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Relationship between financial indicators in the Slovak engineering industry: A panel regression approach

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Abstract. The aim of this article is to analyse the relationship between financial indicators in the Slovak engineering industry. We analyse the dependence of the financial indicator return on assets (*ROA*) on other financial indicators of companies in the engineering industry of the Slovak Republic, namely indicators of indebtedness (*ED, FL, TI*), liquidity (*QR, CR, NWC/A*), productivity (*VA/PC, VA/S*), cost efficiency (*PC/S*), and activity (*TA*). The research sample comprises the data of 34 significant Slovak engineering companies for the period 2008-2020. Tests for slope homogeneity demonstrated heterogeneity, which motivated the use of a partially heterogeneous framework for short panel data models – a regression clustering approach. This method divides the entities into clusters so that the column coefficients are homogeneous inside the clusters. The 4-cluster model appeared to be the most favorable model for the studied group of companies. The conducted procedures can be extended to companies from other economic sectors. Understanding of the relationship between *ROA* and other financial indicators allows for more effective business management.

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1. INTRODUCTION

The modern economy is characterized by extreme complexity, and in today's global world ensuring financial stability and increasing financial performance is a challenge. The development of social and natural sciences has brought various quantitative methods and a methodology with a wide practical application. To ensure economic sustainability, it is important to connect traditional and modern metrics and create multidimensional models (Zhang et al., 2023).

The paper deals with modelling the relationship between the financial indicator of profitability (*ROA*) and other financial indicators. The aim of this article is to analyse the dependence of the financial indicator Return On Assets (*ROA*) on the financial indicators of activity (turnover of assets – *TA*), indebtedness (total indebtedness - *TI*, financial leverage – *FL*, equity to debt ratio - *ED*), productivity (share of value added in sales – *VAIS*, share of value added in personnel costs – *VAIPC*), cost effectiveness (personnel costs/sales – *PC/S*), and liquidity (net working capital to assets ratio - *NWC/A*, current ratio – *CR*, quick ratio - *QR*) of companies in the engineering industry of the Slovak Republic. The research sample consists of the data of 34 important Slovak engineering companies for the period 2008-2020. The engineering industry is one of the main drivers of the Slovak economy and has a strong historical background and a stable position in the Slovak industry.

Our aim is to construct models suitable for evaluating the financial situation in the selected branch of the industry. We use a partially heterogeneous framework for short panel data models – the regression clustering approach. Understanding of the relationship between *ROA* and other financial indicators allows for more effective business management. These procedures and models are also applicable to other industries. The constructed models can be a starting point in improving financial health, prosperity, and competitiveness of the analysed businesses. Our analysis is an important prerequisite for developing a realistic financial plan for companies operating in the engineering sector in the Slovak Republic.

2. LITERATURE REVIEW

The need to know the current financial situation of the company and maintain its proper level in market competition causes the need to develop modern methods for assessing the financial situation of the company (Kocisova et al., 2018; Tong & Serrasqueiro, 2021; Nicolae et al., 2023). In the theory and practice of financial analysis, there are a significant number of methods that are used to determine the financial situation of companies (Myachin et al., 2021; Tlacova & Gavurova, 2023; Gavurova et al., 2020; Janková, 2023; Kufo & Shtembari, 2023).

The aim of the study by Fasolin et al. (2014) was to verify the relationship between the sustainability index and the financial and economic indicators of energy companies listed on the BM&FBovespa. The sample consisted of 31 companies that sent their sustainability reports in 2010 to Aneel. They used descriptive quantitative method, using the technical documentation, and multiple linear regression. A similar approach to measuring the links between financial and innovative activity and sustainability in the business environment was developed by Oliinyk et al. (2023) using the data for the EU. Findings on positive influence are confirmed also in related research by Gallardo-Vázquez & Lizcano-Álvarez (2020) conducted in Spain.

Study by de Jesus et al. (2019) investigated the relationship between economic-financial indicators and non-financial indicators of Health Plan Operators (*HPO*) for the Health Qualification Program (*HQP*) of the National Health Agency (*NHA*). They analyzed the period from 2011 to 2014 to verify whether financial performance is determinant in terms of the operational performance of 916 Health Plan Operators during the following period and vice-versa.

Other authors also investigated the relationship between financial indicators in Slovak industrial sectors, e.g. Valaskova et al. (2023), Gajdosikova et al. (2023), Svabova et al. (2022), Štefko et al. (2021), Kliestik et al. (2020).

Oroud et al. (2023) investigated how audit quality moderates the effect of financial performance indicators on the stock returns of Amman Stock Exchange-listed firms (*ASE*). They used panel data analysis on the sample of 95 *ASE*-listed firms from 2013 through 2021.

Panel analysis is a statistical method widely used in the social sciences and econometrics to analyze bivariate (usually cross-sectional and time) panel data (Maddala, 2001). Data are usually collected over time and from the same individuals and then regressed across these two dimensions. Panel analysis allows applying models with one or more levels of fixed effects or random effects to multilevel longitudinal data. Panel data are measurements of the considered variable for the same set of N cases (entities, individuals, ...) at several time points T. They allow the identification and control of individual effects and dynamics (Baltagi, 2005).

The main advantage of panel data is the solution to problems associated with the interpretation of partial regression coefficients within only multiple regression or only time series. Depending on the assumptions about the error components of the panel data model, we have two types of models, fixed effects and random effects (Vijayamohanan Pillai, 2016).

According to Nerlove (2002), the fixed-effects model of panel data techniques originates from least-squares methods in the astronomical work of Gauss (1809) and Legendre (1805), and the random-effects model or variance components from the English astronomer Airy (1861). The next stage is associated with R. A. Fisher, who developed the methods of variability and analysis of variance (Anova) in 1918 and elaborated both fixed and random effects models in the work Statistical Methods for Research Workers from 1925. However, the difference between the two models was not very clear. In 1947, Churchill Eisenhart came up with his "survey" that clarified the difference between fixed effects and random effects models. Random effects models, mixed and variance components actually presented significant computational problems for statisticians.

In 1953, Henderson developed methods of moments techniques for the analysis of random effects and mixed models, and in 1967, Hartley and Rao proposed maximum likelihood (*ML*) methods for variance component models. Dynamic panel models began with the famous Balestra-Nerlove models (1966). Panel data analysis reached its maturity with the first panel data econometrics conference in August 1977 in Paris, organized by Pascal Mazodier. Since then, this area has witnessed ever-expanding activities in both methodological and applied research.

Hsiao (2014), Baltagi (2005) and Andreß et al. (2013) cite several advantages of using panel data instead of pure cross-sectional or pure time series data. The obvious benefit is obtaining a large sample, which provides more degrees of freedom, greater variability, more information, and less multicollinearity between variables. A panel has the advantage of having *N* cross-sections and *T* time series observations, which contribute to the total number of *NT* observations. Another advantage is the possibility of controlling individual or time heterogeneity, which pure cross-sectional or pure time series data cannot afford. Panel data also opens up a space for dynamic analysis.

The number of works that deal with panel analysis is constantly increasing. An overview of these works is given, e.g. in Baltagi (2015), Elhorst et al. (2021) and Sul (2019). The problems that need to be solved when using panel time series are: time series properties - unit roots, stationarity (Breitung & Das, 2005; Choi, 2001; Hadri, 2000; Im et al., 2003; Levin et al., 2002), cointegration (Kao, 1999; Pedroni, 2004; Westerlung, 2005), heteroskedasticity of residuals (Hoechle, 2007), autocorrelation of residuals (Drukker, 2003), cross-sectional dependence (Chudik et al., 2011; De Hoyos & Sarafidis, 2006) and heterogeneity of coefficients (Pesaran & Yamagata, 2008; Bersvendsen & Ditzen, 2021).

Table 1

Review of empirical studies – panel regression

Author(s)	Object of study	Sample
Macek (2015)	To verify the relationship between individual types of taxes and economic growth.	*OECD* countries.
Savai & Kiss (2017)	To examine the factors influencing public debt.	*GIPS* countries, supplemented by a range of data from the Vyšehrad Group and Cyprus.
Bayar, Gavriletea & Ucar (2018)	To examine the impact of factors such as the development of the financial sector, the inflow of foreign direct investment, trade and financial openness in the field of business.	15 upper-middle-income and high-income countries for the period 2001-2015.
Bayar (2019)	Investigate macroeconomic, institutional and bank-specific factors behind non-performing bank loans as an indicator of banking sector performance.	Developing market economies in the period 2000-2013.
Boz, Mete & Aslan (2020)	To determine the relationship between the risk of catastrophic health expenditures for surgical care and the share of public health expenditures in total health expenditures.	97 countries for the period 2003-2015.
Kumar & Bindu (2021)	To identify firm-specific factors that influence the capital structure decision.	Automotive manufacturing companies in India.
Che Sulaiman, Saputra & Muhamad (2021)	To investigate the relationships between human capital and innovation capacity and economic growth.	Selected *ASEAN* countries namely Malaysia, Thailand and Indonesia.
Štefko et al. (2021)	To examine the connections between the use of renewable energy sources in selected sectors (transport, electricity, heating and cooling) and the prevalence of selected groups of diseases in the European Union.	Data on 27 European Union countries from 2010 to 2019 published in the Eurostat database and the Global Burden of Disease study.

Source: own processing

3. METHODOLOGY

The aim of this article is to analyse the relationship between financial indicators in the Slovak engineering industry. We analyse the dependence of financial indicator return on assets (*ROA*) on other financial indicators of companies in the engineering industry of the Slovak Republic. Financial indicators were calculated based on absolute indicators from the financial statements of non-financial corporations, which were accessed from the Register of Financial Statements of the Slovak Republic. The following financial indicators were used in the analysis:

Return on Assets (ROA) = $Earnings\ before\ interest\ and\ taxes\ (EBIT)/Total\ Assets$
indicators of indebtedness
Total Indebtedness (TI) = $Total\ Debt/Total\ Assets$
Financial Leverage (FL) = $Total\ Assets/Equity$
Equity to Debt Ratio (ED) = $Equity/Total\ Debt$
indicators of activity
Turnover of Assets (TA) = $Sales/Total\ Assets$
indicators of liquidity
Quick Ratio (QR) = $(Current\ Assets - Inventory)/Current\ Liabilities$
Current Ratio (CR) = $Current\ Assets/Current\ Liabilities$
Net Working Capital to Assets Ratio (NWC/A) = $Net\ Working\ Capital/Total\ Assets$
indicators of cost effectiveness
Personnel Costs/Sales (PC/S)
indicators of productivity
Share of Value Added in Sales (VA/S)
Share of Value Added in Personnel Costs (VA/PC),

Descriptive statistics of the variables are presented in Table 2.

Table 2

Descriptive statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
ROA	442	0.0549	0.0991	-0.4712	0.5886
ED	442	1.5585	2.0285	-0.4452	16.529
FL	442	2.8585	5.9611	-38.4692	79.6445
VA/PC	442	1.4790	0.6334	-1.8931	3.9496
VA/S	442	0.2598	0.1195	-0.2219	0.6445
PC/S	442	0.1999	0.1134	0.0190	0.5957
TA	442	1.5851	0.7220	0.0959	5.0528
TI	442	0.5342	0.2324	0.0570	1.4393
CR	442	2.4384	1.7571	0.2540	14.2393
NWC/A	442	0.2624	0.2353	-0.6224	0.8128
QR	442	1.1319	1.1174	0.0297	8.3197

Source: own processing in Stata

The research sample consists of 34 important Slovak engineering companies for the period 2008-2020. The Slovak Republic has a strong industrial tradition and is one of the most industrialized countries in Europe. The dominant position in Slovak industry is held by the automotive industry, which is closely connected with the engineering and electrical industries. The engineering industry is one of the main drivers of the Slovak economy and has a strong historical background and stable position in the Slovak industry. A positive trend in the engineering industry is recorded in the production of steel structures, bearings, railway wagons and chassis, but also in special production and development.

The econometric software Stata 15.1 was used to calculate the parameters of the models. For data processing were used Stata 15 commands – *regress, pwcorr, vif, xtcse2, xtcd2, xthst, xtreg, xtregcluster*.

Panel data is multi-dimensional data involving measurements over time. Panel data contain observations of multiple phenomena obtained over multiple time periods for the same firms, individuals, or countries. Briefly, panel data consists of *N* number of units and *T* number of observations (Yerdelen, 2013). The simultaneous use of both time and unit dimensions in the panel data ensures that many data are available and increase the degree of freedom (Hsiao, 2003). Panel data regression model in general is defined as:

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + u_{it} \qquad (1)$$

In the model, *t* is the time, such as year, day, and months; and *i* represents the units such as countries or firms. *Y* is the dependent variable. *X* is the independent or explanatory variable. β_0 stands for constant parameter. β_1 and β_2 are the coefficients of the independent variables and u is the error term (Yerdelen, 2013).

It is necessary to test the analyzed variables from the point of view of cross-sectional dependence. We used Cross-Sectional Dependence Exponent Estimation Alpha (α) and CD test (Pesaran, 2015). Pesaran (2004) has proposed the following alternative:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\widehat{p_{ij}}\right) \qquad (2)$$

and showed that under the null hypothesis of no cross-sectional dependence $CD \xrightarrow{d} N\ (0, 1)$ for $N \to \infty$ and *T* sufficiently large.

Chudik et al. (2011) (in Ditzen, 2021) proposed four types of cross sectional dependence: weak ($\alpha = 0$), semi-weak ($0 < \alpha < 0.5$), semi-strong ($0.5 \leq \alpha < 1$), strong ($\alpha = 1$).

Depending on whether the slope coefficients are homogeneous or heterogeneous, different econometric methods are used. In the case of homogeneous coefficients, we can use: Fixed Effect (*FE*), Random Effect (*RE*), General Method of Moment (*GMM*), Fully Modified *OLS* (*FMOLS*), Dynamic *OLS* (*DOLS*), Structural Breaks. There are also methods available for models with heterogeneous coefficients: Seemingly Unrelated Regresion Equations (*SURE*), Mean Group Estimation Model (*MG*).

Incorrectly ignoring slope heterogeneity leads to biased results (Pesaran and Smith, 1995). Determining the slope heterogeneity or homogeneity is crucial for model selection. To determine heterogeneity/homogeneity we used the Blomquist and Westerlund (2013) test for testing slope homogeneity using the *xthst* command (Bersvendsen and Ditzen, 2021). We control for cross-section dependence, heteroscedasticity and autocorrelation consistent version using *cr* and *hac* option. We get the value of the Delta statistic 4.46 and $p_{value} = 0.000$. If H_0 is rejected (slope heterogeneity), then one can use heterogenous panel estimation technique (Mean Group family models). This means that we cannot consider the slope coefficients as homogeneous.

The assumption of homogeneity of model coefficients is difficult to justify from both a theoretical and a practical point of view. On the other hand, the assumption of complete heterogeneity may be extreme because it does not provide a generalizable view. Sarafidis and Weber (2015) argue that the modeling framework of homogeneity of slope parameters (pooling) and full heterogeneity of slope parameters can be polar cases and other intermediate cases can often provide more realistic solutions in practice.

Sarafidis and Weber (2015) proposed a partially heterogeneous framework for the analysis of panel data. Christodoulou and Sarafidis (2015, 2017) described the *xtregcluster* command, which implements the panel regression clustering approach.

We consider the following panel data model of Sarafidis and Weber (2015):

$$y_{\omega it} = \acute{\beta}_{\omega} x_{\omega it} + u_{\omega it} \qquad (3)$$

where $y_{\omega it}$ denotes the observation on the dependent variable for the ith individual that belongs to cluster ω at time t, $\beta_{\omega} = (\beta_{\omega 1}, \beta_{\omega 2}, \beta_{\omega 3}, \dots, \beta_{\omega K})'$ is a $K \times 1$ vector of fixed coefficient, $x_{\omega it} = (x_{\omega it1}, x_{\omega it2}, x_{\omega it3}, \dots, x_{\omega itK})'$ is a $K \times 1$ vector of covariates, $u_{\omega it}$ is a disturbance term.

Therefore, each cluster has its own regression structure with $\omega = 1, \dots, \Omega_0$, $i[\epsilon\ \omega] = 1, 2, \dots, N_{\omega}$ and $t = 1, \dots, T$. This means that the total number of clusters equals Ω_0, the ωth cluster has N_{ω} entities, for which there are T time series observations available. The total number of entities in all clusters equals:

$$N = \sum_{\omega=1}^{\Omega_0} N\omega. \tag{4}$$

Residual sum of squares for cluster ω is denoted as RSS_{ω} and the total Residual sum of squares is calculated as the sum of individual RSS_{ω}:

$$\mathrm{RSS} = \sum_{\omega=1}^{\Omega} \mathrm{RSS}\omega. \tag{5}$$

The optimal Ω is such that it minimizes the value of the objective funcion – Model Information Criterion (MIC) (Christodoulou & Sarafidis, 2015):

$$MIC = N \log\left(\frac{RSS}{N\bar{T}}\right) + f(\Omega)\boldsymbol{\Theta}_N \tag{6}$$

where $\bar{T} = \frac{1}{N}\sum_{i=1}^{N} T_i$ is the average time series length for unbalanced panels. For panels with equal-length time series it holds $\bar{T} = T$, $f(\Omega)$ is a strictly increasing function of Ω, Θ_N is a penalty function for overfitting Ω. The defaults are set to $f(\Omega) = \Omega$ and $\Theta_N = 13 \log N + 23N$.

To establish the regression clustering model, we used commnand *xtregcluster* (Stata 15). We control for cross-section dependence, heteroscedasticity and autocorrelation consistent version using *cr* and *hac* option.

4. EMPIRICAL RESULTS AND DISCUSSION

We analyse the dependence of financial indicator return on assets (ROA) on financial indicators of activity, indebtedness, productivity, cost effectiveness and liquidity of companies in the engineering industry of the Slovak Republic. Data were analyzed for all years and companies together. Pairwise correlation is significant in the vast majority of cases (Table 3). Return on assets is correlated with all analyzed variables except ED and FL.

Table 3

Correlation matrix

	ROA	ED	FL	VA/PC	VA/S	PC/S	TA	TI	CR	NWC/A	QR
ROA											
ED	0.074										
FL	-0.035	-0.155									
VA/PC	0.590***	0.089*	-0.007								
VA/S	0.268***	0.269***	-0.088*	-0.036							
PC/S	-0.185***	0.114**	-0.047	-0.499***	0.8005***						
TA	0.366***	-0.263***	-0.073	0.120**	-0.1435***	-0.225***					
TI	-0.282***	-0.804***	0.216***	0.191***	-0.429***	-0.169***	-0.261***				
CR	0.136***	0.844***	-0.036	0.054	0.286***	0.160***	-0.163***	-0.652***			
NWC/A	0.350***	0.494***	0.081*	0.163***	0.246***	0.048	0.014	-0.568***	0.752***		
QR	0.196***	0.650***	-0.056	0.0185	0.361***	0.278***	-0.078	-0.521***	0.818***	0.655***	

Note: *- sig. level 0.1, ** - sig. level 0.05, *** - sig. level 0.01

Source: own processing in Stata

A strong correlation appears between the independent variables. The strongest is between the pairs (*CR, ED*), (*QR, CR*) and (*TI, ED*). Strong multicollinearity between independent variables may cast doubt on the model. The variables are analyzed from the point of view of multicollinearity also using the Variance Inflation Factor indicator. *VIF* values are shown in Table 4.

Table 4

Variation Inflation Factor (the original group of indicators)

Variables	**VIF**
CR	12.44
ED	10.59
PC/S	8.59
VA/S	6.93
TI	5.73
NWC/A	4.73
QR	3.45
VA/PC	2.68
TA	1.29
FL	1.18
Mean VIF	5.76

Source: own processing in Stata

Various recommendations for acceptable *VIF* levels have been published in the literature. Perhaps the most commonly recommended maximum *VIF* level is 10 (Hair et al., 1995). Some authors recommend a maximum *VIF* value of 5 (Rogerson, 2001) and others even 4 (Pan & Jackson, 2008). Not all values calculated by us meet these limits. We omit the three variables with the highest *VIF – CR, ED, PC/S*. The *VIF* values for the reduced set of indicators are shown in Table 5.

Table 5

Variation Inflation Factor (the reduced group of indicators)

Variables	**VIF**
NWC/A	2.31
TI	2.25
QR	1.99
VA/S	1.30
TA	1.21
FL	1.18
VA/PC	1.11
Mean VIF	1.62

Source: own processing in Stata

The *VIF* values calculated by us meet these conditions with a large margin. Next, we present the results of linear regression with independent variables *VA/PC, VA/S, TA, TI and NWC/A* for initial orientation and without further analysis (Table 6).

Table 6

Linear regression model

ROA	**Coef**
VA/PC	0.08086***
VA/S	0.22245***
TA	0.04949***
TI	-0.03248*
NWC/A	0.06369***
cons	-0.1959***

Note: *- sig. level 0.1, ** - sig. level 0.05, *** - sig. level 0.01
Source: own processing in Stata

The *F* test reached a high value *F*(5.436) = 122.21, p_{value} = 0.0000, *R*-squared = 0.5836. Financial indicators have a positive effect on the return on assets, except for total indebtedness (*TI*). It is necessary to test the analyzed variables from the point of view of cross-sectional dependence. In Table 7 are calculated values of exponent of cross sectional dependence Alpha (α) and *CD* test for individual variables using *xtcse2* and *xtcd2* (Ditzen, 2021).

Table 7

Cross-Sectional Dependence Exponent Estimation Alpha (α) and CD test

Variable	Alpha (α)	CD	p_{value}
ROA	0.771	35.36	0.000
FL	0.377	63.71	0.000
VA/PC	-	78.64	0.000
VA/S	-	77.94	0.000
TA	0.874	80.80	0.000
TI	0.924	80.03	0.000
NWC/A	0.764	47.17	0.000
QR	0.558	70.80	0.000

Source: own processing in Stata

Alpha(α) coefficients of all variables except *FL* are well above the established limit (0.5) and also zero p_{values} indicate that the analyzed variables show a strong crosssectional dependency. We used commnand *xtregcluster* (Stata 15) to determine the regression clustering model. We control for cross-section dependence, heteroscedasticity and autocorrelation consistent version using *cr* and *hac* option. Model Information Criterion values for options from 1 to 10 clusters are shown in Table 8.

Table 8

Model Information Criterion (MIC)

Omega	Total RSS	MIC
1	1.223	-195.209
2	0.639	-212.189
3	0.449	-219.105
4	0.355	-222.041
5	0.309	-221.751
6	0.280	-219.995
7	0.236	-220.704
8	0.215	-218.932
9	0.201	-216.094
10	0.178	-215.144

Source: own processing in Stata

The lowest *MIC* value was achieved for the number of clusters 4. The values of the model coefficients for each cluster are shown in Table 9.

Table 9

Panel data fixed effects estimates by omega

Variable	Cluster1	Cluster2	Cluster3	Cluster4	Pooled
FL	-0.0095	0.0032***	0.0234*	-0.0004	0.0006
VA/PC	0.4615***	0.0392***	0.0895***	0.1722***	0.0723***
VA/S	0.1609*	-0.0221	1.1257***	0.0225	0.1434**
TA	0.0304***	0.0278***	0.1511***	0.0495***	0.0483***
TI	-0.0110	-0.1546***	0.3124***	-0.0002	-0.1558***
NWC/A	-0.0339	-0.0454***	0.3524***	0.0789***	0.0121
cons	-0.5974***	0.0383	-0.8559***	-0.2857***	-0.0876***
N_g	5	9	5	15	34
T	13	13	13	13	13
N	65	117	65	195	442
R^2	0.918	0.658	0.827	0.882	0.538

Note: *- sig. level 0.1, ** - sig. level 0.05, *** - sig. level 0.01
Source: own processing in Stata

The number of enterprises included in individual clusters is denoted as *N_g*. The number of enterprises included in the clusters varies from 5 (the first and third clusters) to 15 (the fourth cluster). The coefficients of determination (R^2) for individual clusters are in all cases higher than the original value. In most cases, they reach very high values (0.827, 0.882, 0.918). *VA/PC* and *TA* indicators are significant in each cluster and their impact on *ROA* is still positive. *TI* and *FL* are significant in two cases (cluster 2, 3). Impact of *FL* on *ROA* is positive. *VA/S* is significant (positive) only in the case of cluster 1 and 3. *NWC/A* is significant in the case of cluster 2, 3, 4. Different signs of the variables were noted in the case of *NWC/A* and *TI*, where we recorded a negative value in the second cluster. Cluster 3 has the most significant coefficients.

If we examine the division into clusters from the point of view of production focus, then we can say that the first cluster is dominated by enterprises that produce heavy welds, and the third cluster is dominated by enterprises focused on the production of hydraulic equipment. Cluster 2 and 4 are made up of enterprises with the production of machines and equipment. However, cluster 4 is dominated by enterprises with a higher production of automated production systems.

5. CONCLUSION

Financial aspects are key factors in the company's development process. Knowledge regarding the financial health of the company can help the company in its competitiveness. In the framework of business management, many decisions are influenced by financial and economic analysis. Every manager should strive to understand financial theory. In the framework of financial management and financial analysis, various methods of evaluating and measuring the financial health of business entities have been created. These methods can be very successfully applied in the practice of business entities.

In this paper we aimed to analyse the dependence of financial indicator return on assets (*ROA*) on other financial indicators of companies in the engineering industry of the Slovak Republic. We have used a data set of 34 important Slovak engineering companies for the period 2008-2020. We used partially heterogeneous framework for short panel data models – regression clustering approach. The method divides the entities into clusters so that the column coefficients are homogeneous inside the clusters. The clusters are heterogeneous from each other, that is, the column coefficients are different between the clusters.

The coefficients for individual clusters differ in size, significance and even sign for the examined sample. For each cluster, the coefficient of determination is significantly higher compared to the original total coefficient of determination. This means that the new coefficients better describe the dependence of *ROA* on other financial indicators.

Regression clustering was used on a sample of engineering enterprises, which are not very heterogeneous. All of them belong to the SK NACE 28 - production of machines and equipment. It would be appropriate to examine the mentioned relationship on companies from different industries and in a much higher number.

Knowing the relationship between *ROA* and other financial indicators allows for more effective business management. The constructed models can be a starting point to improve financial health, prosperity, and competitiveness of analysed businesses. Our analysis is an important prerequisite for developing a realistic financial plan for companies operating in the engineering sector in the Slovak Republic. The presented results are the basis for further modelling, and at the same time a source of stimulus for further discussion.

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