in stock trading was justified by overall higher portfolio profits. As a result, the third research hypothesis was accepted.

This paper analysed the use of control charts in stock trading by employing a completely new approach. Therefore, much room for improvement remains. In addition, because the paper introduced a new approach, some limitations are evident. First, only very liquid stocks were observed in this paper. The potential use of control charts with rarely traded (e.g., once a week, once a month) stocks needs to be researched. Second, because the stocks from the CROBEX10 index were analysed, only those stocks in which investors were the most interested were observed. In other words, investors believed in these stocks and were convinced that the enterprises in question have a bright future. However, it would be of interest to examine control charts' profit rates for enterprises that are not so successful. The off-line approach to the analysis is another significant drawback of the analysis. In practise, the on-line approach was used, resulting in new analyses each day because of the new data, which could lead to a different $ARIMA(p,d,q)$ model selection and consequently to different trading signals. Still, if the amount of data is large, it is not likely that one new data point would lead to a different $ARIMA(p,d,q)$ model specification. In the long run. possible data seasonality was not considered in the paper; this should be taken into account in further research as well. When the residual-based EWMA control chart was used, the choice of the weight parameter was provisional in accordance with the literature reviewed. In future research, more attention should be given to the choice of the parameter for each stock separately. In order to keep the analysis as simple as possible, trade commissions were not included in the analyses. This drawback should also be corrected in further research. For simplicity, only one stock market was observed. Future studies should observe more stock markets and compare results and conclusions.

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Zmožnosti nadzornih diagramov, ki temeljijo na statističnih rezidualih, pri kratkoročnem in dolgoročnem trgovanju z delnicami

Izvleček

Namen tega prispevka je predstaviti in razviti dodatna statistična orodja za podporo odločitvenega procesa pri trgovanju z delnicami. Uporabljene so vrednosti delniškega indeksa CROBEX10. Izvedene simulacije trgovanja, ki temeljijo na nadzornih diagramih, temelječih na rezidualih, so v 67,92 % primerov vodile v dobiček investitorja. Kratkoročno je nadzorni diagram kumulativne vsote (CUSUM) vodil v najvišje portfeljske dobičke. Dolgoročno je imel najvišji portfeljski dobiček nadzorni diagram, temelječ na eksponentni uteženi drseči aritmetični sredini rezidualov, pri čemer so bile uporabljene povprečne cene delnic in nadzorne meje 2-sigma. V vseh drugih primerih so se na dolgi rok nadzorni diagrami CUSUM izkazali za najboljšo izbiro. Pričakovati je, da bodo dognanja o možni uspešni uporabi pri trgovanju z delnicami dvignila raven uporabe metod SPC.

Ključne besede: Zagrebška borza vrednostnih papirjev, naložbe, statistični nadzor procesov, avtokorelacija, nadzorni diagrami, temelječi na rezidualih