Associate Professor Victoria BOGDAN, PhD
E-mail: victoria.bogdan10@gmail.com
Professor Claudia Diana SABĂU POPA, PhD
E-mail: dianasabaupopa@yahoo.ro
Assistant Professor Mărioara BELENEŞI, PhD
E-mail: mimibelenesi@yahoo.com
University of Oradea
Professor Vasile BURJA, PhD
E-mail: vasileburja@yahoo.com
1st December 1918 University of Alba Iulia
Associate Professor Dorina Nicoleta POPA, PhD
E-mail: dlezeu@uoradea.ro
University of Oradea

EMPIRICAL ANALYSIS OF INTELLECTUAL CAPITAL DISCLOSURE AND FINANCIAL PERFORMANCE – ROMANIAN EVIDENCE

Abstract *This study aims to identify the most relevant financial indicators for the selected companies, in order to determine a composite performance index, further used in analyzing the correlations between the average degree of intellectual capital disclosure and the performance of companies. Data were collected from the annual reports of 37 Romanian listed companies, from 6 industries, with a strong emphasis on knowledge. The proxy variables used to assess the performance of companies were classified into three categories: value creation indicators, stock indices and profitability indicators. Performing 12 regression models based on panel type data for 2010-2013, we found that the degree of intellectual capital disclosure and its components (the relational and human capital) of the previous year show a significant positive impact on the performance of companies in the current year. Also, we showed that the degree of intellectual capital disclosure aim to help poor-performance companies improve their results.*

Key words: *intellectual capital disclosure, performance, listed companies, composite index, regression models*

JEL Classification: O34, M41, L25

1. Introduction

In the recent decades, knowledgehas become a highly valued commodity, therefore, companies seek to gain competitive advantage on any market by supplying increasing amounts of intellectual capital (IC) (Feleagă et al., 2013). The purpose of this article is to study the correlation between the average degree of intellectual capital disclosure (therefore of its components) and a number of performance measurement indicators of companies, according to the latest relevant studies in the literature (Alipour, 2012; Janošević et al., 2013; Nimtrakoon, 2015; Zeghal and Maalou, 2010; Clarke et al., 2011; Chu et al., 2011; Molodchik and Bykova, 2011; Diez et al.,2010; Shakina and Barajas, 2014; Buszko and Mroziewski, 2009; Wang, 2008; Kamath, 2015). We should highlight that the offence of disclosure of the economic secret is one of the offences from title VII of Romanian Criminal Code, because of the risk to cause damage to the company by disclosing data or information that are not to be revealed to the public (MiheșandArdeleanu-Popa, 2008).

In this study we aimed to build a composite performance index of companies based on the ten proxy variables used to assess the performance of selected companies, for the years 2010-2013, using the multivariate principal component analysis of panel data and the identification of groups of companies in terms of their performance. Further on, we followed the analysis of the potential relationships between the degree of intellectual capital disclosure and of its components on the performance of companies based on the aggregate index previously obtained, using the regression analysis specific to panel data. Unlike other studies carried out by Gruian (2011), Sumedrea (2013), Nedelcu et al. (2014) or Morariu C.M. (2014), analysing the same topic on the Romanian listed companies, our study uses a composite performance index of companies based on ten proxy variables and classifies the companies according to performance in poor-performance companies and high-performance companies.

The paper is organized as follows: a brief introduction that motivates the importance and the contribution of our approach to the research subject, the theoretical background describes the international and national context based on prior literature, the research design and methodology explain the research approach and all the statistical tools used in order to perform the performance measurements and test the correlations between the degree of IC disclosure and companies' performance, discussion of results present the analysis of influence of the degree of intellectual capital disclosure on the performance of companies and the last part outlined the major findings, limits and future research directions.

2. Previous studies related to intellectual capital disclosure and performance

Most studies on IC disclosure and performance are based on factor analysis of content processing the data collected from the companies' annual reports. Chan (2009) and Chu et al. (2011), in their empirical studies examined the intellectual capital (IC) performance of Hong Kong Hang Seng Index listed companies and its association with business performance. Value Added Intellectual Coefficient (VAIC™), was used to evaluate the IC investment of the companies. Chu et al. (2011) showed that no conclusive evidence was found to support the associations between VAIC™ as an aggregate measure and the four financial indicators.

Nimtrakoon (2015) used VAIC™ model for measuring IC efficiency of 213 technology firms listed on five ASEAN stock exchanges and showed that there is no significant difference in modified VAIC™ across five ASEAN countries. Specifically, Nimtrakoon (2015) observed that, IC is found to be positively associated with margin ratio and return on assets. The findings are consistent with those of Alipour (2012), who applied regression model to examine the relationship between IC of Iran selected insurance companies and financial performance during the period 2005-2007 and found that Value added IC and its components have a significant positive relationship with companies' profitability.

However, correlations do not check in all the countries and the companies analyzed. This leads us to the view that the results of studies are comparable only for similar samples of companies from countries that can be grouped in the same basket in terms of economic development. Thus, studies carried out by Zeghal and Maalou (2010) and Clarke et al. (2011), are relevant from the perspective of the analyses which can be performed on more developed capital markets. As regarding similar studies conducted on emerging economies is worth mentioning the study of Janošević et al. (2013), in which IC efficiency was measured using value added intellectual coefficient (VAIC™) for 100 Serbian selected companies and multiple regression model was performed to assess the relationship among individual components of VAIC and financial performance. Janošević et al. (2013), found that net profit, operating revenue and operating profit are not the consequence of the efficient use of IC in Serbian companies. Human and structural capital affects ROE and ROA, whereas relational capital influences ROE.

In a study conducted on Polish construction companies, Buszko and Mroziewski (2009) developed a quantitative method of evaluation of qualitative components of IC as well as a way of finding a relationship between the quality of IC and the growth of net profit earned by a company. The obtained findings support the hypothesis: the higher the value of IC, the greater the net profit growth. Similarly, in a study based on 350 Russian industrial enterprises' annual statistical and account reports from 2005 through 2007, Molodchik and Bykova (2011), using

Pulic's Value Added Intellectual Coefficient (VAIC™) investigated empirically the dynamics and structure of VAIC, and the relation between IC and indicators of organizational performance, such as labour productivity, sales growth and profitability.

Analysing the literature, we found similar studies carried out, having as sample the listed companies in Romania. Sumedrea (2013), pointed out that in crisis time, the development of companies is influenced by the human and the structural capital, while profitability is additionally linked to the financial capital through the value added intellectual capital coefficient. If Gruian (2011), demonstrated that there is a significant positive correlation between intellectual capital and financial performance, Nedelcu et al. (2014) showed that CE positively impacts the company's performance indicators, meaning, as the value of VACE increases, so is the value of ROA, ROCE, SGR or WP.

In their study, Jaba et al. (2013) conducted a panel analysis on a sample of 47 companies listed on the Bucharest Stock Exchange, concluding that companies' profitability and indebtedness resulted from the reported financial information have a significant influence on their value market (price tobookvalueratio). Also, Horobet and Belascu (2012) found thatfundamental analysis has some influence on companies' performance in the Romanian capital market, but only regarding financial indicators, calculated based on the company's financial statements. On the other hand, Morariu C.M. (2014) showed that the capital employed has an insignificant role in both value creation and in reducing the company's production costs, the market value is not necessarily improved by a properly managed structural capital, but is influenced by company size, and human capital plays a major role in productivity variation.

Also, Diez et al. (2010) and Buszko and Mroziewski (2009), used quantitative methods to test the correlations between IC and its components and value creation. Other authors like, Shakina and Barajas (2014), designed a log-linear model and estimated it on a sample of more than 400 European and American companies, related to the empirical validation of the function based on companies' intangibles in the Cobb-Douglas framework, while, Kamath (2015) was interested in empirically investigate the impact of intellectual capital on the financial performance and market valuation of firms in India and the results proved that financial performance and market value are indeed influenced by the IC of the firms. Unlike these studies, the one conducted by Wang (2008), investigated the relationship between IC and company market value in the US Standard & Poor's 500 publicly traded electronic companies from 1996 to 2005 and proved a positive relationship between IC and market value of the company.

3. Research design andmethodology

Considering the above, in order to achieve our objective we formulated the following questions: *to what extent can the improvement of financial statements by providing information on intangible investments contribute to better meet the information needs of users, reflected in improved performance?and which are the correlations between the increase of the level of intellectual capital disclosure and the improvement of economic and financial performance of the company?*

For the beginning, we intend to identify the most relevant financial indicators for the companies analyzed, so that we can determine a composite index of performance of companies that later can be used in studying the correlation between the average degree of intellectual capital disclosure and the performance level of the company. The construction of the performance index of companies was carried out using the SPSS 18.0 statistical software. Composite indices have the advantage of allowing a classification as they represent the overall performance in a number.

In our case, the study requires the creation of a composite index if we want to evaluate the performance of businesses and identify the companies that have made progress or which have worsened their situation. If an indicator represents a single variable, a composite index aggregates several individual indicators to give a synthetic measure of a complex, multidimensional and significant subject. The strength of the approach based on creating a composite index lies in its ability to portray the results of an integrated analytical framework. While individual indicators can be informative, a rigorous, well-designed composite index has the potential to capture the "big picture" and the multidimensionality of complex systems. The quality of a composite indicator and the soundness of messages it sends, does not only depend on the methodology used in its construction, but primarily on the quality of the theoretical framework and data used (OECD 2008).

Data were collected manually from the annual reports of 37 Romanian companies from 6 industries (with a strong emphasis on knowledge) for the period 2010-2013. Proxy variables used to assess the performance of the companies were grouped into three categories: on value creation indicators (Economic Value Added, Market Value Added, Internal Rate of Return, Cash Value Added), stock indices (Earnings per share, Market Capitalization Ratio, Dividend per share) and profitability indicators (Economic rate of return, Financial rate of return). Because in the second section of this study we want to identify the impact of the degree of intellectual capital disclosure and its components on the company performance, the following data relate to this degree of disclosure. Analyzing Abeysekeraand Guthrie(2005), BeattieandThomson(2006), Fădur(2013), Li etal.(2007),we obtained72indicators/items of intellectual capital and they were subjected to content analysis. Data on trading were collected from the website of the Bucharest

Stock Exchange and National Bank of Romania or were provided by Intercapital Invest.

In this paper, we used the multiple imputation technique that considers the missing data, as part of the analysis and attempts to assign values based on regression analysis. In the process of creating a composite index of the performance of selected companies, it is important to take into account the question of different measurement units of the 10 financial indicators on which this index will be constructed, so it is necessary to apply a database normalization technique. Thus, standardization is considered to be a necessary step before applying the aggregation process, as it avoids the potential biases resulting from the inclusion of different scales and different intervals.

In a first step, the Cronbach Alpha Coefficientwas used to determine how well the set consisting of 10 different one-dimensional object measures, by estimating the internal consistency of items in the model. The initial value of the C-Alpha coefficient suggests the abolishing of the SPV (*Share Price Volatility* - Volatility Coefficient of shares) variable from the analysis. The subsequent value of the coefficient based on *z* scores of the remaining 9 indicators is 0.6 for the 37 companies considered in the analysis and it corresponds to an acceptable internal consistency of variables. When the process of creating the composite index involves more than two dimensions (variables observed for several companies in different periods), the *Principal Components Analyses* – PCA method generates the *Multiway Principal Components Analysis*– MPCA. PCA is a dimensionality reduction technique, while MPCA is equivalent to running PCA on a two-dimensional array constructed by holding a three-dimensional matrix, so that data are organized as panel type data (Mourão, 2007). When we are dealing with a large number of variables meant to describe a phenomenon or a fact, much of their variation can often be represented by a smaller number of variables - called principal components or linear relationship of original data that are uncorrelated. The purpose of data reduction is to remove redundant variables (strongly correlated with each other) in the data set and replace them with a smaller number of uncorrelated variables.

The next step in creating the aggregate index of company performance is to select the main components that keep a large amount of quantity of the variance of the original data, cumulated by the PCA method. The components are ordered so that the first component to recover the greatest possible amount of variance from the original variables. The second component is completely unrelated to the first component, and recovers the maximum variation which has not been recovered from the first component and so on. Another issue to be taken into account in determining a composite index is how information aggregates. The problem of aggregation refers to two interrelated issues: assigning weights to components and synthetic function selection. The weights can have a significant effect on the overall composite index and the ranking of companies. The weights can be used to reflect the quality of statistical data and usually higher weights can be assigned to statistics with greater coverage.

Among the possible aggregation strategies presented by the OECD handbook (2008) we decided to use weights derived from principal component analysis using the proportion of variance recovered by each main component in the total of variance recovered, as shares of scores of factors to determine the non-standardized index. This approach seems more objective because the shares are not assigned normatively by the analyst, but are rather obtained on the basis of statistical techniques, being extracted from the data and are not considered to be arbitrary (De Muro et al. 2009). The empirical results of PCA as a multivariate method used to build the multivariate composite performance index indicate that there are six main components, extracted using Kaiser's criterion that states the choice of the principal components above or very close to value 1.

Table 1.MPCAeigenvalues and eigenvectors, total variance explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.425	26.949	26.949	2.425	26.949	26.949	1.966	21.841	21.841
2	1.896	21.066	48.015	1.896	21.066	48.015	1.839	20.438	42.279
3	1.458	16.203	64.217	1.458	16.203	64.217	1.750	19.450	61.729
4	1.011	11.238	75.455	1.011	11.238	75.455	1.018	11.315	73.044
5	0.964	10.706	86.161	0.964	10.706	86.161	1.008	11.196	84.239
6	0.828	9.194	95.356	0.828	9.194	95.356	1.000	11.116	95.356
7	0.230	2.553	97.909						
8	0.150	1.672	99.581						
9	0.038	0.419	100.000						

Extraction Method: Principal Component Analysis.

The table above shows the dispersion explained by the initial solution, by the components extracted and the rotate components. The total column gives the dispersion value, the amount of variation in the original variables justified by each component. The "% of Variance" column calculates the percentage of dispersion value of each component of the total. In the column "Initial Eigenvalues" we identify eigenvalues, in descending order, namely: $\lambda_1 = 2.425$, $\lambda_2 = 1.896$.... $\lambda_6 = 0.828$. By adjusting the cloud of points in a single factorial axis (i.e., accepting only one synthetic indicator) 26.95% of the total variance of the data can be explained. Then, adjusting the cloud of points by two factorial axes (i.e. accepting two synthetic indices) we recover 21.06% of the total variance, representing 48.01% of this variation. The third main component still recovers 16.20% of the total variance, while the following three components considered recover close enough percentages (9% -11%), all six summing up a total amount of recovered variance of 95.36%. Information concerning the interpretation of the main components is obtained by analyzing the calculated correlation coefficients between the two main components and the main financial variables.

The interpretation of the main components is relatively simple. Namely, a main component can be "explained" by the initial variable for which the correlation coefficient is maximum, but, at the same time, the initial variable has with the other main components small correlation coefficients. Therefore, for a more relevant analysis and a more realistic interpretation, it is recommended the use of an option of "rotation axes" that aims to obtain as low as possible correlation coefficients on one or two main components. One of the most used "spins" is known as the "Varimax technique". In this way, the interpretation of the principal components becomes more significant.

Table 2.Rotated principal component matrix[a]

	Component					
	1	2	3	4	5	6
Zscore(EVA)	0.063	0.020	0.947	-0.010	0.015	0.005
Zscore(MVA)	-0.005	0.035	0.169	0.980	-0.006	0.048
Zscore(CFROI	0.985	0.073	0.004	-0.011	0.024	0.015
Zscore(CVA)	-0.043	0.053	0.906	0.233	0.000	0.036
Zscore(EPS)	0.172	0.938	0.048	0.025	0.098	-0.004
Zscore(PER)	0.014	-0.022	0.031	0.046	0.009	0.998
Zscore(DPS)	0.052	0.961	0.025	0.019	-0.030	-0.023
Zscore(ROA)	0.974	0.152	0.022	0.003	0.087	0.002
Zscore(ROE)	0.085	0.050	0.012	-0.006	0.994	0.009

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

Table 2 shows the principal components rotated for the original variables and is a strong suggestion for the percentages that will calibrate each variable in the aggregate index. The results were obtained using the PCA method with the Varimax technique and it is as follows: the first factor has significant positive coefficients with CFROI (0.985) and ROA (0.974) variables, highlighting that the first principal component could be interpreted in terms of an indicator of value creation; the second factor is dominated by variables such as DPS (0.961) and EPS (0.938) aimed at rather stock exchange issues; the third factor is positive and strongly correlated with EVA (0.947) and CVA (0.906) indicators which represent variables on value creation; the fourth main component can be interpreted in terms of MVA initial variable (0.980), while the fifth and sixth principal component are interpreted in terms of ROE (0.994) and PER (0.998) variables.

To assess the quality of the results obtained through PCA, the KMO and Bartlett's sphericity test were applied. KMO measures the sample adequacy and it must exceed the threshold of 0.5 so that a satisfactory analysis to be performed. In our case, the value of KMO is very close to that threshold, we can consider that such analysis may be appropriate. Bartlett test is also statistically significant, the associated probability being less than 0.05 (Approx Chi-Sq = 709.248).

Table 3.Results of KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.494
Bartlett's Test of	Approx. Chi-Square	709.248
Sphericitydf		36
	Sig.	0.000

In the last stage of building the composite index, the weights in the rotated principal component matrix are determined, considering that each main component will have a weight equal to its proportion of the variance recovered from the total of variance explained by all the factors. Thus, the financial performance index (FPI) of companies is determined as follows:

$$= \frac{26.95}{95.35}\cdot PC1 + \frac{21.06}{95.35}\cdot PC2 + \frac{16.20}{95.35}\cdot PC3 + \frac{11.23}{95.35}\cdot PC4 + \frac{10.70}{95.35}\cdot PC5 + \frac{9.19}{95.35}\cdot PC6$$

The final amount given to each observation for each company is rescaled using the percentile rank. Thus, the FPI will indicate how a company has performed in a year compared to the previous year or to another company in the same year or in different years. The index will range between 0 (lowest performance) and 100 (highest performance). A value of 50 represents an average performance.

Further on, we aimed to estimate the potential influence that the degree of intellectual capital disclosure and its components have on the business performance level measured based on the performance index previously built. The analysis will be performed on panel type data for the two categories of companies established in the previous section, in the Eviews 8.1 statistical program. Thus, the analysis will run 12 regression models based on panel type data for 2010-2013, as follows: four that will present the impact of the degree of intellectual capital disclosure and its components on the 37 companies in general; four that will present the impact of the degree of intellectual capital disclosure and its components on the 19 companies with poor performance; four that will present the impact of the degree of intellectual capital disclosure and its components on the 18 companies with good performance.

4. Analysis and discussion of results

In the analysis we started from the approach of Majdalany and Henderson (2013), which showed that several studies have indicated that there is an inevitable time lag between the increase of transparency on the one hand and performance on the other hand, and this time lag is generally perceived as a year. Therefore, we also considered that there is a time lag between the degree of disclosure and the performance of the company. The general form of the regression model on panel type data is:

$$FPI_{it} = \alpha_0 + \alpha_1 \cdot ICDI_{it-1} + \varepsilon_{it}$$

where: the dependent variable is the performance index of companies previously determined (FPI); the independent variable is the degree of intellectual capital disclosure (intellectual capital disclosure index – ICDI) and its components (relational, structural and human capital); ε_{it} are the model errors. To ensure comparability, we decided to transform the degree of both the intellectual capital disclosure and its components using the percentile rank, to create the same measurement unit with that of the performance index.

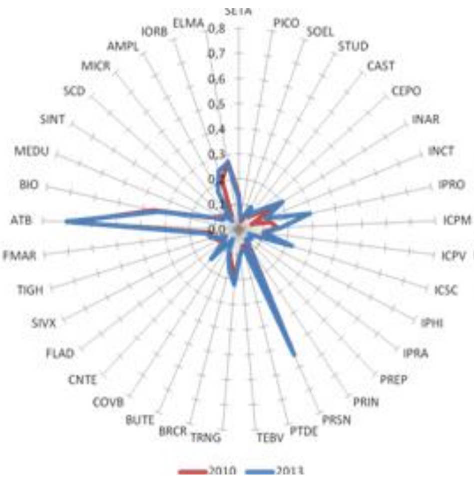

Figure 1.Distribution of the intellectual capital disclosure index in 2010 and 2013 for the companies analyzed

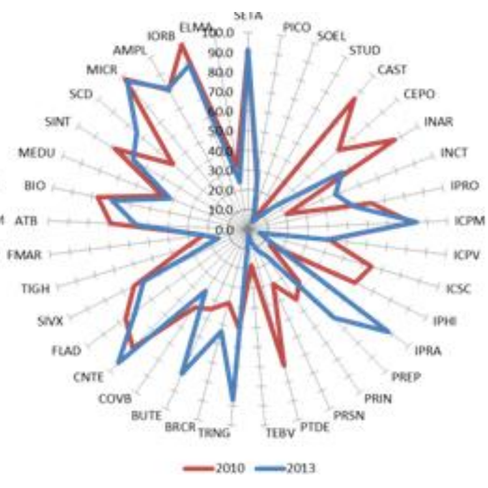

Figure 2.Performance index in 2010 and 2013 for the companies analyzed

Analyzing the intellectual capital disclosure index and its components for the 37 companies in 2010 and 2013, the following can be seen (Figure 1): the companies with the highest degree of intellectual capital disclosure are ATB in the Pharmaceuticals branch and PRSN in the Architecture and Engineering branch; the companies with the highest degree of human capital disclosure are PSRN, ATB and IPRO; the companies with the highest degree of relational capital disclosure are PSRN, ATB, IORB and INAR; the companies with the highest degree of capital structure disclosure are PSRN, ATB and ELMA. In applying the panel type models, it is important to decide the type of fixed-effect or random effect model. Therefore, it must be decided whether these effects are treated as fixed (FEM - *Fixed Effects Models*) or random (REM - *Random Effects Models*), which requires the implementation of Hausman test. This involves in the first phase the estimation of a random effects model. A high value of chi-square statistics (χ^2) ofHausman test, corresponding to a p-value (prob.) lower than the materiality threshold α of 0.05, leads to significant differences in coefficients, which requires the dismissal of random effects as inconsistent and it is found that the panel type estimation based on FEM fixed effects is more appropriate. A relatively low value of that test (accompanied by a greater probability p-value) determines the approach of REM type effects.

The analysis based on panel type data,homoscedasticity is a basic assumption that must be checked. To test the hypothesis of homoscedasticity the White test is used. If the phenomenon does not face homoscedasticity and heteroscedasticity appears, the most common remedy applied is the *Heteroscedasticity Corrected Standard Errors*technique (standard errors corrected in case of heteroscedasticity) - used in estimating the models, which are based on improving the standard deviations of the estimators, without changing the estimates of coefficients. Another assumption of the model to be verified is that there is no linear relationship between two or more explanatory variables. Error autocorrelation testing in estimating the models involves applying the *Durbin-Watson* (DW) statistics which may suggest order 1 autocorrelation of residues. The existence of collinearity can be corrected using the *Generalized Least Squares* (GLS) method. Establishing the validity of the model has in view the application of the *Fisher* test. The interpretation of results has in view the critical probability of the *Fisher* test (*prob*. or *significance*).

Thus, if this probability is below the materiality threshold set by specifying the risk, then the model set is considered valid. Otherwise (*prob*. or *significance* is greater than the materiality threshold set by specifying the risk) we get to the invalidity of the model, which involves a review of the factors involved in its composition. Analyzing the FPI evolution of the companies over the period 2010-2013 (Figure 2), we can outline the following 4 groups of companies: companies with good performance for the entire period analyzed that record high values of the index (SETA, ICPM, TRNG, CNTEE, SINT and IORB); companies that have improved their financial performance over the four years of analysis (BUTE, INCT, TRNG, BRCR, SCD, COVB); companies that have worsened their situation in terms of performance (CAST, INAR, IPRO, ICSC, IPHI, SIVX, SINT, MEDU, PRIN, ELMA, IPRA); companies with poor financial performance for the entire period (PICO, SOEL, STUD, FMAR, PRSN). Analyzing the average scores of FPI for the companies analyzed, we can say that the companies with the best performance over the four years are SETA, ICPM, CNTE and IORB. PICO, SOEL, STUD, PRSN, FMAR and ELMA are the companies with the poorest performance scores in the four years analyzed. Analyzing the values of FPI in 2013 compared to 2010, we find that INCT, IPRA, PREP, TRNG, BRCR, BUTE, CNTEE, SCD improved their performance, while CAST, CEPO, INAR, PTDE, ICSC, IPHI, PRIN, TIGH, ATB, BIO, SINT, IORB recorded poorer performance in 2013 compared to 2010.

Analyzing the performance trend of the companies in the years 2010-2013 we could highlight four groups of companies, as shown above. In Figure 3[1]we have seen that there are major companies with poor performance which rather regressed in the last year compared to the average of the preceding three years, respectively companies that are rather in a phase of stabilization, recording high enough performance levels throughout the entire period analyzed.

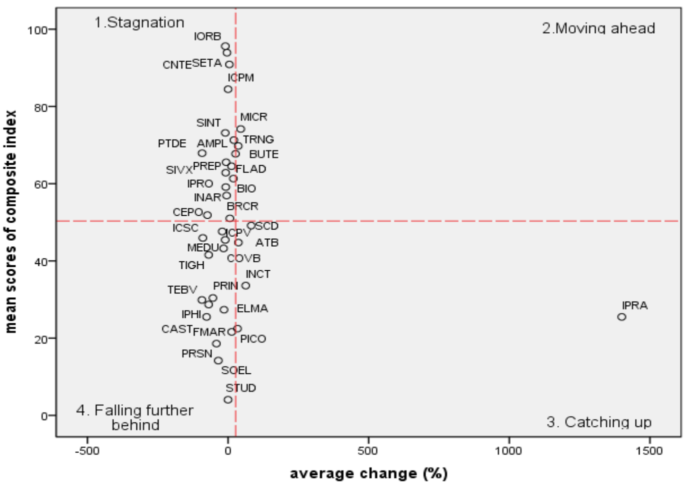

Figure 3.Classification of companies by the average values of the performance index

[1] The dotted line on the abscissa represents the percentage change of the FPI in 2013 compared to the average of previous years. The dotted line on the ordinate represents the average score both at the company level and at the year level.

This is the main reason we will further consider the two groups of companies, those with good performance (for which the FPI average values for the four years is higher than the overall average (50.33)) and low-performing companies (for which the FPI average values for the four years is less than the overall average (50.33)).

Table 4.Companies with good performance versus companies with poor performance

The average score of the composite performance index for 2010-2013 (%) for each company							
Companies with poor performance				Companies with good performance			
PICO	22.47	PRSN	18.58	SETA	93.92	BUTE	67.74
SOEL	14.19	TEBV	29.9	CEPO	51.86	CNTE	90.88
STUD	4.06	COVB	43.24	INAR	59.12	FLAD	64.53
CAST	25.51	TIGH	41.56	IPRO	56.93	SIVX	62.84
INCT	33.62	FMAR	21.62	ICPM	84.46	BIO	61.32
ICPV	47.64	ATB	44.76	PREP	65.54	SINT	73.15
ICSC	45.95	MEDU	45.44	PTDE	67.91	MICR	74.15
IPHI	28.72	SCD	49.16	TRNG	69.77	AMPL	71.29
IPRA	25.51	ELMA	27.36	BRCR	51.01	IORB	95.61
PRIN	30.41						

The composition of the two groups is as follows: 19 companies forming the group of companies with poor performance and 18 forming the group of companies with good performance. Detailed information can be found in Table 4. In order to analyze the influence of the degree of intellectual capital disclosure on the performance of companies considered in the analysis, we considered the dependent variable financial performance index of all companies analyzed (FPI) and the independent variable intellectual capital disclosure index (ICDI) as overall and on components (human capital - HCDI, relational - RCDI and structural - SCDI) as the following regression functions:

1) $FPI_{it} = \alpha_0 + \alpha_1 ICDI_{it-1} + \varepsilon_{it}$
2) $FPI_{it} = \alpha_0 + \alpha_1 RCDI_{it-1} + \varepsilon_{it}$
3) $FPI_{it} = \alpha_0 + \alpha_1 SCDI_{it-1} + \varepsilon_{it}$
4) $FPI_{it} = \alpha_0 + \alpha_1 HCDI_{it-1} + \varepsilon_{it}$

In relation to time, there are invariant factors characterizing the performance of the selected companies. If ignored, the empirical results can lead to inconsistent and moved coefficients (which are included in another basic assumption of the validity of the model through its coefficients), which would invalidate the model and there would not be the possibility to carry out the analysis desired to be unwound. In this respect, the unobservable individual effects will be controlled using fixed effects models (FEM) or random effects models (REM). As was mentioned before, the type of model depends on the potential correlation of unobserved effects explanatory variables (if unobservable effects are uncorrelated with all the explanatory variables it is better to opt for the use of models with REM effects). To choose between the two types of fixed effects models (FEM) and random effects (REM), the Hausman test was applied. The empirical results of the Hausman test showed the use of fixed effects (FEM) for all models, being estimated by using the Panel Least Squares (PLS) and proved to be valid for the purposes of the Fisher test. The results are:

1) $FPI_{it} = 41.92 + 0.14\ ICDI_{it-1}$
2) $FPI_{it} = 41.70 + 0.15\ RCDI_{it-1}$
3) $FPI_{it} = 44.70 + 0.09\ SCDI_{it-1}$
4) $FPI_{it} = 41.97 + 0.14\ HCDI_{it-1}$

The empirical results reveal a positive impact of both the level of intellectual capital disclosure and of its components on the performance of the companies analyzed. Analyzing the probabilities of regression coefficients of the four models (Appendix 2), it can be seen that the influence of the degree of intellectual capital and human capital disclosure is statistically significant, at the threshold of 1%. Instead, the relational capital shows a significant impact on the future corporate performance at the threshold of 10%, while the structural capital does not exhibit a statistically significant impact on the performance of companies (prob.>10%). Thus, if the degree of intellectual, human or relational capital disclosure in the last period increases by one unit, then the company's performance since the current moment will increase by 0.14 or 0.15 units on average, both indicators being measured on scales from 0 to 100. Thus, the impact of the degree of disclosure is not fundamental to the future performance of the company, but it can influence it.

Therefore, without taking into account the type of company, with poor or good performance, the degree of intellectual capital disclosure and its components, the human capital and the relational capital positively influence the future performance of companies, but not in a fundamental way, other factors not included in the analysis having with a much greater influence. In order to analyze the influence of the degree of intellectual capital disclosure on companies with poor performance, we considered the dependent variable the index of financial performance of companies with poor performance (FPI <50) and the independent variable the intellectual capital disclosure index, overall and on components taking the form of the following regression functions:

1) $FPI{<}50_{it} = \alpha_0 + \alpha_1\ ICDI_{it-1} + \varepsilon_{it}$

2) $FPI{<}50_{it} = \alpha_0 + \alpha_1\, RCDI_{it-1} + \varepsilon_{it}$
3) $FPI{<}50_{it} = \alpha_0 + \alpha_1\, SCDI_{it-1} + \varepsilon_{it}$
4) $FPI{<}50_{it} = \alpha_0 + \alpha_1\, HCDI_{it-1} + \varepsilon_{it}$

The empirical results of the Hausman test revealed the use of fixed effects (FEM) for the models that analyze the influence of the degree of intellectual capital disclosure and its component - the structural capital – on the company's performance or the use of effects random (REM) for the models that estimate the influence of human and relational capital on the company performance. All the models were estimated by using the Panel Least Squares (PLS) and proved to be valid. The results are:

1) $FPI{<}50_{it} = -5.64 + 0.53\, ICDI_{it-1}$
2) $FPI{<}50_{it} = 20.20 + 0.015\, RCDI_{it-1}$
3) $FPI{<}50_{it} = -1.90 + 0.45\, SCDI_{it-1}$
4) $FPI{<}50_{it} = 20.92 + 0.0006\, HCDI_{it-1}$

The empirical results of the regression models showed a significant positive impact at the materiality threshold of 1% and 5% of both the level of intellectual capital disclosure and its components (relational and structural capital) on the performance of companies with poor results in the period under review. Thus, if the degree of intellectual capital disclosure from $t_0$increases by one unit, then the company performance from t_1 will increase by 0.53 units, both indicators being measured on scales from 0-100. In terms of its components, it seems that the degree of structural capital has the greatest influence, with a coefficient of 0.45, statistically significant at the 1% threshold. The coefficient of the degree of relational capital disclosure is 0.015, showing a statistically significant impact, but reduced in intensity on the future performance of the company. The exception is the degree of human capital disclosure that does not show a significant positive impact on the performance index (prob.> 0.10). Critically regarding the results, the impact of the degree of disclosure is not fundamental to the future performance of the company, but it can influence it.

In conclusion, for the companies with poor performance, the degree of intellectual capital disclosure has a statistically significant positive impact on the future performance of the company, but rather reduced in terms of size. Regarding its components, it can be proved the significant positive influence of structural and relational capital on the company performance, but a possible influence of human capital is refuted, although the sign of the coefficient is an expected one in economic theory.

In order to analyze the influence of the degree of intellectual capital disclosure on companies with good performance, we considered the dependent variable the index of financial performance of companies with good performance

(FPI> 50) and the independent variable the intellectual capital disclosure index, overall and on components, taking the form of the following regression functions:

1) $FPI{>}50_{it} = \alpha_0 + \alpha_1\, ICDI_{it-1} + \varepsilon_{it}$
2) $FPI{>}50_{it} = \alpha_0 + \alpha_1\, RCDI_{it-1} + \varepsilon_{it}$
3) $FPI{>}50_{it} = \alpha_0 + \alpha_1\, SCDI_{it-1} + \varepsilon_{it}$
4) $FPI{>}50_{it} = \alpha_0 + \alpha_1\, HCDI_{it-1} + \varepsilon_{it}$

The empirical results of the Hausman test showed the use of fixed effects (FEM) for all the models, being estimated by using the Panel Least Squares (PLS) and proved to be valid according to the Fisher test. The results are:

1) $FPI{>}50_{it} = 69.25 + 0.01\, ICDI_{it-1}$
2) $FPI{>}50_{it} = 69.18 + 0.01\, RCDI_{it-1}$
3) $FPI{>}50_{it} = 68.40 + 0.03\, SCDI_{it-1}$
4) $FPI{>}50_{it} = 68.79 + 0.02\, HCDI_{it-1}$

The empirical results of the analysis based on panel type data for the 18 companies identified to have good performance showed that although the degree of intellectual capital disclosure and its components have the expected positive sign, confirmed both by economic theory and empirical studies, they do not show a statistically significant impact on the future corporate performance because the probabilities corresponding to the regression coefficients are higher than the 10% threshold (Appendix 2). Thus, in case of the companies performing very well, the degree of intellectual capital disclosure is not a key factor, but rather there are other fundamental factors to influence the future performance of the companies.

5. Conclusions, limits and future research

This study had as main objective the analysis of the relationship between the average degree of intellectual capital disclosure and the performance of the companies. In this respect, we wanted to identify whether the degree of intellectual capital disclosure of the previous year affects the performance of companies in the current year, and to what effect. The regression analysis based on panel type data revealed sensibly different results. Thus, the analysis overall, for all the 37 companies, for the 4 years considered, revealed that the degree of intellectual capital disclosure and its components (the relational and human capital) of the previous year show a significant positive impact on the performance of companies in the current year. No evidence was found as regarding a possible influence of the structural capital.

Generally, our results are in agreement with those of Gruian (2011), Nedelcu et al. (2014) and Morariu C.M. (2014). In addition, our results show that for low-performance companies, the degree of intellectual capital disclosure and that of the structural and relational capital of the previous year significantly and directly affect the performance of companies in the current year, however a possible influence of the human capital on the poor-performance companies is refuted. For good-performance companies, the empirical analysis revealed that although the degree of intellectual capital disclosure and its components have the expected positive sign, confirmed both by the economic theory and some empirical studies, it does not show a statistically significant impact on the level of performance of the companies included in our study. It may be noted that in the case of the companies performing very well, the degree of intellectual capital disclosure is not a key factor, but rather there are other fundamental factors to influence the future performance of the companies.

Thus, we can conclude that the degree of intellectual capital disclosure and its components aim to help poor-performance companies improve their results from year to year. Aware of the inherent limitations of any study, we still believe that good-performance companies and growing companies are in constant competition, and the voluntary publication of information, in general, through a transparent policy to all the stakeholders, is a shootout factor. Future research will focus on the analysis and measurements of the correlations between the human and relational capital disclosure and business performance using fuzzy models.

REFERENCES

[1] **Abeysekera, I., Guthrie, J. (2005),** ***An Empirical Investigation of Annual Reporting Trends of Intellectual Capital in Sri Lanka***; *Critical Perspectives on Accounting*, 16 (3), pp. 151-163;

[2] **Alipour, M. (2012),** ***The Effect of Intellectual Capital on Firm Performance: An Investigation of Iran Insurance Companies***; *Measuring Business Excellence*, 16 (1), pp. 53-66;

[3] **Beattie, V., Thomson, S.J. (2006),** ***Lifting the Lid on the Use of Content Analysis to Investigate Intellectual Capital Disclosures***; School of Management and Languages, Discussion Paper Series in Accountancy & Finance, ISSN 1741-8232, September 2006,available online at: http://www.sml.hw.ac.uk/documents/dp2006-af01.pdf, retrieved 04.04.2015;

[4] **Buszko, A., Mroziewski, M. (2009),** ***The Intellectual Capital Impact on Polish Construction Companies During the Transformation Period*;** *Journal of Human Resource Costing &Accounting*, 13 (3), pp. 206-220;

[5] **Chan, K.H. (2009),** ***Impact of Intellectual Capital on Organizational Performance: An Empirical Study of Companies in the Hang Seng Index (Part 1)*;***The Learning Organization*, 16 (1), pp. 4-21;

[6] **Chu, S.K.W., Chan, K.H., Yu, K.Y., Ng, H.T., Wong, W.K. (2011),** ***An Empirical Study of the Impact of Intellectual Capital on Business Performance***; *Journal of Information &Knowledge Management*, 10 (1), pp. 11-21;

[7] **Clarke, M., Seng, D., Whiting, R.H. (2011),** ***Intellectual Capital and Firm Performance in Australia*****;** *Journal of Intellectual Capital*, 12 (4), pp. 505-530;
[8] **De Muro, P., Mazziotta, M., Pareto, A., (2009),** ***Composite indices for multidimensional development and poverty: An application to MDG indicators;****Wye City Group Meeting*. Held in Rome, Italy: June, 2009, available online at:http://www.fao.org/fileadmin/templates/ess/pages/rural/wye_city_group/2009/Paper_3_b2_DeMuro-Mazziotta-Pareto_Measuring_progress_towards_MDGs.pdf;
[9] **Diez, J.M., Ochoa, M.L., Prieto, M.B., Santidrian, A. (2010),** ***Intellectual Capital and Value Creation in Spanish Firms***; *Journal of Intellectual Capital*, 11 (3), pp. 348-367;
[10] **Fădur, C.I., (2013),*****Intangible Capital: The Relationship between Profitability and Disclosure. An Empirical Analysis on the Romanian Companies*****;** *Anale. SeriaŞtiinţeEconomice.Tibiscus*, Timişoara, XIX/2013: 264-269,available online at:http://fse.tibiscus.ro/anale/Lucrari2013/Lucrari_vol_XIX_2013_044.pdf;
[11] **Feleagă, L., Feleagă, N., Dragomir, V., Râbu, L.M. (2013),** ***European Evidence on Intellectual Capital: Linking Methodologies with Firm Disclosures***; *ActaOeconomica*, 63 (2), pp.139-156;
[12] **Gruian, C.M. (2011);** ***The Influence of Intellectual Capital on Romanian Companies' financial Performance;*** *AnnalesUniversitatisApulensis: Series Oeconomica*, 13(2), pp. 260-272;
[13] **Horobet A., Belascu L., (2012),** ***Interactions between Fundamental Analysisand Market Performance for Romanian Companies: A Panel Data Approach;****Economic Computation and Economic Cybernetics Studies and Research*, (3), pp 5-25;
[14] **Jaba E. , Mironiuc M., Roman M., Robu I.B., Robu M.A. (2013),** ***The Statistical Assessment of An Emerging Capital Market Usingthe Panel Data Analysis of the Financial in Formation;****Economic Computationand Economic Cybernetics Studies and Research*, (2), pp 21-37;
[15] **Janošević, S., Dženopoljac, V., Bontis, N. (2013),** ***Intellectual Capital and Financial Performance in Serbia****; Knowledge and Process Management*, 20 (1), pp. 1-11;
[16] **Joint Research Centre – European Commission (2008),** ***Handbook on Constructing Composite Indicators: Methodology and User Guide***; OECD publishing.
[17] **Kamath, G.B. (2015),** ***Impact of Intellectual capital on Financial Performance and Market Valuation of Firms in India*****;** *International Letters of Social and Humanistic Sciences Online*. 48, pp. 107-122;
[18] **Li, J., Pike, R., Haniffa, R. (2007),** ***Intellectual Capital Disclosure in Knowledge Rich Firms: The Impact of Market and Corporate Governance Factors***, working paper, no. 07/06, April 2007, available online at:http://www.doc88.com/p-011708041677.html;

[19] **Majdalany, G., Henderson, J. (2013),** ***Voluntary Disclosure of Intellectual Assets and Intellectual Liabilities: Impact on Financial Performance in Publicly Listed Firms in the United Arab Emirates***; *Electronic Journal of Knowledge Management*, 11 (4), pp. 325-338;
[20] **Miheş C., Ardeleanu-Popa C. (2008),** ***Observations Regarding the Disclosure of the Economic Secret***; *Analele Universităţii din Oradea, seria Ştiinţe Economice*, Vol.II, TOM XVII 2008, pp. 717-719, ISSN 1582-5450, http://steconomiceuoradea.ro/anale/volume/2008/v2-economy-and-business-administration/129.pdf;
[21] **Molodchik, M., Bykova, A. (2011),** ***Applying the VAIC™ Model to Russian Industrial Enterprises****; Proceedings of the 3rd European Conference on Intellectual Capital University of Nicosia Cyprus*, April 2011, Edited by Turner G. and Minone C., pp. 268-277;
[22] **Morariu, C.M. (2014),** ***Intellectual Capital Performance in the Case of Romanian Public Companies;*** *Journal of Intellectual Capital*, 15 (3), pp. 392 – 410;
[23] **Mourão, P. (2007),** ***Towards a Fiscal Illusion Index;****MPRA_paper_9760*, available online at:http://mpra.ub.uni-muenchen.de/9760/;
[24] **Nedelcu, A.C., Banacu, C.S., Frăsineanu, C. (2014),** ***The Impact of Intellectual Capital on Automotive Firm's Performance – Case Study***; *Proceedings of the 8th International Management Conference "Management challenges for sustainable development"*, November 6th-7th, Bucharest, available online at: http://conferinta.management.ase.ro/archives/2014/pdf/69.pdf;
[25] **Nimtrakoon, S. (2015),** ***The Relationship between Intellectual Capital, Firms' Market Value and Financial Performance: Empirical Evidence from the ASEAN***; *Journal of Intellectual Capital*, 16 (3), pp. 587–618;
[26] **Shakina, E., Baraja, A. (2014),** ***Value Creation through Intellectual Capital in Developed European Markets****; Journal of Economic Studies*, 41 (2), pp. 272-291;
[27] **Sumedrea, S. (2013),** ***Intellectual Capital and Firm Performance: A Dynamic Relationship in Crisis Time***; *Procedia Economics and Finance*, (6), pp. 137–144;
[28] **Wang, J.C. (2008),** ***Investigating Market Value and Intellectual Capital for S&P 500;****Journal of Intellectual Capital*, 9 (4), pp. 546–563;
[29] **Zeghal, D., Maaloul, A. (2010),** ***Analyzing Value Added as an Indicator of Intellectual Capital and Its Consequences on Company Performance***; *Journal of Intellectual Capital*, 11(1), pp. 39-60.