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Financial threat profiles of industrial enterprises in Poland

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Keywords: *financial threat; bankruptcy; early warning systems; risk management; enterprise crisis*

Abstract

Research background: The nature of bankruptcy has been the subject of interest for economic theories, both positive–identifying relationships between bankruptcy and other economic categories — and normative, shaping the rules for the proper regulation of bankruptcy. In turn, the

functioning of an enterprise in conditions of risk, financial threat, and finally a crisis that could lead to bankruptcy, are of interest to management. The interpenetration of these two dimensions provided the motivation for this study, which assumes a bottom-up approach: from individual results to summarised multi-sectional comparisons.
Purpose of the article: The purpose of the research was to evaluate the level, directions of change, and structure of the degree of financial threat in industrial enterprises. The period under analysis was 2007–2018 and the whole population of industrial enterprises in Poland (15,999 entities) was examined. The enterprises were small and medium-sized enterprises (SMEs) as well as large enterprises (LEs). The financial analysis covered macro-, meso-, and microeconomic levels.
Methods: The analysis was conducted using a comparative approach and financial threat predictions obtained from the original multivariable logit model. Heat maps were used to evaluate the intensity of changes in financial threat. The displacement of objects in structures was studied, ordered, and classified. Four normative standards of threat scenarios were defined and then used to evaluate similarities in the profiles of the structures examined, using the similarity measure. The ranking and its variability were analysed in the assessment of profiles.
Findings & value added: As the result of the research, properties were described and profiles were determined for the structures in terms of the degree of threat and its correlation with rate of bankruptcy and creating added value. The originality of the research comes from the use of novel dynamic logit models. The added value is a unique study on the entire population of industrial enterprises in the national economy and a methodology for identifying financial threat profiles and their similarity at subsequent aggregation levels (the micro-, meso-, and macro-levels). This made it possible to derive patterns and regularities for economic policy and guidelines for business management.

Introduction

The epistemological view adopted in this paper is that enterprises exist to obtain financial effects (the first principle). This view is not universally accepted, however, as the effects of an enterprise's development can vary, especially in terms of the concept of sustainable development and value creation. Still, the financial results underlying Rappaport's theory of value (Rappaport, 1998) are of key importance, as stakeholders' expectations are taken into account only so far as they contribute to improving financial outcomes for the stakeholders. The second principle is the ability of an enterprise to operate under risk conditions. In particular, an aggressive finance management strategy may lead an enterprise to insolvency. Then, it is close to crisis and bankruptcy. Such a threat should be signalled by an early warning system.

This study was driven by certain identified research gaps (the gaps relate both to the international literature and specifically to empirical studies for Polish economy):

1) The theoretical gap is the absence of identified regularities between the financial threat and the affiliation to structures according to the size and aggregation level of an enterprise (i.e. micro-, meso-, or macro-level).

2) The reduction of the methodological gap consists in estimating the threat prediction model with innovative statistical techniques (i.a. non-informative prior distribution put on classic logistic regression as a variant of Bayesian inference, case-control technique). It also means the methodology for identifying and measuring threat profiles similarity, ordering and classification of objects (i.e. structure elements) using ranking as well as normative patterns.
3) The empirical gap is the lack of financial threat studies for the whole population of Polish enterprises. The reduction of this gap came from identifying universal regularities. In terms of application, individual firms may use this methodology to create their own early warning systems.

The subject matter of the research presented in this paper is the identification and quantification of the symptoms of industrial enterprises' deteriorating financial situation. The main scope of the research is focused on evaluating changes in the degree of financial threat of enterprise (i.e. threat of going concern and bankruptcy). The key research problem considered in the paper is the identification of the financial threat profiles of small, medium-sized, and large enterprises and the assessment of their similarity at subsequent aggregation levels.

The core of and value added by the research is the development of tools and their application to the entire population of enterprises in the national economy; this contrasts with the research typically encountered in the literature, which is based only on non-random samples of the population. This opens the way to deriving regularities and patterns at broader levels of aggregation — from microeconomic to meso- and macroeconomic.

The research covered the whole population of industrial enterprises in Poland (15,999 companies). The analysis was based on individual data collected in public statistics (with the protection of statistical confidentiality). The research covered three groups of enterprises: small, medium-sized, and large. The structural cross-sections included the macro-, meso-, and microeconomic level. The period under analysis was relatively long, covering twelve years (2007–2018). The results are compared with two turning points (economic slowdowns), i.e. 2008–2009 and 2012–2013.

The main specific purposes of the research were: 1) to measure and assess the degree of threat, as well as the directions and dynamics of its changes, 2) to determine and classify the features of the study population in terms of object displacement, 3) to make a comparative analysis of the structures profiles, and 4) to evaluate the strength and direction of mutual changes in the degree of threat and bankruptcy.

In the course of the research, the following research hypotheses were formulated and verified:

H1: *At the macrostructure level, manufacturing plays the leading role in determining the degree of threat to industrial enterprises, demonstrating the greatest stability of the financial situation, which applies to large enterprises to a greater extent than to SMEs.*

H2: *The mesostructure profiles for small, medium-sized, and large enterprises vary with regard to the average rank position and its variability (in terms of the degree of threat).*

H3: *An incompatibility of profiles, described by the difference between the normative pattern for small and medium-sized enterprises and for large enterprises at the mesostructural and microstructural levels produces opposite assessments for SMEs and large enterprises.*

H4: *There is a correlation between the direction of the degree of threat changes and the percentage of bankruptcy court proceedings of industrial enterprises, with the recognition of the number of bankruptcies as a potential barometer of economic conditions.*

This paper consists of six parts. The introduction (the subject, scope, and goals of the research and the hypotheses) is followed by a review of the literature in the field of enterprise crisis determinants and symptoms, as well as early identification of threat situations. The methodological part presents the estimation method used in the model for evaluation of threat prediction and the identification and assessment of its profiles. The results are presented in the fourth part, across macro-, meso-, and microstructures, and further discussed. The research conclusions, limitations, implications for practice, and directions for further research are included in the conclusion.

Literature review

Determinants and symptoms of enterprise crisis

In macroeconomics, crisis is a phase of the business cycle and the effect of the economic growth fluctuation — recurring and irregular. The explanation of those fluctuations has been addressed by many economic theories, such as monetary (M. Friedman), innovation (J. A. Schumpeter), overinvestment (F. A. von Hayek), psychological (A. C. Pigou), or political theory (W. D. Nordhaus). In microeconomics, the theory of business enterprise defines crisis in various ways. It has been described as a result of unplanned disturbances or events that threaten the normal operation of an enterprise. Crisis may be perceived as an intensification of adverse phenomena or as the process of adverse changes in the course and results of economic activity. C. K. Prahalad and G. Hamel identify a crisis as a breakthrough between enterprise growth phases within life cycle phases.[1]

Enterprises operating in the economy are affected by regulatory bodies and are threatened by crisis situations caused by external factors emerging in closer business surroundings (microeconomic) and further surroundings (meso- and macroeconomic). A characteristic feature of enterprise crisis is its complexity and the fact that it is usually triggered by a combination of several factors forming a series of events, with an evident escalation path, being a consequence of failing to take remedial action. Crisis factors vary in their type and source. R. Kaplan and D. Norton highlight the role of limited activity in the area of strategic management, a missing relationship between the motivation system and goals, and a lack of understanding of the strategy's vision and objectives (Kaplan & Norton, 2006). C. F. Smart, W. A. Thomson, and I. Vertinsky drew attention to competitive and environmental factors, management features, and organizational attributes (Smart *et al*., 1978). P. F. Drucker emphasised market failures of products, flaws in the management information system, and management's inefficiency and routine (Drucker, 2010). S. Slatter and D. Lovett, on the other hand, refer to deteriorating market conditions, competition, prices, inappropriate financial control, high costs, poor marketing, overinvestment, and the acquisition policy (Slatter & Lovett, 1999, p. 46). Many enterprises going bankrupt demonstrate a prevalence of endogenic factors — mostly errors in management hidden behind a veil of profitability with simultaneous shortages in financial resources (Altman, 1993; Argenti, 1976). Failures in those areas and functions of an enterprise that can be read from its overall condition — mainly economic and financial — are assumed to be symptoms of enterprise crisis. The problem, however, is that the crisis in the enterprise is often easier to sense than to quantify (Obłój, 1987).

[1] J. Argenti as well as O. P. Kharbanda and E. A. Stallworthy described the basic types of the enterprise life cycle (Kharbanda & Stallworthy, 1985, p. 19; Argenti, 1976, p.149). L. E. Greiner distinguished the phases of its development and subsequent crises (Greiner, 1972).

An enterprise crisis may produce two types of effects: negative, leading to a possible bankruptcy, and positive, threatening its existence but becoming a chance for development. This was highlighted by L. E. Greiner and W. H. Stahehle, who stated that enterprises develop through crises. The state between stability and chaos is normal and desirable, providing highly effective enterprise operation (H. von Foester's concept of order derived from chaos).

Early recognition of enterprise threat situations

In practice, it is important not only to be able to counter crises, but also to anticipate and prevent them (Quinn & Cameron, 1983). Therefore, an enterprise should create and use solutions that enable the diagnosis of crisis symptoms, e.g. by developing early recognition and early warning systems (EWSs) (Cabała, 2008). Those systems are tools for risk optimisation (Crocford, 1982; Hudáková & Dvorský, 2018) and constitute an element of evaluating the enterprise's economic and financial situation, yet they do not indicate remedies (Altman & Narayanan, 1997; Platt & Platt, 2002). The threat identification in EWSs uses numerous tools of technical economic and financial analyses, as well as statistical methods. The resulting measures quantify early warning signals. According to Ansoff, EWSs use three types of information: alarm signals, deviations from norms, and weakly structured signals (Lam, 1985; Ansoff, 1985). In practice, financial ratio analysis (Valaskova *et al.*, 2018), scoring models, and multi-criteria models (quantitative and qualitative measures) have been used most often. It is also possible to use EVA (Economic Value Added), SVA (Shareholder Value Added), and MVA (Market Value Added) concepts. Those categories describe value creation as the measure of enterprise effectiveness. Studies on the Polish economy, however, have demonstrated a lack of a significant relationship between the above-mentioned measures and the degree of financial threat (Kaczmarek, 2014).

The early history of the development of econometric modelling in enterprise financial threat prediction can be found in the works of W. Rosendale (1908, as cited in Beaver, 1968) and P. J. Fitzpatrick (Fitzpatrick, 1932, as cited in Winston *et al.*, 1997) (comparison in pairs, case–control for threatened and non-threatened enterprises). C. L. Merwin (Merwin, 1942, as cited in Back *et al.*, 1997) used methods of profile analysis, while W. H. Beaver (1968) researched the validity of using financial ratios in threat prediction. Those studies were continued by P. Weibel (1973, p. 125), who showed that an increase in the number of explanatory variables might not lead to significantly better results in threat assessment. The work of those authors mostly involved one-dimensional methods, while the further developments in the literature focused on multidimensional threat prediction methods. The methods of multidimensional discriminative analysis and logistic regression are prevalent here. They can help not only in determining whether there is a financial threat, but also in determining its probability. The pioneer in using multidimensional discriminative analysis was E. I. Altman, who developed a number of models (Z-score indicator) for listed and over-the-counter companies, for developed and emerging markets (Altman, 1993).

The further development of methods of threat prediction was influenced by many researchers representing different approaches and schools, which Prusak (2005, pp. 129–172) investigated and systematised in his work. Also, in Poland since the beginning of the 1990s progress has been made in threat modelling, as in other Visegrad group countries, yielding many proposals based on discriminant analysis, logistic regression, and neural networks (Kliestik *et al*., 2018).

Research methodology

Estimation of logistic regression model and statistical tools

The models for evaluating the degree of threat which are available in the Polish literature revealed the need to develop a new model. In general, the major disadvantages of the available models were basing their estimations on data from before the 2008 crisis and on small training data sets, usually no more than tens of enterprises (Prusak, 2005, pp. 129–172; Antonowicz, 2007, pp. 32–39; Juszczyk, 2010). The small sample sizes may cause a significant overestimation of those models' predictive abilities as well as overall instability. Also, this study does not include models built for foreign enterprises that can be found in the literature (Kovacova *et al*., 2019). Given the significant differences in business models, sizes, structures, efficiency of capital and asset use, and in the nature of competitive business surroundings and legal and regulatory surroundings, it can be safely assumed that such models would have a non-optimal structure (Svabova & Durica, 2019).

Discriminant models and logistic regression models are classic tools for predicting the degree of financial threat (Jajuga, 2006). However, when compared to newer-generation methods (such as neural networks or random forests) they are more transparent and their results are easier to interpret and compare. In addition, those models in many cases achieve a comparable predictive ability in the subject area being studied (Hafiz *et al*., 2018). Other advantages of the logistic regression model are the lack of assumptions on the probabilistic nature of explanatory variables and a user-friendly interpretation of the estimated model parameters. Therefore, the Firth logistic regression model, which is a modification of the classic logistic regression model, was used in this research. The parameter estimates in this model are almost unbiased, while the confidence intervals have improved probabilistic properties.

Logistic regression is a commonly used tool for binary data analysis that is most often used to evaluate the effect of independent variables on an event's probability (Long, 1997, pp. 56–68), which in this case is understood as a declaration of bankruptcy by an enterprise within one year of its current financial condition being determined. In the classic logistic regression model, it is assumed that the dependent variable $y_i \in \{0,1\}$ $(i = 1, \dots, n)$ is subject to Bernoulli distribution with $F(x_i'\theta)$ probability of success, where F is a distribution function of the following logistic distribution:

$$F(x_i'\theta) = \frac{1}{1 + exp\left[-x_i'\theta\right]} \tag{1}$$

where x_i is a p-dimensional vector of explanatory variables including the intercept and $\theta \in \mathbb{R}^p$ is a p-dimensional vector of parameters.

In order to estimate the model's parameters, the logarithm of the likelihood function is determined, and then its partial derivatives are calculated in regard to $U(\theta)$ model parameters. Calculating the solution of the $U(\theta) = 0$ system of equations is equivalent to finding the vector of estimates θ_{ML}, maximizing the likelihood function. The θ_{ML} vector is obtained using an iterative procedure. In the case of the Firth logistic regression model, the $U(\theta)$ function is replaced with the following modification:

$$U^*(\theta) = \sum\nolimits_{i=1}^{n} \left(y_i - F(x_i'\theta) + h_i(\frac{1}{2} - F(x_i'\theta))\right) x_i \tag{2}$$

where: h_i are diagonal elements of $H = W^{\frac{1}{2}}X(X'WX)^{-1}X'W^{\frac{1}{2}}$ matrix, X is the data matrix, and W is an $n \times n$ diagonal matrix whose i-th diagonal element is equal to $F(x_i'\theta)(1 - F(x_i'\theta))$.

The modification of the $U^*(\theta)$ system of equations is equivalent to the modification of the $L^*(\theta) = L(\theta)|I_\theta|^{1/2}$ likelihood function, where I_θ is an information matrix, while the $L^*(\theta)$ function is called the penalized likelihood function. It can be assumed that the Firth logistic regression model, despite being introduced on the basis of classical statistical inference, has a Bayesian representation. It is equivalent to the classic logistic regression model with Jeffreys' non-informative prior distribution put on its parameters (Firth, 1993; Fijorek & Sokołowski, 2012).

In order to create a training data set for the model estimation, a set of enterprises that went bankrupt (cases) was first gathered, and then assigned with enterprises that were not threatened with bankruptcy (controls) using the case–control method (Hosmer & Lemeshow, 1989, pp. 145–162). It was assumed that each bankrupt firm would be matched by ones not threatened with bankruptcy, being similar in terms of value of assets, net sales revenues, legal and organisational form, and type of business activity — in this case manufacturing. In addition, in order to allow for macroeconomic environmental factors, financial data for the paired enterprises were taken from the same calendar year. In practice, '1-to-1' matching was used, but from the perspective of statistical effectiveness it is justified to use even '1-to-5' matching. As the result of incomplete data elimination and after the introduction of the above-mentioned pairing criteria, the final training set included 207 bankrupt and 916 non-bankrupt enterprises. Thus, an approximate ratio of 5 controls to 1 cases was achieved. The declaration of bankruptcy, i.e. an initiation of bankruptcy court proceedings, was adopted as the classification criterion for the cases.

The initial model incorporated a set of 24 standard financial ratios from the areas of productivity, liquidity, financing structure, profitability, debt, and efficiency. In addition to explanatory variables in the basic form, their non-linear functions and higher-order interactions were examined. The modelling stage was preceded by an analysis of one-dimensional distributions of explanatory variables. Those distributions were analysed based on both their numerical descriptive characteristics (average, deciles, and dispersion measures) and graphs (histograms and box plots). In addition, the analysis of explanatory variable correlation was conducted (financial ratios), in order to determine groups of interrelated variables. The optimal set of explanatory variables constituting the final logistic regression model was established using the best subsets method (models including a maximum of eight explanatory variables were taken into consideration). The Akaike Information Criterion (AIC) was a goodness-of-fit metric. The model prediction abilities were measured with sensitivity, specificity, and area under the curve (AUC). Given the values of those measures (AUC=89%), it was found that the model was highly predictive, which made it an adequate tool for conducting the research on the degree of financial threat in industrial enterprises, presented further in this paper. The estimated model, called

DFTP, is presented in Table 1. The degree of financial threat determined by the DFTP model can analyse changes (direction and intensity) in the financial condition of enterprises and their groups treated as objects (elements of structures), both in static and dynamic approach.

This study uses a number of additional statistical tools in addition to the logistic regression model described above (DFTP). Heat maps were used to assess the intensity of the changes in the objects under analysis. The study on object displacements in selected structures was conducted using the ranking method. Time series of given object ranks were determined by their average ranking position (ARP) and variability of ranking position (VRP), with the standard deviation serving as its measure. Four normative patterns of threat situation were defined and used to evaluate the similarity of examined structures using the probability measure. Using those two criteria, the objects were classified (according to DFTP) as follows:
- pattern 1 – high and stable position,
- pattern 2 – high position with significant variability,
- pattern 3 – low and stable position, and
- pattern 4 – low position with significant variability.

The defined patterns and criteria for their distinction (average ranking position and its variability) were used in the analysis of differences between the examined structures' profiles. The assessment of interdependencies of events (time series) was conducted using Pearson's correlation coefficient (r). The description of results also employed standard descriptive statistical measures: mean, median (5th decile—D5), minimum, maximum, measure of differentiation (MDF=(D9-D1)/2), standard deviation, coefficient of variation, decile distribution, and interdecile ranges.

Scope and structure of the data

The research covered the entire population of industrial enterprises in Poland (15,999 companies). The analysis was based on individual data collected from public statistics by Central Office of Statistics (*Główny Urząd Statystyczny*) in Warsaw (specific databases for the purposes of this project), where enterprises are classified by size:
- small and medium-sized (between 10 and 249 employees):
    a. small (between 10 and 49 employees)
    b. medium-sized (between 50 and 249 employees)
- large (250 and more employees)

The results presented in this paper meet the principles of statistical confidentiality. The analysis does not cover micro-enterprises (up to 9 employees), as the public statistics lack adequate figures for studying the degree of threat on their entire population.

Besides the division into enterprise size classes, the structural analytical ranges include three levels:
- macroeconomic (PKD sections),
- mesoeconomic (PKD divisions), and
- microeconomic (PKD classes).

In the paper, the macroeconomic level covers four Polish Classification of Activities (PKD—*Polska Klasyfikacja Działalności*) sections; the analysis at the mesoeconomic level was conducted in relation to 34 PKD divisions (from 05 to 39); and at the microeconomic level 262 PKD classes were used.

In addition to individual public statistics data, the analysis also used two commercial databases: *Pont Info – System Gospodarka SŚDP* (http://www.pontinfo.com.pl) and *Raport wniosków o upadłość, Coface Polska* (http://www.coface.pl). Additional data sources included *Monitor Sądowy i Gospodarczy, Ministerstwo Sprawiedliwości* (http://www.ims ig.pl), *Wyniki finansowe przedsiębiorstw niefinansowych, GUS Warszawa* (http://stat.gov.pl/publikacje), and *Podmioty gospodarki narodowej, GUS Warszawa* (http://stat.gov.pl/publikacje).

The analysis period is 2007–2018, which provides comparable, up-to-date knowledge on the results of industrial enterprises economic activity. The start of the analysis period (2007) was determined by changes introduced by Statistics Poland in the economic activity classification (PKD 2007 standard), which made information and figures from before this year incompatible. The results of the analysis were compared with two turning points, i.e. the real economic slowdowns (recessions) of 2008–2009 and 2012–2013.

Research results

Degree of financial threat in terms of size and activity type

Since 2007, the operation of small and medium-sized enterprises has been characterised by unfavourable and similar degrees of threat, with a relatively high level and apparent upward trend, a relatively average amplitude of annual fluctuations, a peak in 2018, and two turning points in 2012 and 2015. Small enterprises always demonstrated positive deviation of the degree of threat from the value for all enterprises (+7.0% on average). This deviation for medium-sized enterprises was only slightly smaller (+6.5% on average), and was negative in 2007 and 2008.

While small and medium-sized enterprises experienced a strong increase in the degree of threat until 2012, large enterprises performed better, recording less threat. The situation was not permanent, however, and those enterprises entered the path of gradual increase — even in terms of the rate — of threat (APC=2.0%).[2] The average deviation for SMEs from the value for all enterprises was negative (-4.0%), and only slightly positive in 2008. The correlation with the overall degree of threat curve was very high for large enterprises (r=0.90, p-value=0.000…<α=0.05).

In terms of enterprise size classes, the overall degree of threat (sales revenues as weight) is predominantly associated with large enterprises (58.5%), while medium-sized (25.8%) and small (15.7%) enterprises each have a smaller share (Fig. 1, left panel).

When looking at activity types, it can be seen that there is a relatively high and successively increasing (APC=4.0%) degree of threat for service enterprises: their position deteriorated from 2007 to 2018 by as much as 53.8%. On the other hand, the lowest values were found for manufacturing enterprises. The increase in their degree of threat was 17.9%, which was one percentage point higher than in trade enterprises.

While relativizing the assessment of absolute values, it should be noted that the overall degree of threat (sales revenues as weight) among activity types again highlights the dominant position of manufacturing (48.2%), followed by trade and services (34.2% and 17.6%, respectively). In the case of manufacturing, correlation with the overall degree of threat curve exceeded a high level (r=0.77, p-value=0.003<α=0.05) (Fig. 1, right panel).

The direction of changes in the degree of financial threat according to size reveals characteristics in manufacturing which differ from the entire sector. Those changes were less intensive — the average annual rates of changes for small and medium-sized enterprises did not exceed two per cent — and were even lower for large enterprises (APC=1.4%). After a period of increase lasting until 2012, small enterprises started following a path of changes similar to medium-sized enterprises, decreasing the degree of threat in the medium-term. Meanwhile, large enterprises since that year have been demonstrating successive increases in threat and have come closer to the level specific of small and medium-sized enterprises (Fig. 2).

To conclude the qualitative assessment, it can be argued that despite expectations, small and medium-sized enterprises did not demonstrate greater

[2] This rate was calculated using the formula $APC = \left(\sqrt[n-1]{\frac{x_n}{x_1}} - 1\right) \cdot 100\%$.

flexibility in response to deteriorating economic conditions in 2008–2009 resulting from the previous financial crisis. Their degree of threat increased (or remained high for medium-sized enterprises) until the end of the second period of economic slowdown, i.e. 2013.

The general characteristics of the degree of financial threat outlined above show the similarity between the features of small and medium-sized enterprises, which justifies carrying out future analysis with the enterprises divided into two main groups: small and medium-sized enterprises (SMEs) and large enterprises (LEs).

Descriptive statistics of examined populations

In small and medium-sized enterprises, the mean DFTP value in the period 2007–2018 increased by 19.5%, and that of the 9th decile (D9) by 35.4%. Therefore, the direction of changes for enterprises of a relatively high, average safety level was compatible, but the situation deteriorated more in the former case. There was an increase in measure of differentiation value (MDF=+37.9%), which represented the range between D9 and D1, due to the faster growth of the former. The variability level also increased (SD=+31.6%), whilst the correlation with the mean was weak and statistically insignificant. Distribution function (rk/rp) was shifted in plus, as the values of all deciles increased, at most D9. All interdecile ranges expanded, thus differences between enterprises classified into individual deciles increased. The decile distribution indicates relatively high D9 values, which determine the mean value located high between the seventh and sixth deciles. Thus, the results of weak enterprises at slightly over 30% ‘balance’ the results of almost 70% for better enterprises, determining the mean (Fig. 3).

In general, the DFTP descriptive statistics for large enterprises in the period 2007–2018 were different in their nature and meaning from the statistics of small and medium-sized enterprises. Firstly, the direction of changes in enterprises with the highest (D9) and the average level of safety was not only compatible, but also shared similar dynamics (15.6% and 16.9%, respectively). Secondly, the measure of differentiation (MDF) and variability level (SD) values were much lower than in small and medium-sized enterprises, and their changes were definitely weaker (+8.5% and -5.9%, respectively). Thirdly, the distribution function (rk/rp) was also shifted towards the positive, as the values of all deciles increased, but the lowest ones increased the most. All interdecile ranges expanded (again, the lowest ones the most), while the highest one (D9–D8) shrank. As with small and medium-sized enterprises, the mean was located between the seventh and sixth deciles, but the value range between D9 and D8 was not significantly wider than the others (Fig. 4).

Macrostructure characteristics (PKD sections)

In terms of the macrostructure (PKD sections), the most stable situation was observed in Manufacturing (section C). Small and medium-sized enterprises recorded a decrease in the degree of threat beginning in 2012 (followed by a slight increase), while large enterprises appeared more stable and long-lasting as far back as 2009.

The observation for Mining and Quarrying (section B) reveals a different picture: a strong negative response to deteriorating operational and economic conditions, followed by an improvement. The relationship between the degree of threat changes in large enterprises and a governmental program which restructured the industry (incorporating hard coal mines into energy companies) is clear, especially when it comes to the situation of large enterprises (in addition to hard coal and lignite mining, it is affected by non-ferrous metal mining, especially copper). It is not, however, that section D (Electricity, Gas, Steam, Hot Water, and Air conditioning manufacturing and supply) is free of problems and can absorb the costs of restructuring the hard coal mining industry. The situation of those enterprises has been gradually deteriorating for many years — the degree of threat increase in small and medium-sized enterprises amounted to 122.8% (APC=7.6%), while in large enterprises it was 38.0% (APC=3.0%).

The deterioration of the situation in small and medium-sized enterprises also related to section E (Water Supply, Sewerage, Waste Management, and Remediation Activities). Despite the fact that the threat has not increased in recent years, its cumulative value for 2007–2018 was significant (45.8%). Large enterprises recorded greater fluctuations, which translated into a lower increase in the threat level (13.4%) (Fig. 5).

In summary, the findings made in this part of the analysis justify a general conclusion expressed by Hypothesis H1. The first hypothesis is considered to be verified.

Classification of mesostructures

In terms of mesostructure (PKD divisions), the results of spatial analysis in the class of small and medium-sized enterprises indicate a relatively high degree of displacement in the PKD divisions, measured by the variability of their ranking in regard to DFTP. This figure was slightly higher until 2012 (by 13.2%), which gave the mesostructure greater stability. The displacement was at a similar level in separate parts of the set of PKD divisions (initial, middle, and final).

Areas with a similar degree of financial threat can be indicated through a cumulative assessment of average rankings and their variability. The first pattern (high position) incorporated 25.8%, the second 19.3%, the third 32.3%, and the fourth (low and variable position) 22.6% of PKD divisions. Therefore, firstly, the third pattern is predominant (low and stable position — positive, moderate assessment), as well as a dominance (58.1%) of PKD divisions characterised by below-average variability in their ranking in the mesostructure, which gives it a feature of relative stability (Fig. 6).

The general finding regarding the assignment of PKD divisions to patterns distinguished in accordance with the average ranking and its variability is the different composition of the list of PKD divisions assigned to the first pattern (high and stable position in terms of the degree of financial threat). On the one hand, they represent traditional industries (Manufacture of Metals; Manufacture of Fabricated Metal Products, Except Machinery and Equipment; Manufacture of Products of Wood and Cork, Except Furniture; and Manufacture of Paper and Paper Products), but on the other hand, more modern, constituting a modern cooperative network (Manufacture of Motor Vehicles, Trailers and Semi-trailers; Manufacture of Other Transport Equipment). However, it should be taken into account that enterprises in the latter group are primarily suppliers of components for finished product assemblies. A detailed analysis of these problems may constitute the subject of further research (Table 2).

Among large enterprises, the degree of displacement of PKD divisions, as assessed by the variability of their ranking in the DFTP, was 16.4% lower than in small and medium-sized enterprises; likewise, the average ranking was 7.9% lower. In addition, there were no differences in ranking variability before and after 2012, as was the case for small and medium-sized enterprises. Larger displacements occurred in the final and initial parts of the set of PKD divisions, but more weakly than in small and medium-sized enterprises. Therefore, in general the mesostructure of those enterprises should be assessed as being more stable.

For large enterprises, the first normative pattern incorporated the most PKD divisions, namely 32.3% (high and stable position — strongly negative assessment), the second 16.1%, the third 22.6%, and the fourth 29.0% (low and variable position). Therefore, as with small and medium-sized enterprises, PKD divisions characterised by above-average, high stability of their ranking in the mesostructure dominate (54.9%, thus slightly lower). The smallest representation of PKD divisions can be observed in the fourth pattern (as with small and medium-sized enterprises) (Fig. 7).

Unlike in small and medium-sized enterprises, the composition of PKD divisions assigned to the first pattern (high and stable position) is not strongly diversified by type, and traditional industries prevail (e.g. Manufacture of Products of Wood and Cork, Except Furniture; Manufacture of Fabricated Metal Products, Except Machinery and Equipment; and Manufacture of Tobacco Products). The modern ones appear more often on the lists of the second pattern (e.g. Manufacture of Computer, Electronic, and Optical Products; Manufacture of Motor Vehicles, Trailers, and Semi-trailers) and the fourth pattern (e.g. Manufacture of Basic Pharmaceutical Substances and Medicines and Other Pharmaceutical Products). In general, the degree of similarity in the lists of PKD divisions (the number of the identical divisions) assigned to individual patterns in small and medium-sized enterprises, as well as in large enterprises, is low or very low (pattern 1–5 out of 18, pattern 2–1 out of 11, pattern 3–6 out of 17, and pattern 4–4 out of 16), which is an incentive for further research (Table 3).

The conclusions made above regarding the assessment of mesostructures lead to a general opinion in support of the second hypothesis (Hypothesis H2).

Profiles of the degree of financial threat

When analysing the profiles of both mesostructures in terms of the average ranking and its variability (in regard to DFTP) for each PKD division according to enterprise size — small and medium-sized or large — they seem quite similar. However, it should be noted that the average ranking for large enterprises is lower than for small and medium-sized ones — by 7.9% on average. This feature is associated with the lower variability of rank, measured by average standard deviation, which is lower for large enterprises than for small and medium-sized enterprises (16.4% lower on average) (Fig. 8).

The similarity among the examined mesostructures can be evaluated by analysing deviations in the average ranking and its variability between small and medium-sized and large enterprises.

There was a positive deviation in the average ranking for 23 of the 31 PKD divisions analysed. Most of them were located within the range of +3.0 (20 PKD divisions). Negative deviations were observed in the remaining 8 PKD divisions (including 6 within the range of 3.0); therefore, in no case was the profile of these mesostructures the same. Given the variability in the ranking, positive deviations occurred for 20 PKD divisions and negative ones for the remaining 11. The majority of them were in the range of -3.0 to +3.0. Also, in the case of this measure there were no identical profiles. The dominance of the number of positive deviations in both measures indicates the mesostructure of large enterprises as characterised by less variability in object displacement (a greater permanency profile) (Table 4).

The use of normative patterns for PKD divisions, simultaneously distinguished in terms of the ranking and its variability (with regard to DFTP measure), allows for a comparison of the compatibility of profiles for each class of enterprise size. Such compatibility was observed in the case of 19 PKD divisions (61.3%), while it was non-existent in the remaining 12 PKD divisions; thus, the compatibility was low (Fig. 9).

The incompatibility described by the difference between patterns for small and medium-sized and large enterprises in 6 PKD divisions was a positive difference; the number of negative differences was the same (6). Out of the 6 positive pattern differences, none was clearly negative (from pattern 4 to 1), nor mixed (from pattern 3 to 2). Therefore, all of them indicate a deteriorating position in terms of one of the two criteria for pattern distinction (average ranking or its variability). The evaluation of 6 negative differences was similar — all of them reflect a better position of one of the criteria (Table 5).

The balance of positive and negative differences between patterns for the examined mesostructures of small and medium-sized and large enterprises does not justify the claim that any of them is more favourable. In some regards, the mesostructure of small and medium-sized enterprises may be backed by less representation in the first pattern, representing the worst results. On the other hand, the mesostructure of large enterprises is characterised by the largest representation in the fourth pattern (a positive, moderate assessment). However, given the lower average ranking (7.9% lower) and its lower variability (16.4% lower) for the mesostructure of large enterprises, it can be granted a slightly more favourable general assessment. Of course, it may be argued that the lower variability of rankings is a reflection of less flexibility in business activity, so this may be regarded as a negative feature.

DFTP evaluation in terms of PKD classes (microstructure) requires an extended analysis, as well as the development of appropriate methodology, which shall determine the direction of further research. It is worth presenting here some general conclusions resulting from the comparison of normative patterns (including the average ranking and its variability) which are specific for small and medium-sized and large enterprises. Firstly, the level of pattern compatibility was low: it related to only 38.6% of PKD classes, which can be evaluated as a lack of similarity.[3] Secondly, in terms of pat-

[3] In addition, it can be added that the total measure of similarity (TMS) indicated a lack

tern differences (small and medium-sized ⇨ large), 60.3% were positive: they indicate a slightly worse situation in large enterprises (in regard to one or two combined criteria, ARP and VRP). Thirdly, the first pattern (at least a favourable situation) comprised 25.7% of the classes in small and medium-sized enterprises, and 30.2% in large enterprises, or slightly more. In contrast, the fourth pattern (the most favourable situation) made up 27.0% and 21.5% of classes, respectively (a slight dominance of small and medium-sized enterprises) (Fig. 10).

In summary, the strength of arguments for an explicitly positive assessment of medium and small or large enterprises microstructure, is not significant. However, in general, the microstructure of small and medium-sized enterprises in comparison to large ones is characterised by a lower average ranking (-9.4%), indicating a lower degree of financial threat, accompanied by lower variability (-7.2%), which indicates a higher permanency profile. Those are characteristics specific for the third normative pattern — positive, moderate assessment; therefore, the evaluation is more favourable to a small extent for the microstructure of small and medium-sized enterprises.

The nature of the incompatibility of meso- and microstructure profiles is grounds for accepting Hypothesis H3.

Dependencies between the degree of threat and bankruptcy

A comparison of the measures specific to enterprise bankruptcy in the economic sense (degree of financial threat — DFTP) and in the legal sense (percentage of bankruptcy court proceedings) is not possible without first distinguishing their substantive content. In legal terms, the key criterion is insolvency, which narrows the understanding of bankruptcy. In a broader, economic sense, bankruptcy results from a number of factors related to the enterprise economics and its finance management. In this approach, the condition is evaluated not by a single criterion, but by using numerous criteria from the sphere of economic and financial analysis. However, attempts to define a pattern indicating the emergence of a critical state have

of similarity between microstructures for small and medium-sized enterprises in relation to large enterprises, according to the DFTP normative pattern (TMS=0.64). This measure assumes values from 0 to 1, and the closer the value is to 1, the greater the similarity of the structures being compared. The following similarity levels were assumed: <0.65 — none; 0.65–0.7 — weak; 0.7–0.75 — low; 0.75–0.8 — medium; 0.8–0.85 — high; 0.85–0.9 — very high; 0.9–0.95 — almost complete; >0.95 — complete. This measure is provided by the formula $TMS = \sum_{i=1}^{N} min\ (p_{ij}, p_{ik})$, where p_{ij}, p_{ik} is the share of i-th object in the structure j, k, and N is the number of objects.

failed. Hence, those two dimensions of bankruptcy have been combined, as in the early warning systems: the assessment of an enterprise financial condition is relativized to legal bankruptcy as a critical point.

Considering the above stipulations, it is possible to follow the course of curves describing the degree of financial threat (DFTP) as well as the percentage of bankruptcy court proceedings (BPR). This comparison reveals the similarity of their course in the long-term (analysis of the period 2007–2019, semi-annual periodization, ongoing monitoring of the economy). This similarity was particularly apparent and strong until the beginning of 2015, and despite some dissonance after that year, the trend functions (third-degree polynomial) for both curves indicate compatibility between their direction and the proximity of their course (Fig. 11, left panel).

At the level of macroeconomic inference, positive theories perceive the number of bankruptcies as one symptom of deteriorating economic conditions. When following this aspect of bankruptcies, some compatibility (inversely proportional) emerges between the number of bankruptcies (BP) recorded in the industry and the rate of value added creation (VAD), which is a key indicator of economic conditions. Only the period 2017–2018 witnessed a different, opposite situation: despite a VAD increase, BP was also increasing. Looking for reasons to explain this aberration would require in-depth research that can be undertaken in the future (Fig. 11, right panel).

The findings from earlier in the paper may be an additional argument for positively assessing the effectiveness of the estimated model of financial threat. Primarily, however, they serve to validate the fourth hypothesis (Hypothesis H4), which posits the existence of such a correlation.

Discussion

Enterprises must possess the ability to identify crises in advance, which may save them from bankruptcy. This type of individual approach to enterprises from the perspective of corporate management has been widely discusses in the literature (Odunaiya, 2013; Prusak, 2005, pp. 129–172) and was also highlighted in this paper.

In the authors' opinion, the research challenge is to enter a new area of exploration, learning about regularities and patterns of the population of enterprises in terms of the financial threat on the subsequent levels of structure aggregation — from micro- to meso- and macroeconomic levels. There has been a lack of such studies published so far. However, some general characteristics proved in this paper could be compared with the results of previous research.

Firstly, SMEs do not demonstrate a higher resilience and flexibility in response to a downturn (recession). Their level of financial threat was higher in comparison to large enterprises. These findings also confirm the results of other research, in Europe (Cultrera & Brédart, 2016) and in the US (Gupta *et al.*, 2018). This proves a universal relationship that the probability of failure decreases with increasing an enterprises size. In addition, that relationship is also visible across the individual SME categories: micro, small, and medium. The discussion on the reasons for this relationship by Altman *et al.* (2010) presents the postulate that qualitative variables be included to a greater extent in SME risk assessment. According to the authors of this paper, however, it is necessary to go a step further. A proper solution is to estimate specific models for SMEs, as done by Tobback *et al.* (2017), for example.

Secondly, the type of business is a factor that differentiates the level of financial threat. Service enterprises, especially construction companies, are exposed the most, as they hold significant fixed assets (Špička, 2013). On the other hand, they can be analysed with universal models of threat prediction, with no significant loss of effectiveness of those models (Kanapickiene & Marcinkevicius, 2014). However, it is worth creating specific models, as Bărbuță-Mișu and Codreanu (2014) did. Manufacturing is a conglomerate of many industries, but also the largest research field. The results from this industry are consistent in general, and confirm the relatively low degree of financial threat proved in this paper (Smith & Liou, 2007). The verification of reasons is provided by the availability of many prediction models, but also by the multi-indicator financial analysis (Pozzoli & Paolone, 2017).

Thirdly, the research concludes with an important finding that manufacturing SMEs significantly improved their resilience, reducing the degree of financial threat, while an opposite tendency for was observed large enterprises, as also indicated by Bărbuță-Mișu and Madaleno (2020). Moreover, there is a strong relationship between SMEs' financial threat and large manufacturing enterprises performance. This is particularly evident in mining and quarrying (Sobczyk *et al.*, 2020), as well as in energy production and supply. The specific nature of the industry demands specific prediction models for such businesses (Syamni *et al.*, 2018).

Fourthly, this paper proves the relationship between the degree of financial distress, the percentage of bankruptcy court proceedings, and the rate at which value added is created. Thus, the degree of financial distress may serve as a universal barometer of the economic situation and the effectiveness of the economic policies instituted, as suggested by Hadasik (1998, p. 36). So far, such a relationship has not been identified in the Polish economy, an emerging market — as Zelek confirmed (2003) — but only in highly developed countries (Senbet & Wang, 2012, p. 110). Therefore, it can be concluded that the relationship discovered in the paper is an indication that the Polish economy has reached a higher phase of development.

Conclusions

The purpose of the research was fully achieved. Regularities and patterns were determined for the entire population of industrial enterprises in Poland (15,999 entities) over a long period (2007–2018). The research addressed two intersecting cross-sections — enterprise size (small, medium-sized, and large) and aggregation levels (micro-, meso-, and macro-).

Firstly, in terms of the intensity, direction, and structure of changes in the degree of financial threat, it was found that the average value for the whole population is determined by manufacturing enterprises. However, their financial situation is the most stable. A negative contribution is made by mining and quarrying enterprises. This translates into the poor situation of energy enterprises (coal-fired power plants).

Secondly, thanks to the method of examining the profiles of financial threat, it was proved that SMEs' structures are characterised by greater volatility, but also by greater flexibility in responding to threats and crises. The structures of large enterprises are not only more rigid, but are also dominated by traditional industries.

Thirdly, there was a low level of similarity among profiles at subsequent aggregation levels for structures of SMEs and large enterprises. Moreover, thanks to the method of normative patterns, reasons for those differences and the less favourable picture (i.e. 'profile interior') of the structure of large enterprises were found.

Fourthly, a correlation between the financial threat and bankruptcy court proceedings was proved. Also, the inversely proportional relationship between the financial threat and the value added margin which was found makes the degree of financial threat a possible universal barometer of an enterprise condition.

The research limitations result mainly from its epistemological approach of measuring effects and risk only in financial terms. An additional research limitation is the population type: industrial companies. This may prevent the results being fully generalizable for all types of enterprises. However, in the case of the Polish economy, industrial enterprises dominate.

The implications and recommendations for practice relate to the macroeconomic level. The research serves as a basis for creating and correcting economic policies. The methodology developed in this research may be used to construct a systematic anti-recession tool (Kaczmarek, 2010, pp. 19–25), with pilot projects already made (Fijorek *et al*., 2011). On the macroeconomic level, it is possible for enterprises to use it in the assessment of the competitive environment. In addition, their management can be improved by using the developed methodology to build an individual early warning system.

One direction for further research is to cover the two remaining business types: trade and services. The comparative analysis should produce some interesting conclusions regarding the differences in the manner and results of the operation, management, and risk exposure. The purpose here is to develop further models using the new methodology.

References

Altman, E. I. (1993). *Corporate financial distress and bankruptcy. A complete guide to predicting & avoiding distress and profiting from bankruptcy*. New York: John Wiley & Sons Press.

Altman, E. I., & Narayanan, P. (1997). An international survey of business failure classification models. *Financial Markets, Institutions and Instruments*, *6*(2), 1–57. doi: 10.1111/1468-0416.00010.

Altman, E. I., Sabato, G., & Wilson, N. (2010). The value of non-financial information in small and medium-sized enterprise risk management. *Journal of Credit Risk*, *2*(6), 95–127. doi: 10.21314/JCR.2010.110.

Ansoff, H. I. (1985). *Strategic management*. Warszawa: PWE Press.

Antonowicz, P. (2007). *Methods of evaluation and economic and financial condition of enterprises.* Gdańsk: ODiDK.

Argenti, J. (1976). *Corporate collapse. The causes and symptoms*. London: McGraw–Hill Book.

Back, B., Laitinen, T., Hekanaho, J., & Sere, K. (1997). The effect of sample size on different failure prediction methods. *Turku Centre for Computer Science, TUCS Technical Report, 155*, 1–23.

Bărbuță-Mișu, N., & Codreanu, E.-S. (2014). Analysis and prediction of the bankruptcy risk in romanian building sector companies. *Ekonomika*, *93*(2), 131–146. doi: 10.15388/EKON.2014.2.3542.

Bărbuță-Mișu, N., & Madaleno, M. (2020). Assessment of bankruptcy risk of large companies, European countries evolution analysis. *Journal of Risk and Financial Management*, *13*(3), 58. doi: 10.3390/jrfm13030058.

Beaver, W. H. (1968). Alternative accounting measures as predictors of failure. *Accounting Review*, *43*(1), 113–122. doi: 10.2307/244122.

Cabała, P. (2008). *Enterprise early warning systems*. Kraków: Uniwersytet Ekonomiczny w Krakowie.

Crocford, G. N. (1982). The bibliography and history of risk management. *Geneva Papers on Risk and Insurance*, *7*(2), 169–179. doi: 10.1057/gpp.1982.10.

Cultrera L., & Brédart X. (2016). Bankruptcy prediction: the case of Belgian SMEs. *Review of Accounting and Finance, 15*(1), 101–119. doi: 10.1108/RAF-06-2014-0059.

Drucker, P. F. (2010). *The practice of management*. New York: Harper Business.

Fijorek, K., Kaczmarek, J., Kolegowicz, K., & Krzemiński, P. (2011). *The concept of research on the state and performance of enterprises for the purpose of the Rapid Reaction Instrument. Assumptions of the "Early Warning System" solution - Methods and tools for monitoring the economy in the microeconomic component*. Kraków: Małopolska Szkoła Administracji Publicznej Uniwersytetu Ekonomicznego w Krakowie.

Fijorek, K., & Sokołowski, A. (2012). Separation–resistant and bias–reduced logistic regression: STATISTICA macro. *Journal of Statistical Software*, *47*, 1–12. doi: 10.18637/jss.v047.c02.

Firth, D. (1993). Bias reduction of maximum likelihood estimates. *Biometrika*, *80*(1), 27–38. doi: 10.2307/2336755.

Greiner, L. E. (1972). Evolution and revolution as organizations grow. *Harvard Business Review*, *7/8*, 37–46. doi: 10.1111/j.1741-6248.1997.00397.x.

Gupta, J., Barzotto, M., & Khorasgani, A. (2018). Does size matter in predicting SMEs failure? *International Journal of Finance and Economics*. Advance online publication. doi: 10.2139/ssrn.2638485.

Hadasik, D. (1998). Bankruptcy of companies in Poland and methods of forecasting it. *Zeszyty Naukowe*, *Akademia Ekonomiczna w Poznaniu*, *153*, 1–198.

Hafiz, A. A., Lukumon, O. O., Hakeem, A. O., Vikas K., Saheed, O. A., Olugbenga, O. A., & Muhammad, B. (2018). Systematic review of bankruptcy prediction models: towards a framework for tool selection. *Expert Systems with Applications, 94,* 164–184. doi: 10.1016/j.eswa.2017.10.040.

Hosmer, D. W., & Lemeshow, S. (1989). *Applied logistic regression*. New York: John Wiley & Sons Publishing.

Hudáková, M., & Dvorský, J. (2018). Assessing the risks and their sources in dependence on the rate of implementing the risk management process in the SMEs. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *13*(3), 543–567. doi: 10.24136/eq.2018.027.

Jajuga, K. (2006). Statistical models of early warning - formal methods. *Barometr Regionalny*, *6*, 52–55. Retrieved from http://br.wszia.edu.pl/zeszyty/pdfs/br06_07jajuga.pdf.

Juszczyk, S. (2010). Forecasting of bankruptcy of enterprises. *Ekonomista, 5*, 701–728.

Kaczmarek, J. (2010). Counteracting the crisis in the economies of new EU member states in the context of the development of integration processes. In M. Lanfranchi (Ed.). *The community integration process between Eastern and Southern Europe*. Messina: Edizioni Dr. Antonino Sfaneni, 19–39.

Kaczmarek, J. (2014). A crisis and a treat vs. the financial security aspects of going concern. *Economic Horizons*, *16*, 195–209. doi: 10.5937/ekonhor1403 195K.
Kaczmarek, J. (2019). The mechanisms of creating value vs. financial security of going concern - sustainable management. *Sustainability*, *11*(8), 2278, 1–24. doi: 10.3390/su11082278.
Kanapickiene R., & Marcinkevicius R. (2014). Possibilities to apply classical bankruptcy prediction models in the construction sector in Lithuania. *Economics and Management*, *19*(4). doi: 10.5755/j01.em.19.4.8095.
Kaplan, R., & Norton, D. (2006). *The balanced scorecard: translating strategy into action.* Boston: Harvard Business Press.
Kharbanda, O. P., & Stallworthy, E. A. (1985). *Corporate failure. Prediction, panacea and prevention*. London–New York: McGraw–Hill.
Kliestik, T., Vrbka, J., & Rowland, Z. (2018). Bankruptcy prediction in Visegrad group countries using multiple discriminant analysis. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *13*(3), 569–593. doi: 10.24136/eq.2018.028.
Kovacova, M., Kliestik, T., Valaskova, K., Durana, P., & Juhaszova, Z. (2019). Systematic review of variables applied in bankruptcy prediction models of Visegrad group countries. *Oeconomia Copernicana*, *10*(4), 743–772. doi: 10.24136/oc.2019.034.
Lam, J. (1985). Ten predictions for risk management. *RMA Journal*, *5*, 84–85.
Long, S. J. (1997). *Regression models for categorical and limited dependent variables*. London: Thousand Oaks, SAGE Publications.
Obłój, K. (1987). Organisational crises. *Przegląd Organizacji, 1*, 7–14.
Odunaiya, T. (2013). *A study of the accuracy of bankruptcy prediction models: can impending bankruptcies on the UK high street be predicted?* University of Westminster.
Platt, H. D., & Platt, M. B. (2002). Predicting corporate financial distress: reflection on choice–based sample bias. *Journal of Economics and Finance*, *26*(2), 184–199. doi: 10.1007/BF02755985.
Pozzoli M., & Paolone F. (2017). *Corporate financial distress. A study of the Italian manufacturing industry*. Cham: Springer. doi: 10.1007/978-3-319-67355-4.
Prusak, B. (2005). *Modern methods of forecasting financial risks for companies*. Warszawa: Difin.
Quinn, B., & Cameron, K. (1983). Organizational life cycles and shifting criteria of effectiveness: some preliminary evidence. *Management Science*, *29*(1), 33–51. doi: 10.1287/mnsc.29.1.33.
Rappaport, A. (1998). *Creating shareholder value: a guide for managers and investors*. New York, USA: The Free Press.
Senbet, L. W., & Wang, T. Y. (2012). *Corporate financial distress and bankruptcy: a survey (foundations and trends in finance)*. Boston: Now Publishers Inc.
Slatter, S., & Lovett, D. (1999). *Corporate recovery: managing companies in distress*. Frederick (MD): Beard Books.

Smart, C. F., Thompson, W. A., & Vertinsky, I. (1978). Diagnosing corporate effectiveness and susceptibility to crisis. *Journal of Business Administration*, *9*, 57–96.

Smith, M., & Liou, D. (2007). Industrial sector and financial distress. *Managerial Auditing Journal*, *22*(4), 376–391. doi: 10.1108/02686900710741937.

Sobczyk, E. J., Kaczmarek, J., Fijorek, K., & Kopacz, M. (2020). Efficiency and financial standing of coal mining enterprises in Poland in terms of restructuring course and effects. *Gospodarka Surowcami Mineralnymi*, *36*(2), 127–152. doi: 10.24425/gsm.2020.132565.

Špička, J. (2013). The financial condition of the construction companies before bankruptcy. *European Journal of Business and Management*, *5*(23), 160–169.

Svabova, L., & Durica, M. (2019). Being an outlier: a company non-prosperity sign? *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *14*(2), 359–375. doi: 10.24136/eq.2019.017.

Syamni, G., Majid, M. S. A., & Siregar, W. V. (2018). Bankruptcy prediction models and stock prices of the coal mining industry in Indonesia. *Etikonomi*, *17*(1). doi: 10.15408/etk.v17i1.6559.

Tobback, E., Bellotti, T., Moeyersoms, J., Stankova, M., & Martens, D. (2017). Bankruptcy prediction for SMEs using relational data. *Decision Support Systems*, *102*, 69–81. doi: 10.1016/j.dss.2017.07.004.

Valaskova, K., Kliestik, T., & Kovacova, M. (2018). Management of financial risks in Slovak enterprises using regression analysis. *Oeconomia Copernicana*, *9*(1), 105–121. doi: 10.24136/oc.2018.006.

Weibel, P. F. (1973*). The value of criteria to judge credit worthiness in the lending of banks*. Stuttgart: Bern.

Winston, W., Angrisani, D. P., & Goldman, R. L. (1997). *Predicting successful hospital mergers and acquisitions: a financial and marketing analytical tool*, New York: Routledge.

Zelek, A. (2003). *Corporate crisis management - a strategic perspective*. Warszawa: Instytut Organizacji i Zarządzania w Przemyśle „ORGMASZ”.

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Annex

Table 1. Parameters of DFTP logistic regression model

Financial ratio name (predictor)	Predictor symbol	Predictor scaling	Parameter estimate
Intercept	–	1	– 0.51
Asset productivity ratio	W_1	$Z_1 = (W_1 – 1.64)/0.85$	– 0.44
Equity financing ratio	W_2	$Z_2 = (W_2 – 0.41)/0.32$	– 0.80
Short-term liability ratio	W_3	$Z_3 = (W_3 – 0.45)/0.29$	+ 0.65
Operating return on assets ratio	W_4	$Z_4 = (W_4 – 2.12)/13.51$	– 0.70

Table 2. PKD divisions by their assignment to DFTP normative patterns for small and medium-sized industrial enterprises in 2007–2018

Pattern 1	Pattern 2
16 - Manufacture of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials 17 - Manufacture of paper and paper products 18 - Printing and reproduction of recorded media 24 - Manufacture of metals 25 - Manufacture of fabricated metal products, except machinery and equipment 29 - Manufacture of motor vehicles, trailers and semi-trailers excluding motorcycles 30 - Manufacture of other transport equipment 33 - Repair, maintenance and installation of machinery and equipment	9 - Mining and quarrying support service activities 11 - Manufacture of beverages 12 - Manufacture of tobacco products 13 - Manufacture of textiles 26 - Manufacture of computer, electronic and optical products 39 - Remediation activities and other waste management services
Pattern 3	**Pattern 4**
10 - Manufacture of food products 20 - Manufacture of chemicals and chemical products 21 - Manufacture of basic pharmaceutical substances and medicines and other pharmaceutical products 22 - Manufacture of rubber and plastic products 23 - Manufacture of other non-metallic mineral products 27 - Manufacture of electrical equipment 28 - Manufacture of machinery and equipment not elsewhere classified 32 - Other manufacturing 36 - Water collection, treatment and supply 37 - Sewage disposal and treatment	8 - Other mining and quarrying 14 - Manufacture of wearing apparel 15 - Manufacture of leather and related products 19 - Manufacture and processing of coke and refined petroleum products 31 Manufacture of furniture 35 - Electricity, gas, steam, hot water and air conditioning manufacturing and supply 38 - Waste collection, processing and neutralizing activities; materials recovery

Table 3. PKD divisions by their assignment to DFTP normative patterns for large industrial enterprises in 2007–2018

Pattern 1	Pattern 2
9 - Mining and quarrying support service activities 12 - Manufacture of tobacco products 16 - Manufacture of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials 17 - Manufacture of paper and paper products 18 - Printing and reproduction of recorded media 22 - Manufacture of rubber and plastic products 24 - Manufacture of metals 25 - Manufacture of fabricated metal products, except machinery and equipment 30 - Manufacture of other transport equipment 36 - Water collection, treatment and supply	13 - Manufacture of textiles 26 - Manufacture of computer, electronic and optical products 29 - Manufacture of motor vehicles, trailers and semi-trailers excluding motorcycles 33 - Repair, maintenance and installation of machinery and equipment 38 - Waste collection, processing and neutralizing activities; materials recovery
Pattern 3	**Pattern 4**
10 - Manufacture of food products 15 - Manufacture of leather and related products 20 - Manufacture of chemicals and chemical products 23 - Manufacture of other non-metallic mineral products 27 - Manufacture of electrical equipment 28 - Manufacture of machinery and equipment not elsewhere classified 37 - Sewage disposal and treatment	8 - Other mining and quarrying 11 - Manufacture of beverages 14 - Manufacture of wearing apparel 19 - Manufacture and processing of coke and refined petroleum products 21 - Manufacture of basic pharmaceutical substances and medicines and other pharmaceutical products 31 Manufacture of furniture 32 - Other manufacturing 35 - Electricity, gas, steam, hot water and air conditioning manufacturing and supply 39 - Remediation activities and other waste management services

Table 4. Number of PKD divisions in regard of the difference of rank position and its variability for small and medium-sized and large industrial enterprises in terms of DFTP in 2007–2018

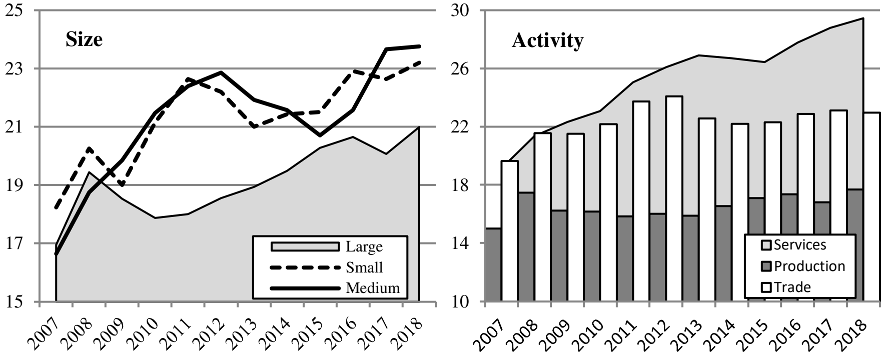
Difference	ARP	VRP	Difference	ARP	VRP
less than 1.0	4	11	greater than -1,0	2	7
between 1.0 and 2.0	6	4	between -1,0 and -2,0	2	3
between 2.0 and 3.0	10	2	between -2,0 and -3,0	2	0
between 3.0 and 4.0	1	0	between -3,0 and -4,0	0	1
between 4.0 and 5.0	0	1	between -4,0 and -5,0	0	0
greater than 5.0	2	2	less than -5,0	2	0

Notes: ARP – average rank position, VRP – variability of rank position.

Table 5. Normative pattern changes in terms of DFTP in regard to small and medium-sized and large industrial enterprises for PKD divisions in 2007–2018

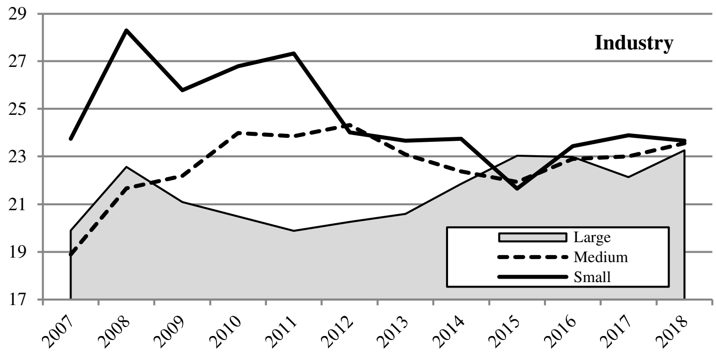
Direction of the pattern comparison	Number of pattern positive differences	Direction of the pattern comparison	Number of pattern negative differences
2 ⇨ 1	2	1 ⇨ 2	2
3 ⇨ 1	2	2 ⇨ 4	2
4 ⇨ 2	1	3 ⇨ 4	2
4 ⇨ 3	1		

Figure 1. Degree of financial threat in enterprises by their size and activity type classes in 2007–2018 (%)



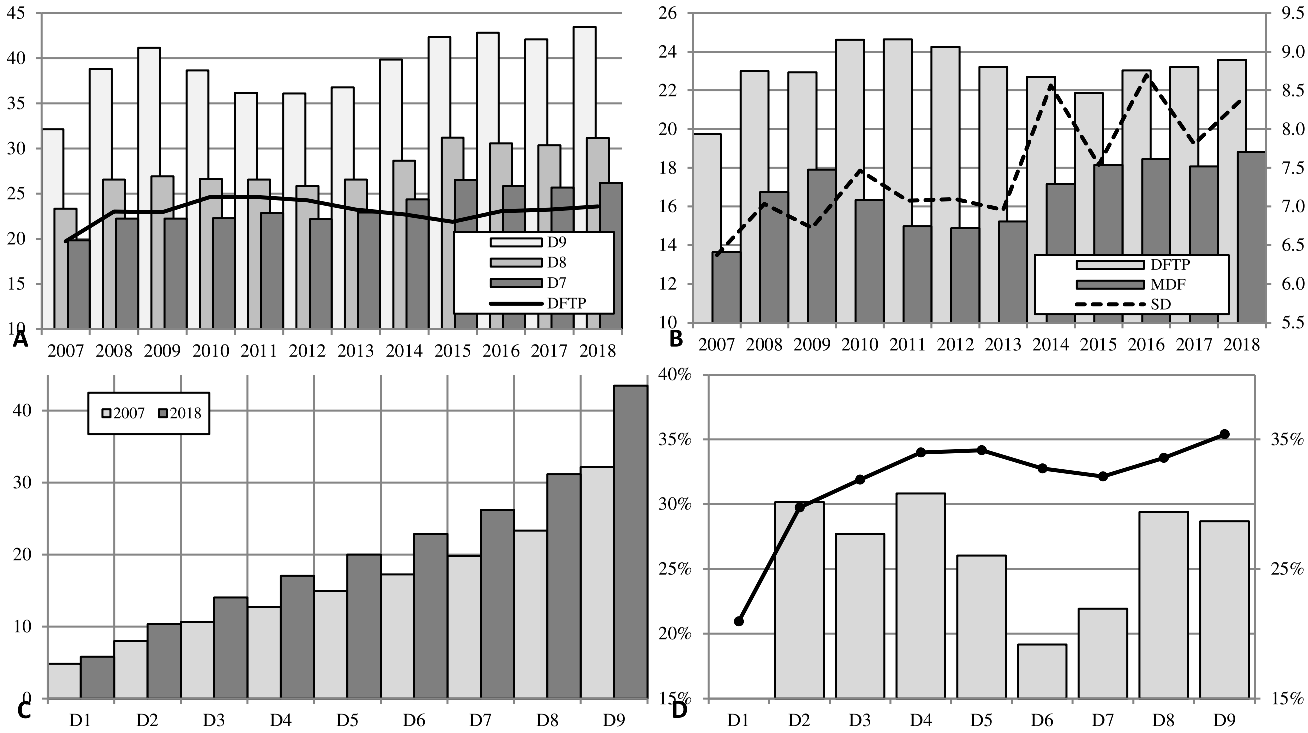
Notes: the all enterprises model was used (Kaczmarek, 2019).

Figure 2. Degree of financial threat in industrial enterprises by their size classes in 2007–2018 (%)



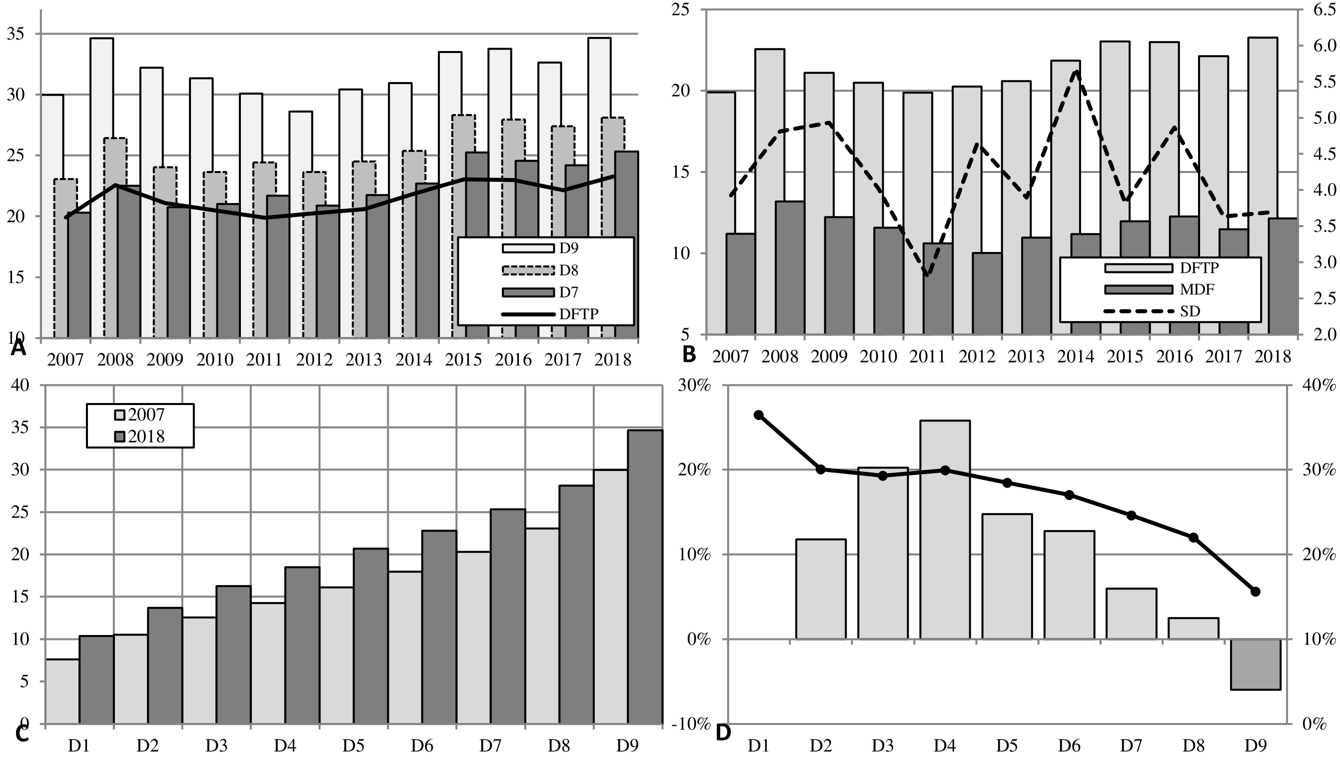
Notes: DFTP model used.

Figure 3. Basic DFTP descriptive characteristics for small and medium-sized industrial enterprises in 2007–2018



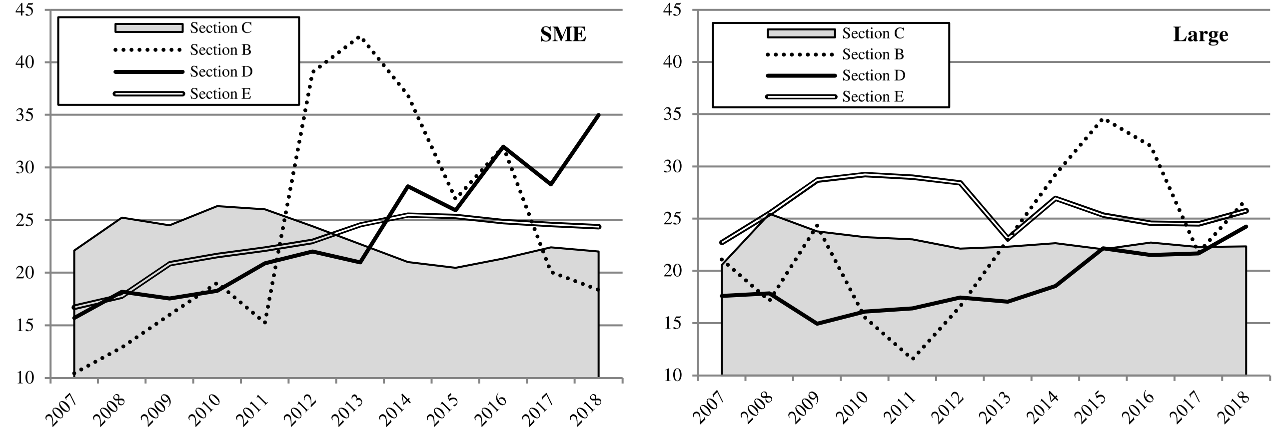
Notes: A – time series of DFTP values, of deciles 9, 8 and 7; B – time series of DFTP values, measure of differentiation (MDF=D9–D1/2) and standard deviation (SD) – right axis; C – decile values for start year (rp=2007) and end year (rk=2018); D – change (rk/rp) in decile values (line chart, right axis) and interdecile ranges (bar chart, left axis).

Figure 4. Basic DFTP descriptive characteristics for large industrial enterprises in 2007–2018



Notes: see Figure 3.

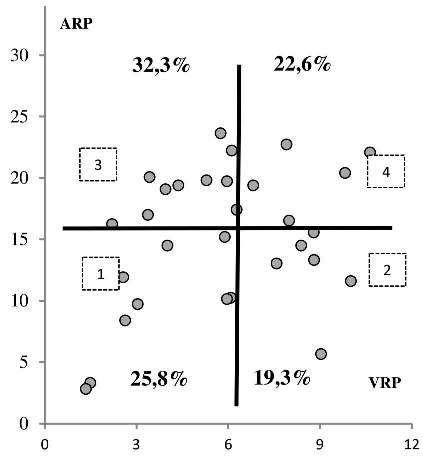
Figure 5. Degree of financial threat (DFTP) in industrial enterprises by their PKD sections in 2007–2018 (%)



Notes: Section B – Mining and quarrying; Section C – Manufacturing; Section D – Electricity, gas, steam, hot water and air conditioning manufacturing and supply; Section E – Water supply, sewerage, waste management and remediation activities.

Figure 6. Rank positions of PKD divisions for small and medium-sized industrial enterprises in 2007–2018 in regard to DFTP (left panel) and their classification (right panel)

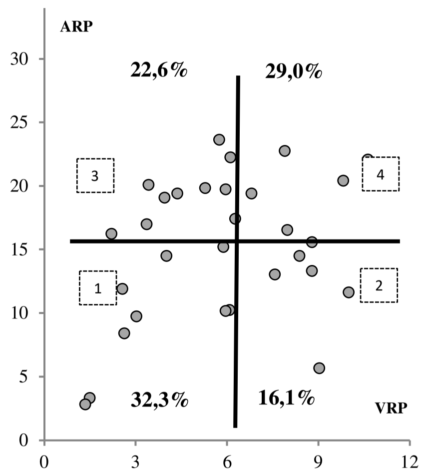
39	38	37	36	35	33	32	31	30	29	28	27	26	25	24	23	22	21	20	19	18	17	16	15	14	13	12	11	10	9	8	PKD
27	25	18	24	23	21	14	9	4	7	17	19	6	16	1	26	15		22	3	8	11	13	20	12	5		2	10		28	**2007**
18	26	21	23	22	5	13	6	2	11	16	24	9	17	4	25	15	28	20	8	7	14	10		19	1		3	12		27	**2008**
	19	17		23	24	20	22	1	4	11	18	6	12	2	15	13	26	16	5	7	10	8		9	3		14	21		25	**2009**
27	24	20	13	26	11	23	15	1	3	12	21	8	6	2	16	14	22	18	28	5	9	7		10	4		17	19	29	25	**2010**
	25	19		21	6	12	24	1	4	22	20	7	10	2	16	15	26	14		5	9	8	23	18	11		3	17	13	27	**2011**
6	26	22	12	23	13	29	27	2	10	28	19	7	15	4	11	17	25	18	30	5	16	9		21	14		8	20	1	3	**2012**
5	13	17	12	22	7	26	27	4	14	24	18	20	16	6	11	19	30	25	31	9	8	15	29	28	21	1	10	23	2	3	**2013**
5	10	13	9	8	7	29	30	3	18	24	16	27	22	4	21	19	28	25	31	12	11	14	15	17	26	2	20	23	1	6	**2014**
3	7	13	9	8	6	29	30	4	25	27	22	31	17	5	28	18	24	21	32	10	15	11	14	16	19	1	24	20	2	26	**2015**
	7	11	23	4	8	28	29	5	10	16	18	14	13	3	17	20		21	27	9	12	6	15	26	24		25	22	1	19	**2016**
	6,5	14		4	8	22	27	3	10	21	9	18	12	2	23	16	19	17	25	11	13	5	6,5	28	24	29	15	20	1	26	**2017**
2	10	19	12	3	6	22	27	4	7	20	25	21	18	5	28	14	9	24	23	13	15	11	17	29	8	31	16	26	1	30	**2018**



Notes: Divisions 05, 06, 07, due to incomplete figures resulting from the principle of statistical confidentiality, were not covered by the analysis.

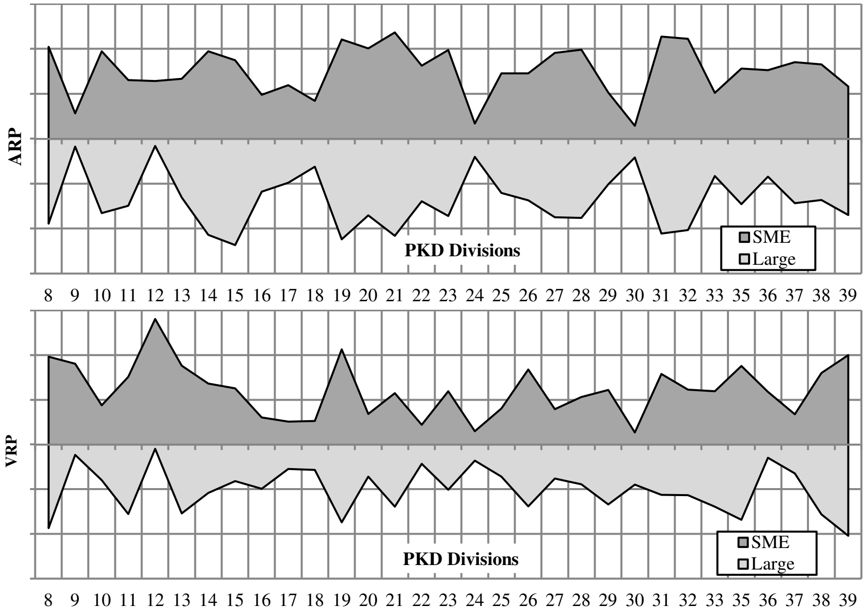
Figure 7. Rank positions of PKD divisions for large industrial enterprises in 2007-2018 in regard to DFTP (left panel) and their classification (right panel)

39	38	37	36	35	33	32	31	30	29	28	27	26	25	24	23	22	21	20	19	18	17	16	15	14	13	12	11	10	9	8	PKD
		20		23	18	11	8	3	7	15	21	10	17	1	24	14		22	4	5	12	13	19	16	6		2	9		25	**2007**
		16		19	20	11	14	1	8	13	18	22	15	3	21	12	23	17	7	4	9	6			5		2	10		24	**2008**
	15	12		22	21	18	19	1	5	10	20	4	9	2	14	11	24	17	25	6	8	7			3		13	16		23	**2009**
27	24	17	11	26	10	21	16	1	4	14	23	7	6	5	15	13	26	19	28	2	8	9		12	3		20	18		22	**2010**
	24	17		21	2	13	22	1	3	19	18	9	8	5	14	15	25	12		4	7	10	23	20	11		6	16		26	**2011**
4	26	18	8	21	7	27	24	1	13	25	20	5	15	6	11	12	23	14	28	3	10	9		22	20		16	17		2	**2012**
20	12	14	10	18	7	26	27	4	19	21	17	13	15	6	9	16	30	23	31	8	5	24	29	28	25	1	11	22	2	3	**2013**
28	10	12	7	9	3	27	26	5	18	23	16	22	13	6	19	15	25	17	29	11	8	14			20	2	24	21	1	4	**2014**
6	8	11	7	9	4	23	28	3	25	22	19	27	16	5	24	17	21	13	29	10	15	12			18	2	20	14	1	26	**2015**
	6	11		5	2	25	24	3	8	14	17	15	9	4	13	18		16	23	7	12	10			19		22	20	1	21	**2016**
	3	10		2	4	22	23	16	6	20	7	14	8,5	1	19	12	17	13	25	5	11	8,5		26	21		18	15		24	**2017**
	9		8	1	2	20	23	11	6	16	15	17	14	5	24	12	3	22	18	10	13	19		26	7		25	21	4	27	**2018**



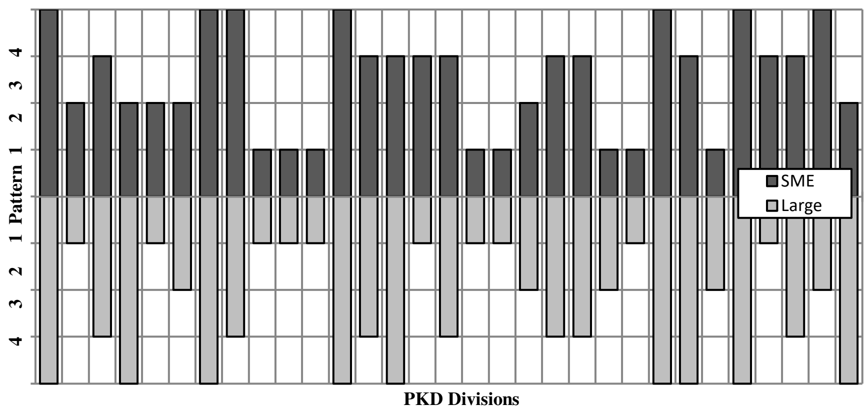
Notes: see Figure 6.

Figure 8. Profiles of PKD divisions in regard of average rank position (ARP, top panel) and its variability (VRP, bottom panel) in terms of DFTP for small and medium-sized and large industrial enterprises in 2007–2018



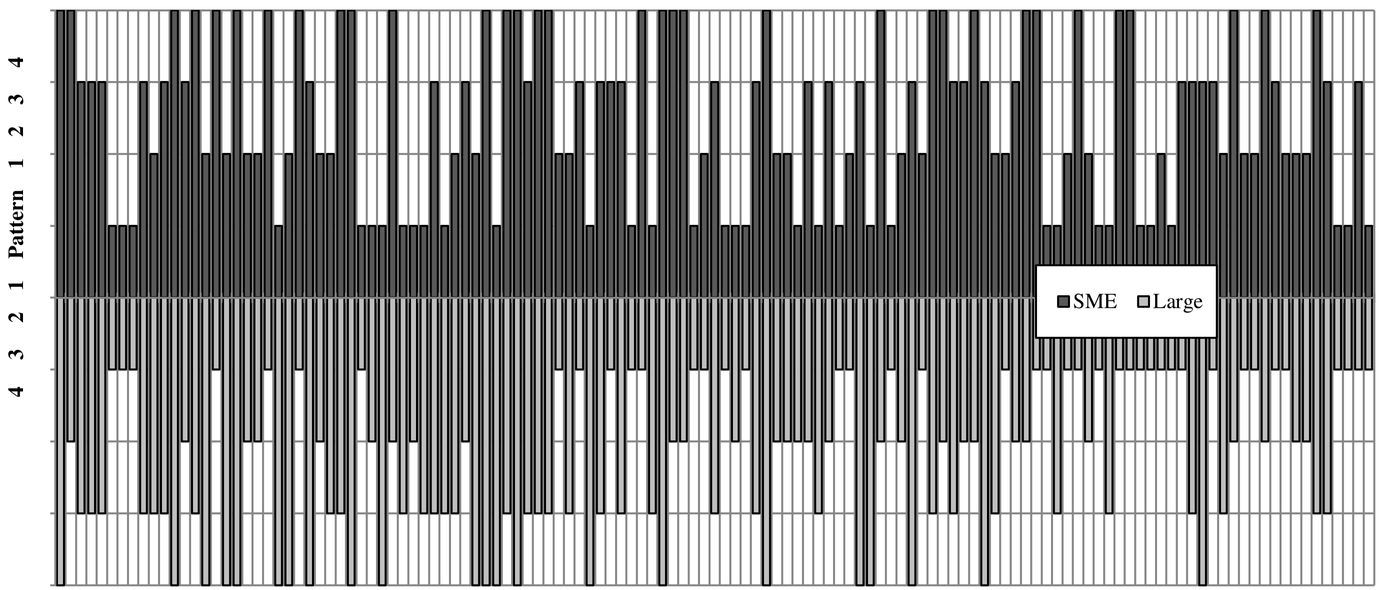
Notes: see Figure 6.

Figure 9. Profiles of PKD divisions in regard of normative patterns in terms of DFTP for small and medium-sized and large industrial enterprises in 2007–2018



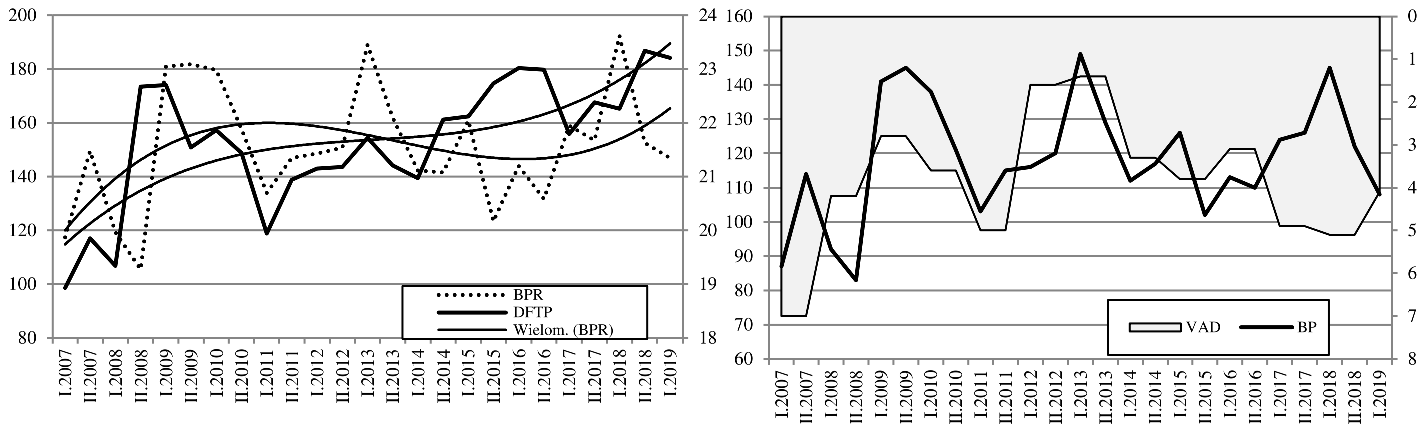
Notes: see Figure 6.

Figure 10. Profiles of PKD classes in regard of normative patterns in terms of DFTP for small and medium-sized and large industrial enterprises in 2007–2018



Notes: 52 PKD classes, due to incomplete figures resulting from the principle of statistical confidentiality, were not covered by the analysis.

Figure 11. Degree of financial threat (DFTP) and the percentage of bankruptcy court proceedings (BPR) (left panel) and the number of bankruptcies (BP) of industrial enterprises and the value added in industry (VAD) (right panel) in 2007–2018



Notes: DFTP – right axis. VAD – values in reverse order, in %, right axis.