THE RISK OF FINANCIAL DISTRESS IN THE ERA OF INDUSTRY 4.0 IN CENTRAL EUROPEAN ECONOMIES. IMPACT OF INDUSTRY AND CORPORATE LIFE CYCLE

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Abstract:

Research background: Industry 4.0 is a challenge for all world economies considering the new technologies and innovations that need to be put into operation. However, these investments can be highly risky and increase the risk of financial distress and/or increase the number of bankruptcies in industries.

Purpose of the article: The aim of this study is to investigate and evaluate the impact of the industry structure and the life cycle of the company on the risk of financial distress of companies in Central Europe.

Methods: The effect of industry structure and corporate life cycle was investigated using two-way analysis of variance and corresponding post hoc tests. More than 30,000 Central European companies were surveyed using financial data for 2019. The industry structure was created according to NACE rev. 2 and the stage of the life cycle was determined according to the cash flow pattern of the Dickinson model.

Findings & Value added: The results of the study show that the risk of financial distress develops dynamically in accordance with an inverted U-shape, where the risk of financial distress of growing enterprises is smaller than the risk of mature enterprises. Start-up, growing, mature and declining businesses have similar risks of financial distress within the life cycle stage regardless of industry structure. The influence of the industry is visible only in companies in the shake-out stage, where some industries are less risky, and the shake-out stage is an extension of the company's maturity. In other industries, the risk of financial distress increases rapidly after the maturity stage. The results of the study can be helpful for the academic community, but also for practice in determining industry support for the introduction of Industry 4.0, where start-ups have a similar starting line in terms of the emergence of financial distress.

Keywords: financial distress; bankruptcy; industry classification; life cycle

JEL Classification: G31; G32

1. Introduction

The current macro and microeconomic environment are pushed by several forces; first, it is the fading pressure of COVID-19 on the entire industry, or to a greater extent on the hospitality industry, transport, and other services. Secondly, the world economy is struggling with unprecedented inflation and the risk of an economic recession. Finally, previous, and emerging crises are pushing the economy to implement new technologies more quickly and move towards a full transition to Industry 4.0.

These influences worsen the performance of companies and thereby increase the pressure for the emergence of financial distress. However, the emergence of financial distress does not automatically mean the emergence of bankruptcy. Platt and Platt (2006) state that financial distress is a condition that is caused by operational decisions or external forces. According to them, bankruptcy is an attempt by corporate management to protect assets from creditors. Fitzpatrick (1932) was one of the first to create a model for predicting the future financial status of a company; he defines financial distress as the state of being unable to pay one's obligations when due. Gilbert et al. (1990) clarifies that financial distress has different properties than bankruptcy, financial distress is the result of a longer-lasting process of losses, poor performance and negative cash flow. Bankruptcy, on the other hand, is only one of the consequences of financial distress. A similar distinction is given by Grice and Dugan (2003), Whitaker (1999), Habib et al. (2020), Bozkurt and Kaya (2023) or Rowland et al. (2021).

In the environment of Central European countries, this issue has been investigated for a long time with an emphasis on research results from developed economies. Recently, however, there has been an increase in research from all Central European countries, such as Kaczmarek et al. (2021), Dvorsky et al. (2020), Kliestik et al. (2018), Kliestik et al. (2020) or Kristof et al. (2019). Kovacova et al. (2019) examined various predictors of financial health in the countries of the Visegrad Four, they state that each of the countries uses specific predictors, but in each of the country’s liquidity indicators stand out. Valaskova et al. (2023) point out that the level of insolvency risk has increased compared to the pre-pandemic period.

Corporate bankruptcy can be predicted more accurately using neural network or machine learning techniques than with conventional discriminant analysis or logistic regression models. Shetty et al. (2021) used machine learning techniques to develop a model for Belgian enterprises that had an accuracy of 82%; the authors highlight the model's ease of use and accuracy using three different metrics. In a comparison between a logistic regression model and neural networks, Gavurova et al. (2022) found that the neural network model produced noticeably better results. Korol (2019) employed decision trees, recurrent and multilayer artificial neural networks, fuzzy sets, and these methodologies to forecast financial health. The findings demonstrate that models built using historical data from European corporations speak of the poor financial condition of those companies. Krulicky and Horak (2021) used neural networks for cluster analysis purposes. The results show that the companies had negative net short-term receivables and tried to increase their funds by selling stocks. The authors also point out the versatility of using their neural network for other businesses. On a sample of Central European businesses, Pavlicko et al. (2021) discovered that the model, which combines RobustBoost, CART, and k-NN with an optimized structure, has good performance accuracy.

The above-mentioned research primarily considered quantitative factors such as financial statement data. Kucher et al. (2020) points out the importance of the age of the company in the occurrence of corporate failure, young and adolescent companies face financial difficulties due to internal problems, mature companies face higher competition and are more sensitive to economic downturns. Akbar et al. (2019) investigated the impact of life cycle on bankruptcy risk and found that bankruptcy risk varies in accordance with a U-shape, where startups and declining businesses have the highest bankruptcy risk. Akbar et al. (2022) examined financial distress in the context of restructuring and found that the mode of restructuring depends on the stage of the life cycle. In another study, Akbar et al. (2021) looked at market sentiment in relation to the life cycle of a firm, they conclude that mature firms are significantly more risk averse than start-ups. Valaskova et al. (2021) points to the influence of the legal form and the country factor on the indebtedness of the company. Durana and Valaskova (2022) emphasize the impact of smart sensors and profit on the risk of company bankruptcy.

Considering previous research and to the best of our knowledge, we do not consider the qualitative factors of financial distress to be sufficiently researched. The aim of this study is to investigate and evaluate the impact of the industry structure and the life cycle of the company on the risk of financial distress of companies in Central Europe. Financial distress was quantified using the Grice and Dugan (2003) modified Zmijewski model. The business life cycle according to Dickinson (2011) was chosen as suitable for its versatility and simplicity of determining the stage of the life cycle according to the cash flow pattern. The industry factor was determined according to the classification of NACE rev. 2. The influence of these factors individually as well as in mutual interaction was examined by two-way analysis of variance. The investigated sample covered more than 30,000 companies from four Central European countries (Slovakia, Poland, the Czech Republic, and Hungary) and accounting data for the pre-pandemic year 2019 to eliminate the impact of the pandemic on the financial health of companies.

2. Methodology

Financial distress and profitability are determined by a variety of factors, as the previous chapter explained; the economic sector itself has a significant role, as does the company life cycle with its unique characteristics. In this study, the NACE Rev. 2 industry factor were used as industry dummy variable. The life cycle stage was determined using the Dickinson (2011) model, where each stage (Introduction, Growth, Maturity, Shake-out, and Decline) is defined by certain cash flow patterns. According to Table 1, there are eight combinations of operating, investing, and financing cash flow for each of the stages.

Table 1: Cash flow patterns of Dickinson (2011) life cycle model

Cash flow	Introduction	Growth	Maturity	Shake-out			Decline	
Operating	-	+	+	-	+	-	-	-
Investing	-	-	-	-	+	+	+	+
Financing	+	+	-	-	+	-	+	-

Source: Author according to Dickinson (2011)

Financial distress was the variable under study, and while there are several ways to evaluate a company's financial vulnerability, Grice and Dugan's (2003) modified Zmijewski model was selected since it holds, unlike other bankruptcy models, that not all financially distressed companies must collapse, and vice versa. This probit model assumes that an increased risk of financial difficulty is determined by a computed probability greater than 50% and vice versa.

A two-way analysis of variance was used to investigate the effect of the industry factor and business life cycle on the probability of financial distress. The advantage of this approach is the possibility of analysing the influence of the mutual influence of these factors on the investigated variable, i.e., to answer the question whether the risk of financial distress of the average company varies across industries depending on the stage of the corporate life cycle. Assumptions of this method such as normality of subsamples, equality of variances of subsamples were tested by Kolmogorov-Smirn test and Levene test. If the conditions are not met, then a suitable alternative is to use the ANOVA test with robust standard errors. If the given factors were significant at the 0.05 level, then group differences can be tested by Scheffé or Tukey post hoc test.

A two-way ANOVA model can be described in regression form as:

$$FD_i = \mu + Life\ cycle_j + Industry_k + Life\ cycle \cdot Industry_{j \cdot k} + \varepsilon_{ijk} \tag{1}$$

Where: FD – financial distress proxy, $i = 1,2, \dots, 31\,333$ – number of cases in the net sample, $j = 1, 2, \dots, 5$ – number of life cycle stages (1 – Introduction, 2 – Growth, 3 – Maturity, 4 – Shake-out, 5 – Decline), $k = 1,2, \dots, 19$ – number of industry categories (1 - A. Agriculture, forestry and fishing, 2 - B. Mining and quarrying, …, 19 - S. Other service activities), $Lifecycle \cdot Industry_{j \cdot k}$- interaction term ($j \cdot k = 1,2, \dots, 76$).

Based on the following three criteria, a sample was obtained from the Orbis database:

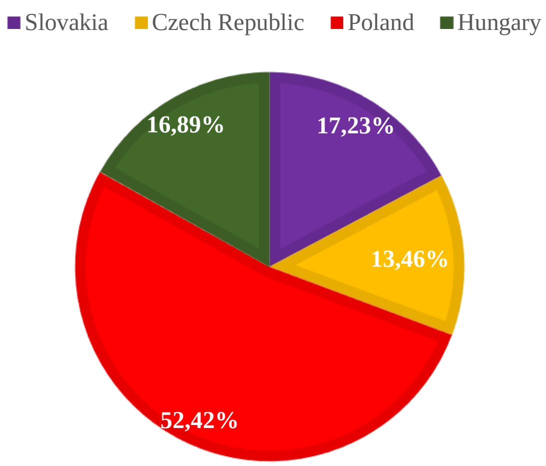
- a place of business in Slovakia, Poland, the Czech Republic, or Hungary,
- total asset worth of at least €2,000,000 in 2019,
- a minimum of EUR 100,000 in Turnover for 2019.

Businesses that matched those criteria were included in the gross sample (35 421 companies). The accounting data covered the year 2019 and included businesses from four countries in Central Europe as was mentioned above. To generate the net sample, missing data needed to be first removed, and then outliers were removed by wisorizing at the 1% and 99% levels.

3. Results

The net sample contained 31,333 enterprises meeting the specified selection criteria. Figure 1 shows the distribution of enterprises according to country affiliation. Considering the size of the Polish economy, Polish companies account for more than half of the created sample. The second largest group are Slovak companies, which make up more than 17% of the surveyed companies. Hungarian companies have a similar share. Czech companies have the smallest share, which was caused by many companies with incomplete or missing data.

Figure 1 Proportions of companies on net sample by country affiliation



Source: Author

In the second step, the descriptive statistics of the variable probability of financial distress were analysed. Descriptive statistics (Table 2) show that the life cycle of the company has an impact on the average probability of financial distress of the investigated companies. Start-up businesses are the riskiest, on the contrary, growing businesses have on average the lowest risk of financial difficulties. The average growing business can be considered financially sound with a below average-to-average probability of bankruptcy. The ambiguity of the shake-out stage reflects the average risk of financial distress of these enterprises. Shake-out companies form the largest group in the sample, their share is more than 44% of the entire sample.

In terms of place of operation, Slovak companies are on average among the riskiest, where the average Slovak company has more than 60% probability of financial difficulties. Conversely, the least numerous Czech companies have the lowest possibility of financial difficulties, with a value of just under 50%. The analysis shows that while belonging to the country is not a significant dividing element between the financial health of companies, on the contrary, the life cycle and the associated cash flow has an impact on the risk of bankruptcy to a higher degree.

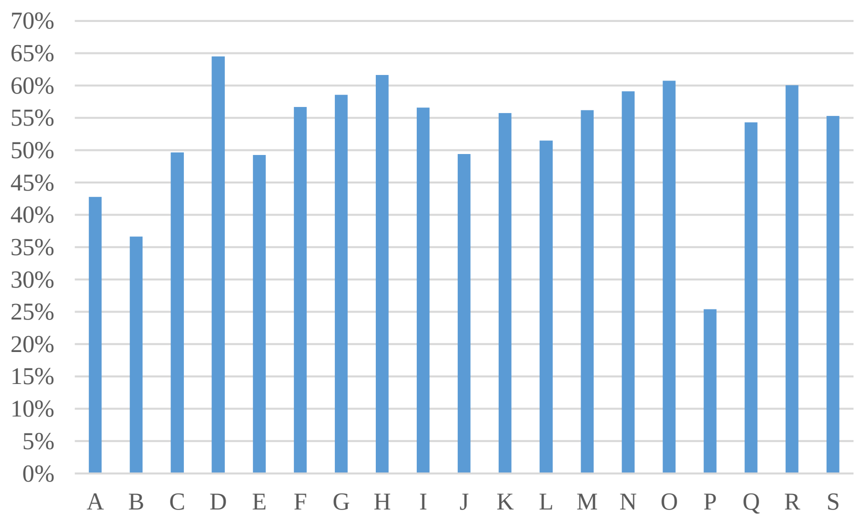
Table 2: Descriptive statistics of financial distress dummy

Independent variable	**Life cycle stage**		
	Mean	**Std. Deviation**	**N**
Introduction	0.7185	0.3434	134,444
Growth	0.4667	0.3769	689,090
Maturity	0.5809	0.3788	571,616
Shake-out	0.5080	0.3884	1,379,393
Decline	0.6471	0.3834	359,,090
Independent variable	**Country**		
	Mean	**Std. Deviation**	**N**
Czech Republic	0.4601	0.3837	421,616
Hungary	0.5182	0.3833	529,191
Poland	0.5257	0.3870	1,642,626
Slovakia	0.6511	0.3734	540,000
Total	0.5372	0.3877	3,133,,333

Source: Author

Figure 2 shows the average risk of financial distress by industry affiliation.

Figure 2 Average probability of financial distress by industry



Source: Author

On average, the riskiest businesses are category D Electricity, Gas, Steam and Air Conditioning Supply, which have almost a 65% risk of financial difficulties. On the contrary, businesses oriented to educational activities have a low financial distress, with only 25% facing financial difficulties. Agricultural and mining enterprises also show a below-average risk of financial distress. This refers to the strong position of these companies within the economies of Central European countries. Other industries show around a 50% probability of financial difficulties.

Table 3: Results of two- way ANOVA

Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	**Partial Eta Squared**
Corrected Model	261.865	93	2.8157	19.7740	0	0.056
Intercept	861.3812	1	861.3812	6049.1771	0	0.162
Life_cycle	14.62343	4	3.6559	25.6738	0	0.003
Industry	31.31331	18	1.7396	12.2168	0	0.007
Life_cycle * Industry	23.73883	71	0.3343	2.3480	0	0.005
Error	4448.322	31,239	0.1424			
Total	13752.03	31,333				
Corrected Total	4710.187	31,332				

R Squared = ,056 (Adjusted R Squared = ,053)

Source: Author

The analysis of variance itself was preceded by testing the assumptions of the model. First, the high variability of the subsamples according to the Life cycle dummy indicates a different than normal distribution of values, this assumption was confirmed based on the results of the Kolmogorov-Smirn test at the 0.05 level. The homogeneity of the Life cycle and Industry variable tested by the Levene test was not confirmed and the heterogeneity of the subsamples exists. Failure to meet these conditions makes it impossible to use the standard Two-way ANOVA model, the alternative is to use ANOVA with robust standard deviations, which reduces the occurrence of Type I error.

The results of the ANOVA model show that both factors as well as their interaction are significant at the 0.05 level. In other words, the risk of financial distress varies between industries within the stages of the business life cycle. The Industry factor has the highest explanatory power, almost 0.07%, on the contrary, the life cycle itself is only 0.03%. Partial Eta Squared confirms the assumption found from the analysis of descriptive statistics, i.e. there is a statistically significant difference in the probability of financial distress between industries. The life cycle itself also significantly differentiates firms from each other in terms of financial distress, but to a lesser extent than their industry focus. This fact also points to the fact that existing changes in industries as part of the onset of Industry 4.0 can significantly weaken some industries than others, which have a lower risk.

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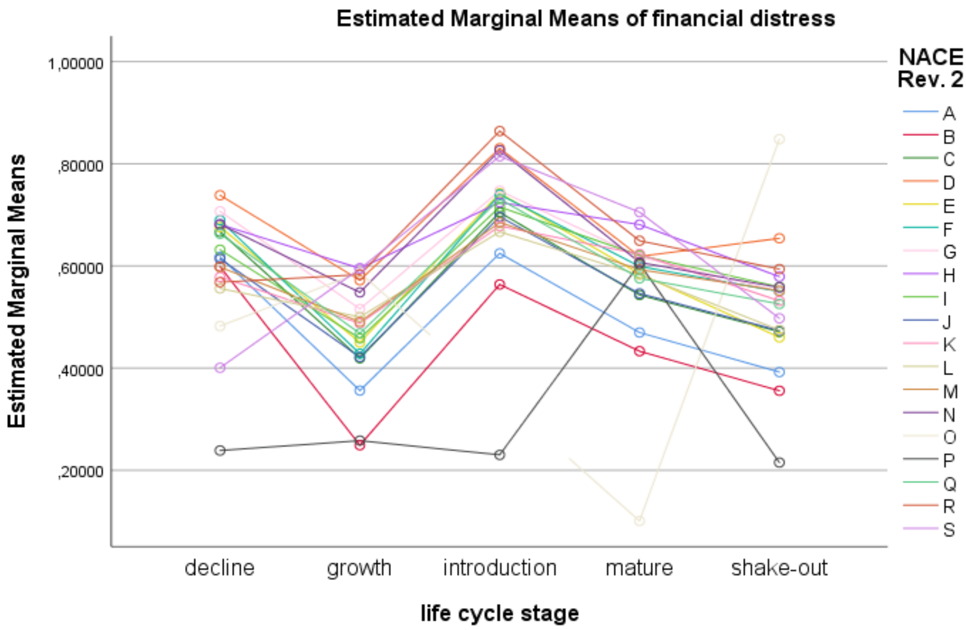
Figure 3: Interaction effect between Life cycle and Financial distress



Source: Author

The interaction between the Life Cycle and Industry factors is significant as illustrated in Figure 3, where the non-parallel lines show the interaction between the factors. The NACE P - Education sectors, as well as the NACE D sector and the NACE H - Transport and storage sector, differ significantly.

Table 4: Results of post hoc tests (shortened)

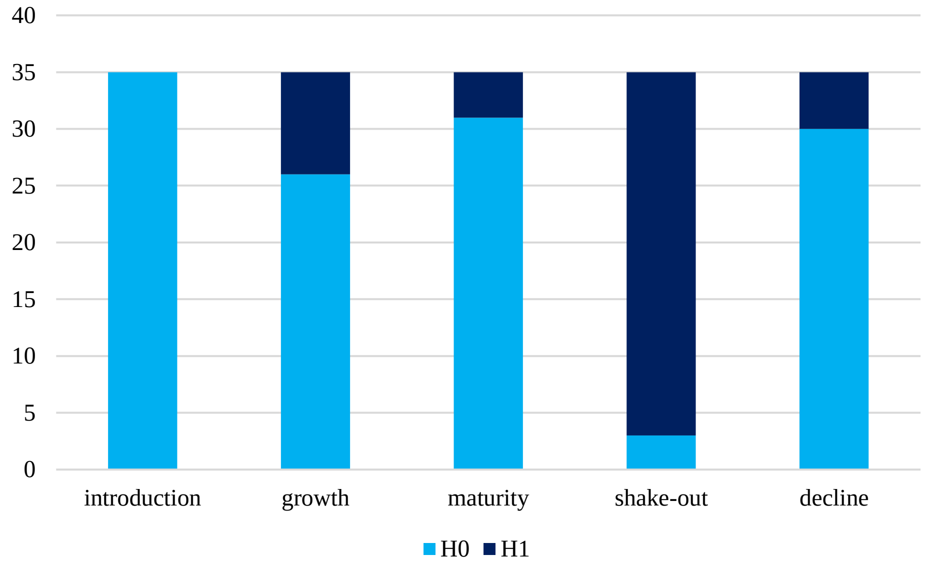
Pair difference		**Results of post hoc tests**				
		Life cycle stage				
NACE	**NACE**	**Introduction**	**Growth**	**Mature**	**Shake-out**	**Decline**
A	**D**	H0	H1	H0	H1	H0
A	**F**	H0	H0	H0	H1	H0
A	**G**	H0	H1	H1	H1	H0
A	**H**	H0	H1	H1	H1	H0
A	**I**	H0	H0	H0	H1	H0
A	**L**	H0	H1	H0	H0	H0
A	**M**	H0	H0	H0	H1	H0
A	**N**	H0	H1	H0	H1	H0
A	**R**	H0	H0	H0	H1	H0
B	**D**	H0	H0	H0	H1	H0
B	**H**	H0	H1	H0	H0	H0
C	**D**	H0	H0	H0	H1	H0
C	**G**	H0	H1	H1	H1	H0
C	**H**	H0	H1	H1	H1	H0
C	**P**	H0	H0	H0	H1	H1
D	**E**	H0	H0	H0	H1	H0
D	**G**	H0	H0	H0	H1	H0
D	**J**	H0	H0	H0	H1	H0
D	**L**	H0	H0	H0	H1	H0
D	**P**	H0	H0	H0	H1	H1
E	**P**	H0	H0	H0	H1	H0
F	**H**	H0	H1	H0	H0	H0

Pair difference		**Results of post hoc tests**				
		Life cycle stage				
NACE	**NACE**	**Introduction**	**Growth**	**Mature**	**Shake-out**	**Decline**
F	**P**	H0	H0	H0	H1	H1
G	**L**	H0	H0	H0	H1	H1
G	**P**	H0	H0	H0	H1	H1
H	**L**	H0	H0	H0	H1	H0
H	**P**	H0	H0	H0	H1	H0
I	**P**	H0	H0	H0	H1	H0
J	**P**	H0	H0	H0	H1	H0
K	**P**	H0	H0	H0	H1	H0
L	**P**	H0	H0	H0	H1	H0
M	**P**	H0	H0	H0	H1	H0
N	**P**	H0	H0	H0	H1	H0
P	**Q**	H0	H0	H0	H1	H0
P	**R**	H0	H0	H0	H1	H0

Source: Author

The mutual interaction between the factors conditions the testing of one of the factors as a simple main effect, i.e., in each subsample separately. The sample was therefore divided according to life cycle stages, and inter-industry differences were examined by the post-hoc test.

Figure 4: The prevalence of differences in the level of financial distress between industries within the life cycle



Source: Author

Table 4 and Figure 4 show the frequency of differences between the level of financial distress between industries within the life cycle of the enterprise. For the most part, there are no significant differences between the average level of financial distress between industries within the stages of the life cycle. Figure 4 shows the structure of post hoc test results in more detail. Within start-ups, the differences between industries in the probability of bankruptcy are small; the results of One-way ANOVA for start-ups pointed to the insignificance of Industry factor for these enterprises.

4. Discussion

The results of the variance analysis point to two important facts: firstly, the risk of financial distress is influenced by the life cycle of the company, where on average start-ups have the highest risk of financial distress, declining companies also have a similarly high risk. The risk of financial distress has an inverted u-shape during the life cycle, similar results were obtained by Akbar et al. (2019), Gulec and Karacaer (2017) or Akbar et al. (2021). Tian et al. (2015) found that indebtedness also has an inverted U-shape within the life cycle of the company, similarly, discretionary accruals also develop as an indicator of profit manipulation (Hussain et al., 2020; Durana et al., 2021; Can, 2020). It follows from the above that the development of financial indicators, including the risk of financial distress, is not static during the life cycle, but develops dynamically in accordance with the maturing of the company.

In the second row, the industry factor is an important factor of financial distress, but in interaction with the life cycle, its significance is not clear. All the startups studied had a similar risk of financial distress, regardless of industry. The growth stage is on average less risky than the Introduction stage, the higher risk of financial distress is shown by agricultural enterprises (NACE Rev. 2 class A). Mature and declining businesses, on the other hand, have similar risk of financial distress on average across industries; the influence of the industry was significant only in the comparison of four (five) pairs of industries. The opposite case to start-up companies are companies in the shake-out stage. These businesses have significantly varying risk of financial distress across industries, i.e., quantitative, and qualitative characteristics of the industry significantly affect their probability of bankruptcy. Some industries achieve lower risk on average and the shake-out stage is an extension of the maturity of the business. Other industries, on the other hand, are riskier and move from the stage of maturity to the stage of Decline more quickly.

A similar position of start-ups is of great importance precisely for the onset of Industry 4.0. The principles of Industry 4.0, such as the Internet of Things, Digital Twins or digitization of industry, are mainly implemented by young innovative companies, i.e., start-ups. The results imply that state support for the introduction of these new principles should be similar in all sectors.

5. Conclusions

The current economic environment is subject to many changes, including the onset of new technologies in the industry, such as digitization of the production process, virtual reality or the Internet of Things. All these factors have a turbulent effect on the performance of enterprises, including their financial health and the risk of financial distress.

The aim of this study was to investigate and evaluate the impact of industrial classification and life cycle on the risk of financial distress of Central European enterprises. The financial data of more than 30,000 enterprises from the emerging markets of Central Europe for the year 2019 were examined. Using the non-sequential Dickinson (2011) model, it was found that the risk of financial distress develops in accordance with an inverted U-shape like other financial factors (indebtedness, earnings manipulation). The industry factor has a significant impact on the emergence and growth of financial distress; in accordance with the subject of business, this risk changes. From the point of view of individual stages of the life cycle, the most significant differences in the risk of financial distress occur in shake-out companies.

The results of the study point to the need for a more detailed examination of the risk of financial distress within the life cycle of the company. In the light of the advent of new Industry

4.0 technologies, it is necessary to distinguish not only industries, but also the life cycle of companies for better understanding and predicting the emergence of financial distress.

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