COMPANIES'FINANCIAL STATUS AND THE BUSINESS TURNOVER ON EMERGENT MARKETS: THE ROMANIAN CASE

Ştefea Petru, Pantea Mioara Florina
[1] *Department of Management, Faculty of Economics and Business Administration, West University from Timişoara, Timişoara, România*
[2]*"Department of Economic Sciences, Faculty of Economic Sciences, Aurel Vlaicu" University from Arad, Arad, România*
petru.stefea@upcmail.ro
miofp75@yahoo.com

ABSTRACT *The aim of this study is to test for the relevance of some financial ratios as descriptors of companies' financial status in explaining the evolutions of their business turnover. We are considering a data sample of 36 companies quoted on the Romanian capital market for a time span between 2007 and 2010.The predictive capacity of some significant financial ratios for the companies' business turnover is analyzed and a methodology for the evaluation of their financial status based on these ratios is advanced. We found that the predictive capacity of some relevant financial ratios for the dynamic of some quoted companies' turnovers is non-uniform across the two conventional sectors in which we have grouped these companies according to their field of activity. Based on these results, an synthetic indicator of the companies' financial status is constructed at the level of each individual sector and the non-linear correlation between this indicator and the business turnover is tested.*

Key words: financial ratios, financial status, quoted companies

JEL classification: M41

Introduction

The study aims to reveal the potential connections between some relevant descriptors of companies' financial status and their results for some quoted Romanian companies in order to fill a gap in the empirical evidences of the financial status' impact on companies' performances in emergent markets. Due to the institutional, structural and functional particularities of these markets, it is expected to provide some insights about the involved transmission channels and to highlight some specificity of these. In the next section, a methodology designed to evaluate the predictive capacity of the selected financial ratios for the business turnover' dynamic and also to construct of a synthetic indicator of the financial status is advanced. Section 3 describes the data while Section 4 reports the results. Some conclusions are dropped and some further analytical directions are indicated in the last section.

Methodological framework

For a preliminary evaluation of the predictive capacities of the financial ratios, we construct a binary variable designed to reflect the cases in which the companies are achieving better performances in terms of relative business turnover comparing with the averages outcomes in their sector:

$$BT^{binary}_{it} = \begin{cases} 1 & if\ BT_{it} > \bar{BT}_{jt} \\ 0 & otherwise \end{cases} \qquad (1)$$

Here BT_{it} is the (natural logarithm) business turnover of the company "i" in the current period "t" while BT_{jt} stands for the average turnover of the sector "j".

The main properties of the binary variable are reported in Table 1. It appears that these data are displaying a relatively significant degree of dispersion, with "fat tails" effects. This implies that the individual companies from each sector are behaving in a distinctive fashion in terms of their business outcomes. Thus, the choice of methodology should account for the distinctive patterns of business turnovers at the level of each sector.

Table 1: The main statistic characteristics of the business turnover (binary)

	Sector "A"	Sector "B"
Std. Dev.	0.50	0.49
Skewness	-0.19	0.41
Kurtosis	1.04	1.17
Jarque-Bera	10.67	13.43
Probability	0.00	0.00
Observations	64	80

Source: own processing

Such specification of the binary variable allows for the identification of "over" and respectively "under" performances cases and for a further check of the capacity of financial ratios to discriminate between such cases. In other words, such frameworks allow an investigation of the connections between the companies' financial status and their economic performances.

The next step implies the running of a binary equation with the next specification (with ***X*** being the set of the considered explanatory financial ratios):

$$\Pr\left(BT^{binary}_{i} = 1 \mid X_i, \beta\right) = 1 - F\left(-X'_i \beta\right) \qquad (2)$$

Here ***F*** is a continuous, strictly increasing function that takes a real value and returns a value ranging from zero to one.

In order to account for the mentioned heterogeneity of the data, we are using a particular specification of cumulative distribution function ***F*** based on the *extreme value distribution*:

$$\Pr\left(BT^{binary}_{i} = 1 \mid X_i, \beta\right) = 1 - (1 - \exp(-e^{(-X'_i \beta)})) = \exp(-e^{(-X'_i \beta)}) \quad (3)$$

If the considered financial ratios appear to be relevant for the prediction of the companies' relative performances, then is possible to aggregate them in a synthetic descriptor of their financial condition and to further test the connections between such aggregate and the evolutions of business turnover.

A critical issue in the construction of such descriptor concerns the selection of the corresponding weights of financial ratios. At least three approaches can be considered: 1) the construction of an equiponderate measure with equal weights for each ratio; 2) the assignation of some ad hoc weights to reflect the perceived relative importance of the individual ratios in the description of the company financial status and, respectively, 3) the involvement of an multi-factorial analysis. Since the first two approaches can be affected by subjective biases, we are choosing to construct the synthetic descriptor of the financial status through a *principal components* analysis.

Principal components analysis is a variable reduction procedure. Thus, it is similar in many respects to exploratory factor analysis but there are significant conceptual differences between these two procedures. Perhaps, one of the most important differences deals with the assumption of an underlying causal structure: factor analysis assumes that the co-variation in the observed variables is due to the presence of one or more latent variables (*factors*) that exert causal influence on these observed variables. In contrast, principal component analysis makes no such special assumptions about an underlying causal model and permits the analysis of more various empirical situations. Its central idea is to reduce the dimensionality of a set of interrelated variables, while retaining as much as possible from the variation which is present in dataset. The procedure is currently widely applied from climatology to economics, genetics, psychology or quality control (see for details Jolliffe, 2002).

This type of analysis models the variance structure of a set of observed variables by using linear combinations of the variables. These linear combinations, or *components*, may be used in subsequent analysis, and the combination coefficients, or *loadings*, may be used in interpreting the components.

The *principal components* of a set of variables are obtained by computing the eigenvalue decomposition of the observed variance matrix. The first *principal component* is the unit-length linear combination of the original variables with maximum variance. Subsequent *principal components* maximize variance among unit-length linear combinations that are orthogonal to the previous components.

From the singular value decomposition, a (*nxp*) data matrix *Y* of rank *r* could be represented as:

$$Y = UDV' \qquad (4.)$$

U and *V* are orthonormal matrices of the left and right singular vectors, and *D* is a diagonal matrix containing the singular values.

More generally, one could write:

$$Y = AB' \qquad (5)$$

A is an *(nxr)*, and *B* is a *(pxr)* matrix, both of rank *r*, and

$$A = n^{\frac{\beta}{2}} U D^{1-\alpha}$$

$$B = n^{\frac{-\beta}{2}} V D^{\alpha} \qquad (6)$$

Thus $0 \leq \alpha \leq 1$ is a factor which adjusts the relative weighting of the left (observations) and right (variables) singular vectors, and the terms involving β are scaling factors where $\beta \in \{0, \alpha\}$.

The basic options in computing the scores *A* and the corresponding loadings *B* involve the choice of (loading) weight parameter *α* and (observation) scaling parameter *β*.
In the *principal components* context, let ∑ be the cross-product moment (*dispersion*) matrix of *Y*, and let perform the eigenvalue decomposition:

$$\sum = L\Lambda L' \qquad (7)$$

Here *L* is the *pxp* matrix of eigenvectors and Λ is the diagonal matrix with eigenvalues on the diagonal. The eigenvectors, which are given by the columns of *L*, are identified up to the choice of sign. It could be observed the facts that since the eigenvectors are by construction orthogonal, $L'L = LL' = I_m$.

There could be done some settings as $U = YLD^{-1}, V = L, D = (n\Lambda)^{\frac{1}{2}}$, so that:

$$A = n^{\frac{\beta}{2}} YLD^{-\alpha}$$
$$B = n^{-\frac{\beta}{2}} LD^{\alpha} \qquad (8)$$

A can be interpreted as the *weighted principal components scores*, and *B* as the *weighted principal components loadings*.
Others detail of this procedure concerns an appropriate choice of the weight parameter *α* and the scaling parameter *β* through which different *scores* and *loadings* with various properties could be constructed.
If the loadings of the first principal component are "closely enough" (i.e. there is not a disproportioned estimation of the relative importance of the individual financial ratios) then this component can be considered as an indicator of the companies' financial status.
Such indicator can be further used in order to analyse the (short-run) impact of the changes in financial status on companies' turnover and to highlight the potential structural changes in the involved linkages. Due to the existence of some important distinctions between sectors, the methodology should be distinctively applied for each individual sector.
An important issue of this evaluation concerns the fact that there are not, at least from an ex ante point of view, enough reasons to consider that the connections between financial status and business turnover have a linear nature. In fact, is more plausible to consider that these variables are linked in a non-linear fashion due to the complex involved causality. Thus, it is more adequately to check for the existence of such non-linear transmission channels. A possible way to perform such check is to consider the possibility of a non-linear co-trending linkage between the variables. Such nonlinear co-trading can appear when one or more linear combinations of the time series are stationary about a linear trend or a constant; hence, the series have common nonlinear deterministic time trends. The corresponding test is based on the eigenvalues of matrices constructed from the partial sum of the variables. It is nonparametric, since the non-linear trends and serial correlation processes do not need to be formally specified and is related to the Kwiatkowski et al. (1992) stationarity test for a univariate time series. There are at least two motivations for the construction of such a test (for a more detailed discussion about the relevance of this issue, see Bierens, 2000). Firstly, some long series perceived as unit root processes are displaying in fact a behavior more in accordance with a nonlinear

trend stationary hypothesis. Secondly, only few series that are not unit root processes still behave like co-integrated processes, in that the series move together over time in a similar way. But co-integration is only possible for unit root processes, thus, another approach is necessary.
The test statistic for the existence of such co-trending relationship as proposed by Bierens (2000), is $\boldsymbol{\lambda_r}$ for r = 1 through k, where r is the number of co-trending vectors under the null, and k is the number of variables. The alternative hypothesis is that there are r - 1 co-trending vectors. The test procedure also gives estimates for the co-trending vector parameters. More analytical, let $\boldsymbol{y_t}$ being the demeaned and possibly de-linear-trended vector of variables, and define:

$$\hat{M}_1 = \left(\frac{1}{n}\right)\sum_{t=1}^{n}\hat{F}\left(\frac{t}{n}\right)\hat{F}\left(\frac{t}{n}\right)^T,$$

$$\hat{F}(x) = \left(\frac{1}{n}\right)\sum_{t=1}^{[nx]} y_t,\ if\ \ x \in \left[n^{-1}\, 1\right],\ \hat{F}(x) = 0\ if\ \ x \in \left[0\ n^{-1}\right]$$

$$\hat{M}_2 = \left(\frac{1}{n}\right)\sum_{j=s}^{n}\left(\sum_{j=0}^{s-1}\frac{1}{s}y_{t-j}\right)X\left(\sum_{j=0}^{s-1}\frac{1}{s}y_{t-j}\right)^T \qquad (9)$$

Then it is solve:

$$\left|\hat{M}_1 - \lambda\hat{M}_2\right| = 0 \qquad (10)$$

Taking the ordered solutions of this, the test statistics are calculated as: $n^{1-\alpha}\,\hat{\lambda}_r$ **.**

Results and comments

Table 2 shows the estimated binary equations parameters. One of the most striking results appears to be the clear inter-sectors cleavage in the existing associations between the considered financial ratios and the business turnover. While for sector "A" all the corresponding coefficients appears to be statistically significant, for sector "B" only the coefficient of the fixed-to-total assets ratio is relevant. Thus, for sector "B" the model should be re-specified by dropping out the non-relevant explanatory variables and including others. Since the companies from this sector are typically characterized by an disequilibrium at the level of the ratios between their own and, respectively, borrowed financial resources, an appropriate choice of such alternatively explanatory variable can be for instance the total equity plus short-term liabilities-to-total liabilities ratio as a proxy of the companies' financial structure. Indeed, accordingly to the results reported in the last column of Table 2 this ratio is together with the fixed-to-total assets ratio negatively and statistic significantly associated with the business turnover in sector "B". It can be argued that the companies from sector "B" are more sensitive to the need for borrowed financial resources since their own resources are frequently insufficient to sustain the investments programs and the business expansion. And, as Clementi and Hopenhayn (2006), as well as Almeida and Campello (2001), argue, borrowing constraints have important implications for firm growth and survival. One of the key arguments is that such constraint arises as a feature of the optimal long-term lending contract, and that such constraints relax as the value of the borrower's claim to future cash-flows increases. A similar line of argumentation is considered in Gilchrist and Himmelberg (1994) which found evidences that for firms with only limited access to capital markets (as indicated by lack of participation in public debt markets) investments (and, correlatively, the engaged volume of financial resources) appears to be "excessively" sensitive to fluctuations in cash flow.

Table 2: Binary regression estimations

Variable	***Sector "A"***	***Sector "B" (first model)***	***Sector "B" (second model)***
Fixed to total assets ratio	3.99** (1.71)	1.21** (0.53)	2.02** (0.92)
Current to total assets ratio	5.73*** (1.96)	-0.70 (0.70)	
Total equity to total liabilities ratio	-6.43*** (2.13)	-0.96 (0.74)	
Operating result to total assets ratio	11.72** (5.35)		
(Total equity+ short-term liabilities) / total liabilities			-1.63** (0.75)
Akaike info criterion	0.85	1.37	1.32
Schwarz criterion	0.99	1.41	1.38
Hannan-Quinn criter.	0.91	1.42	1.34
Avg. log likelihood	-0.36	-0.64	-0.63

Source: own processing

Also, for sector "A", these results highlight that the largest impact on business turnover is exercised by operating results-to- total assets while the smallest one is corresponding to the fixed-to-total assets ratio. The total equity- to -total liabilities ratio appears to have a negative impact on short-run turnover dynamic as reflecting the importance of a *financial leverage effect* for the companies from this sector.
The binary equation also allows an estimation of the model predictor capacity through the so-called *classification table*. The fraction of observations that are correctly predicted is termed *sensitivity*, while the fraction of observations that are correctly predicted is labelled as *specificity*. The content of such classification is displayed in Table 3 with prediction results based upon expected value calculations.

Table 3: Expectation-Prediction Evaluation for Binary Specification

Sector "A"

	Estimated Equation			Constant Probability		
	BT^{binary} dummy=0	BT^{binary} dummy=1	Total	BT^{binary} dummy=0	BT^{binary} dummy=1	Total
$E(BT^{binary} = 0)$	21.29	7.51	28.81	13.14	15.86	29
$E(BT^{binary} = 1)$	7.71	27.49	35.19	15.86	19.14	35
Total	29	35	64	29	35	64
Correct	21.29	27.49	48.78	13.14	19.14	32.28
% Correct	73.42	78.53	76.22	45.31	54.69	50.44
% Incorrect	26.58	21.47	23.78	54.69	45.31	49.56
Total Gain*	28.11	23.84	25.78			
Percent Gain**	51.4	52.62	52.01			

Hosmer-Lemeshov Statistic	5.26	Prob. Chi-Sq(8)	0.73

Sector "B"

	Estimated Equation			Constant Probability		
	BT^{binary} dummy=0	BT^{binary} dummy=1	Total	BT^{binary} dummy=0	BT^{binary} dummy=1	Total
$E(BT^{binary} = 0)$	29.86	17.58	47.44	28.80	19.20	48.00
$E(BT^{binary} = 1)$	18.14	14.42	32.56	19.20	12.80	32.00
Total	48.00	32.00	80.00	48.00	32.00	80.00
Correct	29.86	14.42	44.27	28.80	12.80	41.60
% Correct	62.21	45.05	55.34	60.00	40.00	52.00
% Incorrect	37.79	54.95	44.66	40.00	60.00	48.00
Total Gain*	2.21	5.05	3.34			
Percent Gain**	5.52	8.42	6.97			

Hosmer-Lemeshov Statistic	11.45	Prob. Chi-Sq(8)	0.18

Notes: *-Change in "% *Correct* from default (constant probability) specification; **-Percent of incorrect (default) prediction corrected by equation; For Goodness-of-Fit Evaluation tests: Grouping based upon predicted risk (*randomized ties*). Success if probability is higher than 80%.
Source: own processing

In the lower right-hand table, we can compute the expected number of $BT^{binary} = 0$ and $BT^{binary} = 1$ observations for a model estimated with only a constant. For this restricted model, E ($BT^{binary} = 0$) is computed as $n(1-p)$, where p is the sample proportion of $BT^{binary} = 1$ observations. A classification is labelled as "correct" when the predicted probability is less than or equal to the cut-off (80% in our estimation) and the observed $BT^{binary} = 0$, or when the predicted probability is higher than the cut-off and the observed $BT^{binary} = 1$.

Overall, the estimated model predicts for sector "A" 76.22% of the observations (73.42% of the observations with dependent = 0 and 78.53% of the observations with dependent = 1) correctly. It appears that the levels of *sensitivity* and, respectively, *specificity* for our model are almost the same, implying that it can discriminate both „extreme" and „regular" cases. The gain in the number of correct predictions obtained by moving from the right table to the left table provides a measure of the predictive ability of our model. Roughly, there is in the case of sector "A", an improvement of 52.01% over the constant probability model with our estimation. The *Goodness-of-Fit* tests (*Hosmer-Lemeshow*) compare the expected fitted values to the actual values by group. If these differences are "small enough", the model is fitting the data adequately. The values of these tests, also reported in Table 3, suggest that this is the case with the binary specification for sector "A".

However, for sector "B" the predictive capacity of the considered financial ratios is poorer. In the case of this sector, the re-specified model predicts overall correctly only 55.34% from the observations (62.21% of the observations with dependent = 0 and 45.05% of the observations with dependent = 1). Also, the improvement over the constant probability model is far lower (only 6.97%). Finally, the value of the *Hosmer-Lemeshow* suggests that even the re-specified model predicts less adequately the data comparing with the case of sector "A".

Based on these preliminary results, it can be argued that the companies from the two sectors are operating in specific business conditions and with different structural and functional elements. Thus, the impact exercised on the evolution of their business turnover by the financial conditions appears to be a distinctive one with particular transmission channels involved.

Table 4: Principal components analysis

Sector "A"

Eigenvalues: (Sum = 4, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	3.12	2.67	0.78	3.12	0.78
2	0.45	0.07	0.11	3.58	0.89
3	0.38	0.34	0.10	3.96	0.99
4	0.04	---	0.01	4	1

Eigenvectors (loadings):

Variable	PC 1	PC 2	PC 3	PC 4
Fixed to total assets ratio	0.50	-0.65	-0.04	0.57

Current to total assets ratio	0.47	0.65	-0.53	0.28
Total equity to total liabilities ratio	0.55	-0.24	-0.22	-0.77
Operating result to total assets ratio	0.47	0.32	0.82	0.01

Sector "B"

Eigenvalues: (Sum = 4, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	1.96	1.92	0.98	1.96	0.98
2	0.04	---	0.02	2.00	1.00

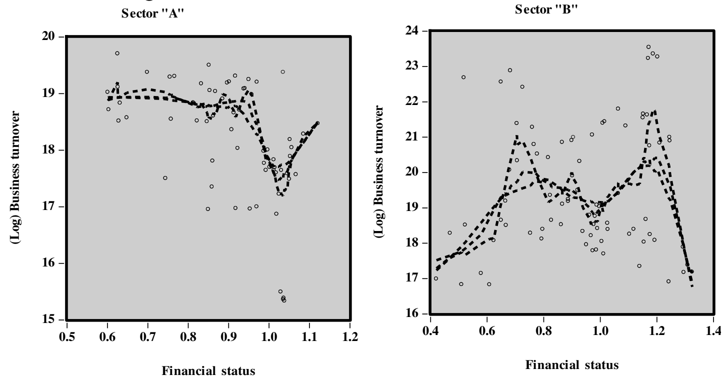
Eigenvectors (loadings):

Variable	PC 1	PC 2
RAI	0.71	-0.71
RAC	0.71	0.71

Notes: Computed using: Ordinary (un-centered) correlations; all possible components extracted.
Source: own processing

The first section of Table 4 summarizes the eigenvalues, showing the values, the forward difference in the eigenvalues and the proportion of total variance explained. Since we are performing principal components on a correlation matrix, the sum of the scaled variances for the four (two in the case of sector "B") explanatory ratios used to describe the financial conditions for the companies included in sector "A" is equal to 4 (respectively 2 in the case of sector "B"). The first principal component accounts for 78% of the total variance of (98% in the case of sector "B"), while the second accounts for 11% (2%) of the total. The first two components account for over 89% (100%) of the total variation.
For both sectors, the second section describes the linear combination coefficients. It can be noticed that the first principal component (labelled "PC1") is a roughly-equal linear combination of all four (two) financial ratios. Thus, in both cases, it might reasonably be interpreted as a global indicator of the companies' financial status.
Once such indicator of financial status is constructed based on principal components methodology, it is possible to carry out a more detailed analysis.
The scatter plot from Figure 1 suggests that the relationship between the financial status indicator and business turnover is a non-linear one (somehow with a "U" style shape for sector "A") and display a distinctive pattern for each sector. So, it is necessarily to consider a non-linear approach to the analysis of this relationship.

Figure 1: Nearest Neighbor Fit for financial status indicator and business turnover



Notes: Polynomial degree:1; Bandwidth (sample fraction):0.3;Local weighting (*Tricube*); Evaluation method: *Exact*
Source: own processing

The panel unit root tests from Table 5 indicates that the business turnover variable for sector "A" can be viewed as a unit root process while for the rest of the variables the evidences are less clear.

Table 5: Panel unit root tests

	Sector "A"		***Sector "B"***	
	Financial status indicator	*Business turnover*	*Financial status indicator*	*Business turnover*
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-43.84	-2.95	-30.82	-10.37
	(0.00)	(0.00)	(0.00)	(0.00)
Null: Unit root (assumes individual unit root process)				
ADF - Fisher Chi-square	27.28	12.08	52.91	36.94
	(0.04)	(0.44)	(0.00)	(0.01)
PP - Fisher Chi-square	20.97	7.22	15.10	20.75
	(0.01)	(0.12)	(-0.06)	(0.11)

Notes: Exogenous variables: Individual effects; Automatic selection of maximum lags; Automatic lag length selection based on MHQC: 0; Newey-West automatic bandwidth selection and Quadratic Spectral kernel; Balanced observations for each test
Source: own processing

However, is the tests for the existence of a co-trending relation between business turnover and the proposed indicator of the companies' financial status is performed, it appears that there can be highlighted the existence of a co-trending vector in the case of sector "A" but of two such vectors in the case of sector "B". In other words, for sector "B" both variables are stationary and no co-integration / co-trending relationship can be considered.

Table 6: Tests of the null hypothesis that there are r co-trending vectors against the alternative that there are r-1 co-trending vectors

Sector "A"

r	test statistic (conclusion)	10% critical region (conclusion)	5% critical region
1	0.13	>0.35 (accept)	>0.47 (accept)
2	0 .56	>0.54 (reject)	>0.67 (accept)

Conclusion (at 10%): r=1

Sector "B"

r	test statistic (conclusion)	10% critical region (conclusion)	5% critical region
1	0.04	>0.35 (accept)	>0.47 (accept)
2	0 .39	>0.54 (accept)	>0.67 (accept)

Conclusion (at 10%): r=2

Source: own processing

The existence of the co-trending vector between financial conditions and growth allows in the Bierens' methodology the decomposition of non-linear trend in growth. This can be done based on the fact that one can write F(x) = Q2Q2'F(x), where Q2 is the matrix of orthogonal eigenvectors of M1 corresponding to the positive eigenvalues. The vector Q2'F(x) can be interpreted as the vector of common cumulative nonlinear trends.

Similarly, F'(x) = Q2Q2'F'(x), where Q2 is the matrix of orthogonal eigenvectors of M2 corresponding to the positive eigenvalues. The vector Q2'F'(x) can be interpreted as the vector of common nonlinear trends.

Thus, for sector "A" we have:

Common cumulative nonlinear trend =

-0.151 x Component of F(t/n) corresponding to FINANCIAL STATUS INDICATOR
+0.98 x Component of F(t/n) corresponding to BUSINESS TURNOVER

Common nonlinear trend =

-0.06 x Component of F'(t/n) corresponding to FINANCIAL STATUS INDICATOR
+0.99x Component of F'(t/n) corresponding to BUSINESS TURNOVER

Overall, these results shows that for sector "A" the proposed indicator of the companies' financial status form a non-linear relationship with the dynamic of business turnover whiles for sector "B" such relationship cannot be evidenced.

Conclusions

This study is focused on the relations between the financial conditions characteristic for a set of Romanian quoted companies and the dynamic of their business turnover. The predictive capacity of some significant financial ratios for the companies' business turnover is analyzed and a methodology for the evaluation of their financial status based on these ratios is advanced. We found that the predictive capacity of some relevant financial ratios for the dynamic of some quoted companies' turnovers is non-uniform across the two conventional sectors in which we have grouped these companies. While for the companies with tertiary and quaternary activity the operating results-to- total assets ratio together with current -to -total assets and total equity-to-total liabilities ratios with appears to be relevant one in explaining the evolutions of their results, for the companies with primary and secondary activity only the fixed-to-total assets ratio and the structure of their financial resources displays statistical relevance. Based on these results, an synthetic indicator of the companies' financial status is constructed at the level of each individual sector and the non-linear correlation between this indicator and the business turnover is tested.

The study reveals some important inter-sectors differences in the nature, amplitude and relative importance of the involved transmission channels. Several explanations can be advanced for such differences.

Firstly, it can be argued that there is certain inter-sectors scale-differential effect with the companies from sector "B" usually displaying a larger scale and different organizational and functional structures comparing with the ones from sector "A". Such effect can leads to distinctive restrictions in the configuration of the companies' financial architecture and particular financing requirements.

Secondly, the companies from the two sectors display individual financial profiles with divergent own-to-borrowed financial resources ratios. Thus, the weighted costs of borrowed capital as well as the level and structure of this capital are influencing in particular manners the companies' results. Also, it can be presumed a non-uniform magnitude of the financial leverage effect between sectors.

Thirdly, the companies from the two sectors are operating in specific market environments with non-uniform efficiency of allocation and prices mechanisms and distinctive relationship between supply and demand. Fourthly, it is plausible to consider that due to imperfect information issues the decisions adopted by the managers from the two sectors are facing various moral hazard, adverse selection and residual loses issues which affects their companies' financial and economic performances.

This study does not explicitly address such explanations. Thus, further analyses are required for a better understanding of the involved transmission channels of the financial status' impact on companies' evolutions.

References

Almeida, H. and Campello, M. (2001). *Financial Constraints and Investment-Cash Flow Sensitivities: New Research Directions* (December 12, 2001). *Twelfth Annual Utah Winter Finance Conference*, Available at SSRN: http://ssrn.com/abstract=298027 or doi:10.2139/ssrn.298027.

Bierens, H.J.(2000). *Nonparametric nonlinear co-trending analysis, with an application to interest and inflation*. *U.S. Journal of Business and Economic Statistics*, 18, 323-337.
Clementi, L. and Hopenhayn, H. (2006).*A theory of financing constraints and firm dynamics*. *Quarterly Journal of Economics* , 54, 229-265.
Dima B., Taplos I., Moldovan N.C. (2012), Fiscal Policy and Economic Competitiveness, **Globalization and Higher Education in Economics and Business Administration (GEBA 2012)**
Dima B.,Cuzman I., Dima S.M. (2010), New Empirical Evidences on the Linkages between Governance and Growth, Social Science Research Network
Gilchrist, S. and Himmelberg,C. (1994) *Evidence on the role of cash flow for investment.* Journal of Monetary Economics, 36,541–72.
Kwiatkowski, D., Phillips, P.C.B., Schmidt, P. and Shin, Y. (1992). Testing the null hypothesis of stationary against the alternative of a unit root. *Journal of Econometrics*, 54, 159-178.
Jolliffe, I.T. (2002). *Principal Component Analysis*. Springer Series in Statistics, Springer-Verlag: Ney York.

DATA APPENDIX

Nr. crt.	Company	Market symbol	Field of activity	Codification of sector
1	ALRO S.A.	ALR	Heavy Industry	A
2	ALTUR S.A.	ALT	Heavy Industry	A
3	ALUMIL ROM INDUSTRY S.A.	ALU	Light Industry	B
4	AMONIL	AMO	Heavy Industry	A
5	ANTIBIOTICE S.A.	ATB	Light Industry	B
6	AZOMUREŞ SA	AZO	Heavy Industry	A
7	BERMAS S.A.	BRM	Light Industry	B
8	BOROMIR PROD S.A. BUZĂU	SPCU	Light Industry	B
9	CASA DE BUCOVINA-CLUB DE MUNTE	BCM	Light Industry	B
10	CEMACON SA ZALĂU	CEON	Heavy Industry	A
11	C.N.T.E.E. TRANSELECTRICA	TEL	Heavy Industry	A
12	COMELF S.A.	CMF	Heavy Industry	A
13	COMPANIA ENERGOPETROL S.A.	ENP	Heavy Industry	A
14	CONCEFA SA SIBIU	COFI	Heavy Industry	A

15	CONDMAG S.A.	COMI	Heavy Industry	A
16	DAFORA S.A.	DAFR	Heavy Industry	A
17	FARMACEUTICA REMEDIA SA DEVA	RMAH	Light Industry	B
18	IMPACT DEVELOPER & CONTRACTOR S.A.	IMP	Light Industry	B
19	OLTCHIM S.A. RM. VÂLCEA	OLT	Heavy Industry	A
20	OMV PETROM	SNP	Heavy Industry	A
21	PETROLEXPORTIMPORT S.A.	PEI	Light Industry	B
22	PREFAB SA BUCURESTI	PREH	Heavy Industry	A
23	PRODPLAST S.A.	PPL	Light Industry	B
24	ROMPETROL RAFINARE	RRC	Heavy Industry	A
25	ROMPETROL WELL SERVICES S.A.	PTR	Light Industry	B
26	SANTIERUL NAVAL ORSOVA S.A.	SNO	Heavy Industry	A
27	S.N.T.G.N. TRANSGAZ S.A.	TGN	Heavy Industry	A
28	SOCEP S.A.	SOCP	Light Industry	B
29	TERAPLAST S.A.	TRP	Light Industry	B
30	TITAN S.A.	MPN	Light Industry	B
31	SC TRANSILVANIA CONSTRUCŢII S.A.	COTR	Heavy Industry	A
32	T.M.K. – ARTROM S.A.	ART	Heavy Industry	A
33	TURBOMECANICA S.A.	TBM	Heavy Industry	A
34	TURISM FELIX S.A. BĂILE FELIX	TUFE	Light Industry	B
35	TURISM, HOTELURI, RESTAURANTE MAREA NEAGRA S.A.	EFO	Light Industry	B
36	ZENTIVA S.A.	SCD	Light Industry	B