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ORIGINAL SCIENTIFIC PAPER

The Identification of Blue Chip Stocks in Underdeveloped Stock Markets of South-Eastern Europe

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ABSTRACT *– The main goal of this paper is to explain the discriminatory variables between the blue chip and second-grade stocks in the underdeveloped stock markets of the South Eastern European (SEE) region. Since there is relatively less empirical research on the stock selection in underdeveloped markets, with even less studies on the markets in the transition economies of the SEE region, this paper is designed to shed some light on the identification of blue chip stocks from this region. Results presented in this paper provide confirmatory evidence that the blue chip stocks from the selected underdeveloped stock markets of the SEE region can be identified by examining their dividend yields, price to cash flow and EPS. Therefore, both institutional and individual investors need to focus on these variables when selecting stocks from these markets in order to reduce the risk associated with investing in equities.*

KEY WORDS: *blue chip stocks, discriminant analysis, SEE region*

Introduction

According to Graham and Dodd (2009) the functions of security analysis may be described under three headings: descriptive, selective and critical. Here, descriptive analysis consists of marshalling the important facts relating to a security and presenting them in a coherent manner. In its selective function, security analysis goes further and seeks to determine whether a given security should be bought, sold or retained.

While there is a substantial body of literature on stock selection in developed markets (Markowitz, 1952; Merton, 1969; Samuleson, 1969; Treynor and Black, 1973, etc.), there is relatively little research on underdeveloped markets.

In stock selection process various methodologies so far were used, i.e. from simple technical trading rules (Dannet al., 1977; Brock et al.,1992; Mills, 1997; Gencay and Stengos, 1997; Allen and Karjalainen, 1999, etc.), classification and regression tree (Sorensen et al., 2000), multiple criteria decision making (Lee et al., 2009) to more complex neural network approach (Kaastra and Boyd, 1996; Quah and Srinivasan, 1999; Linet al., 2006; Fernándezand

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Gómez, 2007; Yuet al., 2008; Şenolet al., 2012, etc.). Discriminant analysis, as one of the possible methodologies for stock selection has, since the pioneering work of Altman (1968), been predominantly used to predict corporate failure. However, in the recent literature, there is evidence of using discriminant analysis in case of predicting stock price performance (Yoonet al., 1993; Aono and Iwaisako, 2010; Ionescu et al., 2008; Kheradyar et al., 2011; Oz et al., 2011; Khan et al., 2012; Siqueira et al., 2012; Vu, 2013, etc.).

The purpose of this research is to provide potential investors with useful information on basic criteria for selecting stocks in underdeveloped stock markets. Investors rely on different allocation strategies when planning to invest. Depending on their investment styles and horizons, they seek out stocks that have met the criteria they look for. In order to do this, stocks need to be categorized according to their certain characteristics.

Although there are different kinds of such categories, in this research we will use only two, i.e. first-grade (blue chip) and second-grade stocks, where, according to the Graham and Dodd (2009), the blue chip is, generally respected and widely owned stock. Although there has been extensive research into the empirical and theoretical aspects of stock selection process, most of these studies have focused almost exclusively on the well-developed financial markets. Motivational grounds for this paper lies in the fact that to our best knowledge, very few publications can be found in the literature that discuss this issue in case of underdeveloped capital markets.

Hence, as Achour et al. (1998) have already pointed out, these markets present an ideal testing ground for the efficiency of asset allocation approaches that are common place in developed markets. Therefore, the main goal of this paper is to *explain the discriminatory variables between the blue chip and second-grade stocks in the underdeveloped stock markets.* In the research we will try to give answer to the following question: *Which variables are the best predictors of two types of stocks, blue chip and second-grade, in the selected underdeveloped stock markets?*

Having in mind the above said, the central research hypothesis shall be as follows: Discriminatory variables between *blue chip and second-grade stocks in the selected underdeveloped stock markets predominantly refer to* dividends, cash flows and earnings per stock. The main limitations of this study are to be found in the missing data for selected issuers from the SEE region.

The remainder of this paper is organized as follows. After introduction, part two brings description of the research methodology and data. Subsequently, part three discusses the empirical results. Finally, conclusions are drawn in the last part of the paper.

Data and research methodology

Data

The research is focused on the underdeveloped stock markets of South Eastern European Region (SEE). As a representative of this region we will use following countries: Slovenia, Croatia, Serbia, Bulgaria and Romania. The issuers from these countries are included in the

South-Eastern Europe Traded Index[3] (SETX) that is a tradable benchmark for the SEE region. Structure of the SETX is given in Appendix A.

According to the MSCI Inc. (2014) all capital markets can be classified as developed, emerging, frontier or standalone. This classification is done as the results of an evaluation of the four criteria, which are: (1) openness to foreign ownership, (2) ease of capital inflows/outflows, (3) efficiency of the operational framework and (4) stability of the institutional framework (MSCI Inc., 2014).In order to be classified in a given instrument universe, a country must meet the requirements of all three criteria as described in the table below.

Table 1.The MSCI market classification framework

Criteria	Type of the capital market		
	Frontier	**Emerging**	**Developed**
A Economic development			
A.1 Sustainability of economic development	No requirement	No requirement	Country GNI per capita 25% above the World Bank high income threshold for 3 consecutive years.
B. Size and liquidity requirements			
B.1 Number of companies meeting the following Standard Index criteria:	2	3	5
Company size (full market cap)	USD 630 mm	USD 1260 mm	USD 2519 mm
Security size (float market cap)	USD 49 mm	USD 630 mm	USD 1260 mm
Security liquidity	2,5% ATVR	15% ATVR	20% ATVR
C Market Accessibility Criteria			
C.1 Openness to foreign ownership	At least some	Significant	Very high
C.2 Ease of capital inflows/outflows	At least partial	Significant	Very high
C.3 Efficiency of the operational framework	Modest	Good and tested	Very high
C.4 Stability of the institutional framework	Modest	Modest	Very high

Source: MSCI Inc. (2014)

According to previously mentioned criteria selected capital markets from Slovenia, Croatia, Serbia, Bulgaria and Romania are classified as frontier markets. Assessment results for these capital markets are given in Appendix B. Furthermore, specificities of the selected markets are (MSCI Inc., 2014):

- In Bulgaria there is no offshore currency market. In this country, the process to set up an account is lengthy due to the requirement to provide several documents in notarized form. In Bulgaria, stock market information is occasionally not disclosed in a timely manner and there is no formal segregation between custody and trading accounts. Finally, there is a lack of efficiency in terms of communication between the central registry/central depository and the custodians/brokers.

[3] The SETX is one of the CEE and CIS indices of the Vienna Stock Exchange.

- When it comes to Croatia, investor registration is mandatory and the process can take up to five days. Additionally, investors are required to open segregated accounts for trading and for taxation. Here the central depository acts as a central registry, and registration of few securities is executed at the issuer level. Limited level of competition between brokers can lead to relatively higher trading costs.
- In Romania, and when it comes to equal rights to foreign investors, relevant information for investors is not always readily available in English. The same goes for market regulations and detailed stock market information. On the Bucharest Stock Exchange, there is an absence of a real delivery versus payment system. Also, there is no formal segregation between custody and trading accounts, and there is a lack of efficiency in terms of communication between the central depository and the custodians/brokers. Limited level of competition between brokers can lead to relatively higher trading costs. In-kind transfers and off-exchange transactions are prohibited.
- In Serbia, relevant information for investors is not always readily available in English. The same goes for market regulations and detailed stock market information. Due to some administrative requirements, repatriation of funds can take up to two weeks. Registration is mandatory and all foreign investors need to a point a legal and tax representative and documents must be filed in Serbian language. Overdraft facilities are restricted to foreign banks. Limited level of competition between brokers can lead to relatively higher trading costs. Off-exchange transactions are allowed but they require approval from the authorities.
- When it comes to Slovenia, limited level of competition between brokers can lead to relatively higher trading costs. Exchange transactions are now settled on a linked delivery versus payment system with a gross settlement of securities followed by a multilateral netting of funds.

In this research all data on the selected companies from the SEE region were obtained from the Investing.com portal in July 2014. Investing.com is a global financial portal that provides news, analysis, streaming quotes and charts, technical data and financial tools about the global financial markets, i.e. a broad variety of financial vehicles including stocks, bonds, commodities, currencies, interest rates, futures and options (Fusion Media Ltd., 2014).

Sample, variables and indicators

Our sample consists of two groups of stocks, i.e. blue chip and second – grade stocks. As mentioned earlier, the SETX is made up of the most actively traded and highest capitalized stocks from the SEE region. Therefore, these stocks can be classified as first-grade or simply blue chip stocks. The second group consists of all of those stocks that are included in one of the equity indices from the analyzed capital markets (SOFIX from Bulgaria, CROBEX from Croatia, ROTEX from Romania and SBITOP from Slovenia) but are not included in the SETX. Due to missing data, stocks included in BELEX15 (Serbia) were excluded from the further analysis. The structure of the entire sample which consists of 56 stocks is given in Appendix C.

As a dependent variable in this research we used type of the stock, i.e. blue chip or second-grade stocks. It is a dichotomous nominal variable.

We used following 35 independent variable with a possible discriminatory power: P/E ratio, P/E ratio TTM[4], beta, price to sales TTM, price to cash flow MRQ, price to free cash flow TTM, price to book MRQ, price to tangible book MRQ, revenue/stock TTM, basic EPS, diluted EPS, book value/stock MRQ, tangible book value/stock MRQ, cash/stock MRQ, cash flow/stock TTM, dividend yield, return on equity TTM, return on equity 5YA, return on assets TTM, return on assets 5YA, return on investment TTM, return on investment 5YA, EPS(MRQ) vs. qtr. 1 yr. ago, EPS(TTM) vs. TTM 1 yr. ago, 5 year EPS growth, sales (MRQ) vs. qtr. 1 yr. ago, sales (TTM) vs. TTM 1 yr. ago, 5 year sales growth, 5 year capital spending growth, quick ratio MRQ, current ratio MRQ, LT debt to equity MRQ, total debt to equity MRQ, asset turnover TTM, inventory turnover TTM and receivable turnover TTM.

Based on the selected variables we will use discriminant analysis to explain whether selected variables will discriminate between two groups of stocks, i.e. blue chip and second – grade stocks.

Discriminant analysis: a short methodological overview

In this paper, discriminant function analysis is used to determine which of the 35 independent variables best discriminate between two groups: blue chip and second-grade stocks from the SEE region. Discriminant analysis is a multivariate statistical method designed to set up a model to predict group memberships. It results with the discriminant function, i.e. a variate of the independent variables selected for their discriminatory power used in the prediction of group membership (Hair et al., 1998, p. 241).

The main objectives of discriminant analysis are as follows (Malhotra, 2004, p. 534):

- Development of discriminant function which will best discriminate between the categories of the criterion or dependent variable (groups).
- Examination of whether significant differences exist among the groups, in terms of the predictor variables.
- Disrimination of which predictor variables contribute to most of the intergroup differences.
- Classification of cases to one of the groups on the values of the predictor variables.
- Evaluation of the accuracy of classification.

Discrimination is achieved by setting the variate's weights for each variable to maximize the between – group variance relative to the within – group variance (Hair et al., 1998, p. 244). Each discriminant function has the general form (Brown and Wicker, 2000, p. 219):

$$D = a + b_1 x_1 + b_2 x_2 + \cdots + b_p x_p, \tag{1}$$

[4] Here, TTM refers to trailing twelve months, 5YA refers to 5-year average and MRQ refers tomost recent quarter.

where D is the discriminant score, a is the y – intercept of the regression line, b is the discriminant function coefficient, x is the discriminator variable raw score, and p is the number of discriminator variables. Discriminant analysis multiplies each independent variable by its weight and adds these products together. As a result, *discriminant score* for each independent variable in the analysis is calculated. By averaging these scores we get the group mean, which is referred to as *centroid* that indicate the most typical location of any independent variable from a particular group, and comparison of the group centroids shows how far apart groups are along the dimension being tested (Hairet al., 1998, p. 245).

Empirical results and discussion

First step in discriminant analysis is to examine whether there are any significant differences between groups on each of the independent variables. If there are no significant group differences it is not worthwhile proceeding any further with the analysis.

In this research, by using tests of equality of group means we found statistical evidence of significant differences between means of blue chip and second-grade stocks from the SEE region, particularly in case of dividend yield (p-value =,008) and 5 year capital spending growth (p-value =,024).

We used stepwise method that basically removes independent variables that are not significant.

In our case, out of initial 35 independent variables, we are left with only three of them: dividend yield (x_1), price to cash flow MRQ (x_2) and EPS(MRQ) vs. qtr. 1 year ago (x_3). Summary of relevant results is presented in the following section. First, we will briefly discuss the eigenvalues presented in Table 2.

Table 2. Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	6.461	100.0	100.0	.931

Source: Authors' calculations

The larger the eigenvalue, the more of the variance in the dependent variable is explained by the particular function. One more result presented in the previous table is the canonical correlation that represents the measure of association between the discriminant function and the dependent variable. This measure is important because its square represents the percentage of variance explained in the dependent variable. In our case, that means that this model accounts for 86,68% ($,931^2$) of the between group variance.

Results of Wilks' lambda are presented in Table 3. Wilks's lambda, is an inverse measure of the importance of the functions where values close to 1 indicate that almost all of the variability in the discriminator variables is due to within-group differences and values close to 0 indicate that almost all of the variability in the discriminator variables is due to group differences (Brown and Wicker, 2000, p. 223). The smaller the value of Wilks' lambda refers to greater discriminatory ability of the function.

Table 3. Wilks' lambda

Test of function(s)	Wilks' lambda	Chi-square	df	Sig.
1	.134	17.082	3	.001

Source: Authors' calculations

Results presented in Table 3 indicate a highly significant function ($p < .005$). Here, the null hypothesis (H_0: The function has no discriminating ability) is tested by using the Chi-square statistic. Since there are only two groups, we will have only one discriminant function, as follows:

$$DF = 2{,}233x_1 + 1{,}485x_2 - 1{,}245x_3.$$

Coefficients in discriminant function indicate the partial contribution of each independent variable to the discriminate function. Good predictors tend to have large weights. In our case, dividend yield (x_1) score was the strongest predictor while price to cash flow MRQ (x_2) and EPS(MRQ) vs.qtr. 1 yr. ago with negative sign(x_3) were next in importance as a predictors. These variables stand out as those that strongly predict allocation to the blue chip or second-grade stocks. Others variables were less successful as predictors. Another way to interpret these results is to describe each group in terms of its profile, using the centroids, i. e. group means of the predictor variables.

Centroids are displayed in Table 4. In our example, blue chip stocks have a mean of 2.475 while second-grade stocks produce a mean of –1.961.

Table 4.Functions at group centroids

Groups	Function
	1
Blue chip stocks	2.745
Second-grade stocks	-1.961

Source: Authors' calculations

So, if stock's score on the discriminant function is closer to 2.745, then this stock is probably blue chip. If stock's score on the discriminant function is closer to -1.961, then this stock is probably second grade.

The final phase is classification presented in Table 5.

Table 5.Classification results

		Groups	Predicted Group Membership		Total
			Blue chip stocks	Second-grade stocks	
Original	Count	Blue chip stocks	10	5	15
		Second-grade stocks	6	33	39
	%	Blue chip stocks	66.7	33.3	100.0
		Second-grade stocks	15.4	84.6	100.0

Source: Authors´ calculations

The overall predictive accuracy of the discriminant function is called the 'hit ratio'. According to the results presented in Table 5, the hit ratio is 0.7963 $\left(\frac{10+33}{10+5+6+33}\right)$ which means that 79.63% of original grouped cases were correctly classified into blue chip or second-grade group. What is an acceptable hit ratio? As Burns and Burns (2008) have already pointed out, one must compare the calculated hit ratio with what could be achieved by chance, meaning that if two samples are equal in size then there is a 50/50 chance anyway.

Let us now examine the practical implications of these results.

Out of 35 selected variables, only three of them (dividend yield, price to cash flow MRQ and EPS(MRQ) vs. qtr. 1 yr. ago) stood out as those that strongly predict allocation to the blue chip or second-grade stocks in the selected stock markets. Contrary to the findings of previous research of Lee et al. (2009) and Siqueira et al. (2012) beta coefficient didn't have discriminatory capabilities in stock selection. Also, contrary to the findings of Vu (2013) P/E ratio didn't empirically discriminate between those stocks of high-value (blue chip) and those not (second-grade).

All of the identified discriminatory variables are very important in creating investment strategy. Dividend yield, as the strongest predictor, shows to investor how much a particular company pays out in dividends each year relative to its stock price. As second best predictor in this analysis, price to cash flow MRQ, as an indicator of a stock's valuation, is nothing else but the ratio of a stock's price to its cash flow per stock. Next important predictor, EPS(MRQ) vs. qtr. 1 yr. ago, is calculated as the most recent quarterly (MRQ) earnings per share (EPS) minus the EPS for the quarter one year ago divided by the EPS for the quarter one year ago and multiplied by 100. This is consistent with the findings of Kheradyar et al. (2011) who have also confirmed that dividend and earning yield have the predictive power of stock returns in developed stock markets. The practical implications of this study are that blue chip stocks from the selected underdeveloped stock markets of the SEE region can be identified by examining their dividend yields, price to cash flow and EPS. Therefore, both institutional and individual investors need to focus on these variables when selecting stocks from these markets in order to reduce the risk associated with investing in equities.

Although further work is required to gain a more complete understanding of the discriminatory variables between blue chip and second-grade stocks in the selected underdeveloped stock markets from the SEE region, results presented in this paper provide confirmatory evidence that the blue chip stocks from the selected underdeveloped stock markets of the SEE region can be identified by examining their dividend yields, price to cash flow and EPS.

Conclusion

Providing solid measures that can help foreign and domestic investors to reliably identify investable companies in less developed, less transparent and less liquid stock markets is of crucial importance for the entire economic region.

On the basis of theoretical inferences and empirical evidence presented in this paper, it seems fair to suggest that discriminatory variablesbetweenblue chip and second-grade stocks in the selected underdeveloped stock markets predominantly refer todividends,price to cash flow and earnings per stock.

Alam et al. (2008) find that in the period between 2002 and 2008 Central, Eastern and Southeastern European economies significantly surpassed growth rates experienced in other Western European countries. In the era of historically low interest rates and stock markets following the expansion of balance sheets of major national banks, many investors are looking for sources of solid growth and turning to less developed economies where low labor costs, highly skilled work force and diversified consumer profile are driving the organic growth.

The companies listed on SEE stock markets, growing organicallly will have to look to diversify their investor base and constantly seek compliance with improved capital market regulation as well as corporate governance practices in order to do so. Informational efficiency and transparency are fundamental issues in the design and regulation of markets. Transparency helps to link dispersed markets and improve the price discovery, fairness, competitiveness and attractiveness of markets. Especially in underdeveloped stock markets, where informational efficiency and transparency do not always meet the strict rules of more developed and regulated exchanges, investors need much more solid parameters in order to perform equity analysis and allocation.

The results presented in this paper provide confirmatory evidence that the blue chip stocks from selected underdeveloped stock markets of the SEE region can be identified by examining their dividend yields, price to cash flow and EPS.

When determining the price of shares EPS is one of the most important variables. Using solely this determinant investors are often mislead as it ignores the capital required to generate the earnings. Two companies having the same EPS measure would wrongly be compared when one of them would be using less equuity to generate the same earnings. In the time of earnings manipulations and speculations it is important to say that EPS should not be used alone, but always in conjuction with other measures. One of these measures is cash flow. Cash flow as a measure is widely used in the investment to value stocks as it measures the health of a company to manage its debt, revenues and pay its taxes. This measure too is not purely free from manipulation, although companies do have a much harder time to deceit on their cash flows, but the decision process should be aided by others measures mentioned in this paper.

Dividend paying stocks are an attractive alternative for a risk neutral investor requiring a minimum stream of free cash flow from their investment portfolio. Such stocks allow the investor to take part in the company profits and reinvest the dividends what has resulted in higher yields over longer periods of time. Usually, companies paying high dividends are utillities, experiencing stable, forseeble but lower growth rates and lower stock price volatility. High dividend paying stocks and low retained earnings per share are usually avoided by investors, because companies must invest some profits in order to sustain and grow their operations.

References

Achour, Dana, Harvey, Campbell, Hopkins, Greg, and Lang, Clive. 1998. "Stock Selection in Emerging Markets: Portfolio Strategies for Malaysia, Mexico and South Africa." *Emerging Markets Quarterly*, 2 (Winter): 38-91.

Alam, Asad, Caser, Paloma Anós, Khan, Faruk, and Udomsaph, Charles. 2008. *Unleashing Prosperity Productivity Growth in Eastern Europe and the former Soviet Union*. Washington D.C.: The International Bank for Reconstruction and Development/The World Bank.

Allen, Franklin, and Karjalainen, Risto. 1999. "Using genetic algorithms to find technical trading rules."*Journal of Financial Economics*. 51: 245-271.

Altman, Edward. 1968."Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy." *The Journal of Finance*.XXIII(4): 589-609.

Aono, Kohei, and Iwaisako, Tokuo. 2010. "On the Predictability of Japanese Stock Returns Using Dividend Yield." *Asia-Pacific Finance Markets*.17(2): 141-149.

Brock, William, Lakonishok, Josef, and LeBaron, Blake. 1992. "Simple Technical Trading Rules and the Stohastic Properties of Stock Returns." *The Journal of Finance*. 47(5): 1731-1764.

Brown, Michael, and Wicker, Lori. 2000. "Discriminant Analysis." In *Handbook of Applied Multivariate Statistics and Mathematical Modeling*, ed. Tinsley, Howard, and Brown, Steven. 209-235. London: Academic Press.

Burns, R. P. and Burns, R. 2008. *Business Research Methods and Statistics Using SPSS***.**New York: SAGE Publications, Ltd.

Dann, Larry, Mayers, David, and Raab, Robert. 1977. "Trading rules, large blocks and the speed of price adjustment." *Journal of Financial Economics*. 4(1): 3–22.

Fernández, Albertoand Gómez, Sergio. 2007. "Portfolio selection using neural networks." *Computers & Operations Research*. 34(4): 1177-1191.

Fusion Media Ltd. 2014. *Investing.com*. http://www.investing.com/ (accessed August 1, 2014)

Gencay, Ramazan, and Stengos, Thanasis. 1997. "Technical trading rules and the size of the risk premium in security returns."*Studies in Nonlinear Dynamics and Econometrics*. 2: 23–34.

Graham, Benjamin, and Dodd, David. 2009. *Security Analysis: Principles and Technique* (6th Ed.). New York: The McGraw-Hill Companies, Inc.

Hair, Josef, Anderson, Rolph, Tatham, Ronald, and Black, William. 1998. *Multivariate Data Analysis* (5th Ed.). New Jersey: Prentice – Hall, Inc.

Ionescu, Stefan, Murgoci, Cristiana, Gheorghe, Camelia, and Ionescu, Emilia. 2008. "Profitability on the Financial Markets; A Discriminant Analysis Approach." *International Journal of Applied Mathematics and Informatics*. 3(2): 76-87.

Kaastra, Iebeling, and Boyd, Milton. 1996. "Designing a neural network for forecasting financial and economic time series." *Neurocomputing*. 10: 215-236.

Khan, Muhammad Bilal, Gul, Sajid, Rehman, Shafiq, Ur Rehman, Razzaq, Nasir, and Kamran, Ali. 2012. "Financial Ratios and Stock Return Predictability (Evidence from Pakistan)." *Research Journal of Finance and Accounting*.3(10): 1-6.

Kheradyar, S., Ibrahim, I. and Mat Nor, F. 2011. "Stock Return Predictability with Financial Ratios."*International of Trade Economics and Finance*.2(5): 391-396.

Lee, Wen-Shiung, Tzeng, Gwo-Hshiung, Guan, Jyh-Liang, Chien, Kuo-Ting, and Chien Huang, Juan-Ming. 2009. "Combined MCDM techniques for exploring stock selection based on Gordon model." *Expert Systems with Applications*. 36(3): 6421-6430.

Lin, Chi-Ming, Huang, Jih-Jeng, Gen, Mitsuo, and Tzeng, Gwo-Hshiung. 2006. "Recurrent neural network for dynamic portfolio selection." *Applied Mathematics and Computation.* 175: 1139–1146.

Malhotra, Karesh. 2004. *Marketing Research: An Applied Orientation* (4th Ed.). New Jersey: Pearson Education, Ltd.

Markowitz, Harry. 1952. "Portfolio Selection." *The Journal of Finance*. 7(1): 77-91.

Merton, Robert. 1969. "Lifetime Portfolio Selection under Uncertainty: The Continuous Time Case." *Review of Economics and Statistics*. 51(3): 247–257.

Mills, Terence. 1997. "Technical Analysis and the London Stock Exchange: Testing Trading Rules Using the FT30." *International Journal of Finance & Economics*. 2(4): 319-331.

MSCI Inc. 2014. MSCI Market Classification Framework. http://www.msci.com/resources/products/indexes/global_equity_indexes/gimi/stdindex/MSCI_Market_Classification_Framework.pdf (accessed June 15, 2014)

Oz, Bulent, Ayricay, Yucel,.andKalkan, Gokturk. 2011. "Predicting Stock Returns with Financial Ratios: A Discriminant Analysis Application on the ISE 30 Index Stocks."*Anadolu University Journal of Social Sciences*. 11(3): 51-64.

Quah, Tong-Seng, and Srinivasan, Bobby. 1999. "Improving returns on stock investment through neural network selection." *Expert Systems with Applications*. 17: 295–301.

Research Centre International Economics. 2010. Policy Brief No. 4. http://www.fiw.ac.at/fileadmin/Documents/Publikationen/Policy_Briefs/04.FIW_PolicyBrief.Which_Growth_Model_for_Central_and_Eastern_Europe_after_the_Crisis_final.pdf (accessed February 16, 2015)

Samuelson, Paul. 1969. "Lifetime Portfolio Selection by Dynamic Stochastic Programming." *Review of Economics and Statistics*. 51(3): 239–246.

Şenol, Emir, Dinçer, Hasan, and Timor, Mehpare. 2012. "Stock Selection Model Based on Fundamental and Technical Analysis Variables by Using Artificial Neural Networks and Support Vector Machines." *International Review of Economics & Finance*. 02(03): 106-122.

Siqueira, Elisa, Otuki, Thiago, and da Costa, Newton. 2012. "Stock Return and Fundamental Variables: A Discriminant Analysis Approach." *Applied Mathematical Sciences*. 6(115): 5719-5733.

Sorensen, Eric, Miller, Keith, and Ooi, Chee. 2000. "The Decision Tree Approach to Stock Selection." *The Journal of Portfolio Management*. 27(1): 42-52.

Treynor, Jack and Black, Fisher. 1973. "How to Use Security Analysis to Improve Portfolio Selection." *The Journal of Business*. 46(1): 66-86.

Vu, Jo. 2013. "Predictability of High-value Stocks on Australian and Shanghai Stock Exchange. "*International Review of Business Research Papers*.9(4): 22-32.

Wiener Börse AG. 2014. *Index values.* http://en.indices.cc/indices/details/sxe/composition/ (accessed July 10, 2014)

Yoon, Youngohc, Swales, George., and Margavio, Thomas. 1993. "A Comparison of Discriminant Analysis versus Artificial Neural Networks."*Journal of the Operational Research Society*.44(1): 51-60.

Yu, Lean, Wang, Shouyang, and Lai, Kin. 2008. "Neural network-based mean–variance–skewness model for portfolio selection." *Computers & Operations Research*. 35(1): 34-46.

Appendix A

Table II Current composition of the SETX

Issuer	Country	Number of stocks	Capitalization EUR	Index portion
ADRIS GRUPA P	Croatia	6,784,100	262,991,514	3.73%
AIK BANKA	Republic of Serbia	9,045,756	49,683,011	0.70%
BANCA TRANSILVANIA	Romania	2,559,179,315	436,893,930	6.19%
BRD-GROUPE SG	Romania	696,901,518	262,611,002	3.72%
ERICSSON NIKOLA TESLA	Croatia	1,331,650	145,780,043	2.07%
FONDUL PROPRIETATEA	Romania	13,778,392,208	1,148,503,276	16.28%
HRVATSKI TELEKOM	Croatia	81,888,535	811,597,579	11.50%
KRKA	Slovenia	35,426,120	1,265,456,433	17.93%
MERCATOR	Slovenia	3,765,361	128,022,274	1.81%
NIS	Republic of Serbia	163,060,400	250,010,941	3.54%
OMV PETROM	Romania	56,644,108,335	872,107,903	12.36%
PETROL	Slovenia	2,086,301	421,839,631	5.98%
SOPHARMA	Bulgaria	132,000,000	114,159,973	1.62%
TELEKOM SLOVENIJE	Slovenia	6,535,478	337,230,665	4.78%
TRANSELECTRICA	Romania	73,856,084	90,982,736	1.29%
TRANSGAZ	Romania	11,773,844	136,931,246	1.94%
TRIGLAV	Slovenia	22,735,148	216,438,609	3.07%
VALAMAR ADRIA HOLDING	Croatia	7,467,235	105,172,324	1.49%

Source: Wiener Börse AG (2014)

Appendix B

Table II Assessment results for the selected capital markets

Criteria	Countries				
	Bulgaria	Croatia	Romania	Serbia	Slovenia
Openness to foreign ownership					
Investor qualification requirement	++	++	++	++	++
Foreign ownership limit (FOL) level	++	++	++	++	++
Foreign room level	++	++	++	++	++
Equal rights to foreign investors	++	++	+	+	++
Ease of capital inflows / outflows					
Capital flow restriction level	++	++	++	+	++
Foreign exchange market liberalization level	+	++	++	+	++
Efficiency of the operational framework					
Market entry					
Investor registration & account set up	+	-/?	++	-/?	++
Market organization					
Market regulations	++	++	+	+	++
Competitive landscape	++		++		++
Information flow	+	++	+	-/?	++
Market infrastructure					
Clearing and Settlement	++	-/?	+	+	++
Custody	-/?	++	-/?	++	++
Registry / Depository	+	+	+	++	++
Trading	++	+	-/?	+	+
Transferability	++	++	-/?	+	++
Stock lending	-/?	-/+	-/?	-/?	-/?
Short selling	-/?	-/?	-/?	-/?	-/?
Stability of institutional framework	+	+	+	+	+

++: no issues; +: no major issues, improvements possible; -/?: improvements needed / extent to be assessed. Competitive landscape for some Frontier Market countries is still being assessed.

Source: MSCI Inc. (2014)

Appendix C

Table III Sample

Country/Index	Code	Issuer	Ticker
Bulgaria/SOFIX	1	Sopharma	3JR
	2	Central Cooperative Bank AD	4CF
	2	Chimimport AD	6C4
	2	Corporate Commercial Bank ad	6C9
	2	Eurohold Bulgaria AD	4EH
	2	First Investment Bank AD	5F4
	2	Industrial Holding Bulgaria PLC	4ID
	2	M+S Hydraulic AD	5MH
	2	Monbat AD	5MB
	2	Neohim AD	3NB
	2	StaraPlanina Hold AD	5SR
	2	Advance Terrafund REIT	6A6
	2	Bulgarian Real Estate Investment Fund	5BU
	2	Bulgartabac Holding AD	57B
Croatia/CROBEX	1	Adrisgrupad.d.	ADRS-P-A
	1	Ericsson Nikola Tesla	ERNT-R-A
	1	Hrvatski Telekom	HT-R-A
	1	ValamarAdria Holding	KORF-R-A
	2	Arenaturistd.d.	ARNT-R-A
	2	Atlantskaplovidbad.d.	ATPL-R-A
	2	Krašd.d.	KRAS-R-A
	2	Podravkad.d.	PODR-R-A
	2	Zagrebačkabankad.d.	ZABA-R-A
	2	Dalekovodd.d.	DLKV-R-A
	2	Atlantic Grupad.d.	ATGR-R-A
	2	Petrokemijad.d.	PTKM-R-A
	2	AD Plastikd.d.	ADPL-R-A
	2	Viaduktd.d.	VDKT-R-A
	2	Luka Rijeka d.d.	LKRI-R-A
	2	HUP - Zagreb d.d.	HUPZ-R-A
	2	Ledod.d.	LEDO-R-A
	2	UljanikPlovidbad.d.	ULPL-R-A
	2	Luka Pločed.d.	LKPC-R-A
	2	Ingra d.d.	INGR-R-A
	2	Vupikd.d.	VPIK-R-A
	2	Virotvornicašećerad.d.	VIRO-R-A
	2	INA d.d.	INA-R-A
	2	Beljed.d. Darda	BLJE-R-A
	2	ĐuroĐaković Holding d.d.	DDJH-R-A
Romania/ROTEX	1	BancaTransilvania	TLV

Country/Index	Code	Issuer	Ticker
	1	FondulProprietatea	FP
	1	OmvPetrom	SNP
	1	Transgaz	TGN
	1	BRD-groupesg	BRD
	2	Romgaz	0QHQ
	1	Transelectrica	TEL
	2	Bursa De Valor	BVB
	2	Erste Group Bank AG	EBS
	2	Biofarm S.A.	BIO
	1	Krka	KRKG
	1	Mercator	MELR
	1	Telekom Slovenije	TLSG
Slovenia/SBITOP	1	Petrol	PETG
	1	Triglav	ZVTG
	2	Pozavarovalnica Sava	POSR
	2	Gorenje	GRVG

Note: 1 denotes 'blue chip stocks' (the ones included in the SETX), while 2 denotes second-grade stocks

Identifikacija prvorazrednih deonica na nerazvijenim tržištima kapitala Jugoistočne Evrope

REZIME *– Osnovni cilj ovog rada je da se objasne diskriminirajuće varijable između prvorazrednih i drugorazrednih deonica koje kotiraju na nerazvijenim tržištima kapitala Jugoistočne Evrope (JIE). S obzirom da su emprijska istraživanja selekcije deonica sa nerazvijenih tržišta kapitala uopšte, a posebno tržišta kapitala tranzicijskih zemalja sa prostora JIE, retka, ovaj rad je koncipiran tako da se pokuša rasvetliti identifikacija prvorazrednih deonica kojima se trguje na predmetnim tržištima. Na osnovu rezultata sprovednog istraživanja potvrđeno je da se prvorazredne deonice sa nerazvijenih tržišta kapitala JIE mogu identifikovati na osnovu dividendnog prinosa, gotovinskih tokova i zarade po deonici. Stoga bi se institucionalni i individualni investitori, u cilju redukcije investicionog rizika, prilikom selekcije deonica sa JIE regiona trebali fokusirati upravo na prethodno pomenute varijable.*

KLJUČNE REČI: *prvorazredne deonice, diskriminaciona analiza, JIE region*

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