Firm failure processes and components of failure risk : an analysis of European bankrupt firms

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*Title Page (WITH AUTHOR DETAILS)

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Abstract

This paper aims to extract firm failure processes (FFPs) by using failure risk and rank the importance of failure risk contributors for different stages of FFPs. The dataset is composed of 1234 bankrupt firms from different European countries and three theoretically motivated FFPs are detected. For the dominant FFP found (73% of cases), failure risk becomes high very shortly before bankruptcy is declared. Annual and accumulated profitability are the most important failure risk contributors for these stages of all FFPs, where failure probability exceeds 50%. The obtained results provide important implications for bankruptcy prediction research and practice, especially in terms of identifying the most important financial predictors.

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1. Introduction

Firm failure is an eternal topic in business research. The development of subdomains in this literature stream has remained unbalanced, the failure prediction domain being represented with a myriad of studies (see e.g. Ravi Kumar & Ravi, 2007; Sun et al., 2014), but in turn the processual context being in serious minority (Lukason, Laitinen & Suvas, 2016; Amankwah-Amoah, 2016). The processual context is more broadly linked to the stage theory of business failure, which originates from the idea that before failure, firms go through numerous observable stages (Weitzel & Jonsson, 1989; Amankwah-Amoah, 2016). Of these stages, the recent focus has mainly been set on firm turnaround (Trahms, Ndofor & Sirmon, 2013; James, 2016; Mann & Byun, 2017; Zorn et al., 2017). On the other hand, studies focusing on the stages of processes ending with bankruptcy are infrequent and Amankwah-Amoah (2016: 3392) has noted that "there remains a lack of consensus on the exact processes of decline leading to exit".

Firm failure process (FFP) has been conceptualized in several studies (e.g. Crutzen & van Caillie, 2008; Ooghe & de Prijcker, 2008; Amankwah-Amoah, 2016) and relevant empirical research has also been re-emerging in recent years (e.g. du Jardin, 2015; Lukason, Laitinen & Suvas, 2016; Nummela, Saarenketo & Loane, 2016), but some core aspects still remain understudied. FFP is an important concept since it allows to consider the behaviour of failing firms in the longer perspective, while failure prediction studies often focus on financial performance only 1-2 years before bankruptcy is declared (Balcaen and Ooghe, 2006). This longer perspective helps management and all stakeholders of the firm to understand different stages of the process, redirect the course of action, and potentially avoid the crisis.

The existence of different FFPs is by now a well-established fact and there is enough evidence how FFPs differ in respect to financial situation evolvement in time. Also, the study by D'Aveni (1989) provided initial evidence that FFPs are distinguishable in respect to failure risk development in time, but did not elaborate the interconnection of FFP stages and failure risk further, and therefore, this study relies on that gap in the literature. The main aim of the paper is to disclose how different stages of FFPs vary in respect to the failure risk contributors. As literature is lacking specific guidelines for the latter, we propose a conceptual model relying among other sources on the theoretical FFPs proposed by D'Aveni (1989) and the probabilistic bankruptcy theory by Scott (1981). In the empirical validation of the conceptual model, we rely on Altman et al.'s (2017) modified Z''-Score model to calculate the failure risk and a variety of different clustering strategies to disclose different FFPs. Unlike in previous research, this study uses best correspondence to theoretical FFPs when searching for the empirical solution. The study shows that in line with Scott's (1981) probabilistic theory of bankruptcy, the most important contributor to the failure risk for all three extant FFPs is negative profitability. This finding provides important implications for the bankruptcy prediction domain, especially in respect to which financial ratios can be most useful in the latter research.

The rest of the paper is structured as follows. The literature review section offers an insight to the previous theoretical and empirical findings in respect to FFPs, and based on these previous studies, proposes a conceptual model of the failure risk development for the stages of different FFPs. The data and methods section describes the sample of firms used in the analysis, detection of theoretical and empirical FFPs applied in this study and the disaggregation of firm failure risk. The empirical portion of the paper consists of the following parts. First, FFPs are detected by finding the empirical solution out of 32 that would best represent the theoretical FFPs proposed by D'Aveni (1989). Second, the best empirical solution is described, also in respect to how the stages of FFPs differ from each other. Third, for the detected FFPs, the failure risk is disaggregated into components to find out how different financial ratios contribute to it, and the results are discussed in the light of the conceptual model proposed in the literature review section. Then, implications for bankruptcy prediction domain are discussed and the paper ends with a conclusion part including limitations and some future research directions.

2. Review of literature

2.1. Firm failure process

Argenti (1976) was the first scholar to elaborately study FFPs. Using case studies, he detected three failure trajectories portrayed with the deterioration in firms' financial health. Since this seminal work, FFP has obtained various meanings in studies. Still, majority of research considers either only the reasons of failure, only the observable symptoms before failure, or both of them together (e.g. Laitinen, 1991; Ooghe & de Prijcker, 2008; Crutzen & van Caillie, 2008; Lukason, Laitinen & Suvas, 2016). The failure reasons have mainly been detected with qualitative analysis without specifically accounting when the specific events took place (e.g. Ooghe & de Prijcker, 2008; Crutzen & van Caillie, 2010; Lukason & Hoffman, 2015).

In turn, the pre-failure symptoms have mostly been modelled by using financial ratios (e.g. D'Aveni, 1989; Laitinen, 1991; du Jardin, 2015; Lukason & Laitinen, 2016; du Jardin 2017). Also, in failure research bankruptcy (i.e. court declared permanent insolvency) has been the most popular definition (Mellahi & Wilkinson, 2004; Balcaen & Ooghe, 2006). This is also logical as in case of bankruptcy, the content (i.e. inability to pay outstanding debt) and the time of the event are exactly known (Lukason & Laitinen, 2016). Thus, in this study we consider FFP as a pathway depicted with firm's financial health until its bankruptcy is declared.

2.2. Different failure processes in previous studies

Earlier studies about FFPs have provided a consensus that three different types of them exist (see Argenti, 1976; D'Aveni, 1989; Laitinen, 1991). Argenti (1976) proposed three FFPs indicating: 1) a firm never becoming successful enough, 2) a firm with a very good performance and a sudden decline after that, and 3) a firm for which problems become worse step by step. The three FFPs brought out by Argenti (1976) were based on case study evidence and this study was the first to apply firms' financial health in portraying FFPs, but no specific guidelines were provided how to measure financial health. A more profound approach was provided by D'Aveni (1989), who used a specifically composed D-score to portray FFPs covering five years before bankruptcy declaration.

D'Aveni (1989) proposed three types of theoretical FFPs, namely suddenly, gradually and lingeringly failing firms, and also showed how the resource munificence of firms following these processes changes. In the concept of D'Aveni (1989), suddenly failing firms became non-viable not before one year to bankruptcy declaration and this happened very quickly; gradually failing firms started having problems two to three years before bankruptcy declaration with a more observable decline; and finally, firms classified as lingerers were non-viable for a long time before bankruptcy declaration. The empirical findings in D'Aveni (1989) obtained by clustering the D-scores (calculated based on equity to debt ratio and managerial prestige) supported the theoretical FFPs proposed.

The presence of three different FFPs was confirmed by Laitinen (1991), who used factor analysis of six theoretically motivated financial variables (five financial ratios and one growth variable). In Laitinen's study, the FFPs were respectively named: a) chronic, b) revenue financing, and c) acute failure firms. The return on assets (ROA) for these three types of firms in Laitinen (1991) indicated that for the chronic FFP the value was negative already four years before bankruptcy, for the revenue financing FFP two years before bankruptcy and for the acute FFP one year before bankruptcy. Thus, the FFPs detected in Laitinen (1991) share strong similarities with the theoretical and empirical FFPs described in D'Aveni (1989). Therefore, both of these studies confirmed that three types of FFPs exist and the main distinction between them relies in the fact when a firm becomes poorly performing or having high failure risk. Thus, relying on the studies by D'Aveni (1989) and Laitinen (1991), we can derive that three theoretical types of FFPs exist and they are portrayed by the failure risk development as follows.

The first type is a FFP for which high failure risk is observable either only in the first year before bankruptcy is declared or there are no signs of failure at all. We will call such type a short-range FFP (denoted as SFFP afterwards). For the second type of FFP, high failure risk is observable two or three years before bankruptcy is declared and remains high throughout the rest of the years. We will call such type a medium-range FFP (denoted as MFFP afterwards). The last type of FFP is a firm for which high failure risk is observable more than three years before bankruptcy declaration and remains high throughout the rest of the years. We will call it a long-range FFP (denoted as LFFP afterwards).

Several recent studies have empirically studied FFPs. All of such studies (e.g. Laitinen & Lukason 2014; Laitinen, Lukason & Suvas, 2014; Lukason & Laitinen, 2016; Lukason, Laitinen & Suvas, 2016; Flores-Jimeno and Jimeno-Garcia, 2017; Jimeno-Garcia, Rodriguez-Merayo & Vidal-Blasco, 2017) have applied classical statistical analysis methods (i.e. factor and/or cluster analyses) on financial variables for the extraction of FFPs. All of the afore-noted studies published from 2014 to 2017 either directly rely on Laitinen's (1991) model or use it in an extended form. These recent studies vividly indicate that different FFPs can be distinguished by varying levels of liquidity, solidity and profitability during the pre-failure years. Still, none of these studies has used failure risk variables as an input when detecting different FFPs, and derived from that, they do not consider whether the failure risk contributors vary for different stages of FFPs.

2.3. Failure risk and its contributors at different stages of FFPs

While the extant literature indicates, that different FFPs exist and these FFPs can be distinguished based on the failure risk development in time, no studies have so far deconstructed the failure risk development for different stages of FFPs. Thus, evidence from different theories and empirical research must be integrated into a unified concept that can be further tested in the empirical part of the paper.

The stage theory of FFPs was first developed by Laitinen (1993), who outlined that for different stages of different FFPs, different failure predictors could be useful. Still, this study focused on how the variables should be calculated for different stages (i.e., either differences, trends or levels), not specifically on the contribution of financial ratios portraying different financial domains to the failure risk for various stages of different FFPs. Literature reviews about bankruptcy prediction studies have indicated that liquidity, profitability and leverage ratios are the most useful predictors of corporate failure (Dimitras et al., 1996; Ravi Kumar and Ravi, 2007; Sun et al., 2014). In addition to empirical importance, the significance of these domains is theoretically well motivated. The probabilistic theory of bankruptcy by Scott (1981) considers a firm in a gambler ruin framework, where annual profitability and total equity are the core variables in determining firm's fate. Leverage is interconnected with

Beaver's (1966) cash flow theory of bankruptcy, which indicated that additional debt *ceteris paribus* increases the likelihood of bankruptcy. Liquidity's role in bankruptcy prediction is first-hand based on legal considerations, as the inability to pay outstanding debt serves as a sufficient precondition to start insolvency proceedings in most of the legislations. Thus, it is justified to rely on these financial domains when portraying the components of the failure risk for different stages of FFPs, and derived from that, a failure prediction model incorporating these domains should be implemented. The most robust recent failure prediction models including these domains have been developed in Altman et al.'s (2017) study composed on the example of a very large dataset of European firms. In that study, four theoretically justified financial ratios were applied to portray annual and accumulated profitability, liquidity and leverage. In the following discussion, we will focus on the theoretical expectations about the failure risk contributors for different stages of FFPs. The results have been consolidated into a conceptual model in Table 1.

[insert Table 1 about here]

Observable failure risk might even not be present in t-1 for SFFP, thus in the long-run (LR) or medium-run (MR) we do not expect these firms to indicate any problems observable through financial ratio values. Indeed, such a tendency can be followed through various bankruptcy prediction models, in which prediction accuracies from t-2 and further years decrease and no signs of poor performance are present (du Jardin, 2017). We expect that firms following SFFP are subject to (an extreme version of) the probabilistic bankruptcy theory by Scott (1981), namely they witness high abrupt losses (i.e. negative profitability) in the short-run (SR), which can be conditioned by serious mismanagement or environmental conditions (Ooghe and de Prijcker, 2008; Crutzen and van Caillie, 2010; Lukason and Hoffman, 2015). Liquidity of firms following SFFP is likely to decrease after high losses and is therefore still on a sustainable level in t-1, thus not contributing to the failure risk. As SMEs normally do not make additional equity injections after initial allocation of capital at foundation, we expect that leverage could be high at different stages of SFFP, and thus, it does not play an important role in determining the failure risk. Thus, if the failure risk is >50% in t-1, we expect it to be conditioned mainly by negative profitability.

In case of MFFP the failure risk becomes observable either in t-2 or t-3. We expect these firms to witness gradual accumulation of losses, the speed of which can vary through firms.

This is consistent with the logic proposed in Laitinen (1993) and would best reflect the idea proposed in the theory by Scott (1981). The gradually accumulating losses eventually turn accumulated profitability negative, thus in the MR we expect annual profitability to be the most important predictor, while in the SR accumulated profitability. Based on the general model of financial developments in the FFP by Laitinen (2005), we can also expect that in the MR and SR, the aforementioned (annual or accumulated) profitability is not the only contributor. In the MR, firms might engage additional debt increasing leverage (and attempt an unsuccessful turnaround). In the SR, when the problems are already severe in various financial domains, all domains (i.e. liquidity, profitability and leverage) could be important failure risk contributors, and thus, it is not possible to theoretically assume their exact contribution. In the LR we expect the failure risk not to be >50%, and thus, no contributors are outlined for that stage.

In case of LFFP, the failure risk is constantly high throughout the last studied stages. Thus, these firms obviously witness high leverage, low annual and accumulated profitability for all stages (as shown in Laitinen, 1991), so the exact ranking of these contributors to the failure risk cannot be outlined and is mainly an empirical question. Still, as the constant earning of losses makes the accumulated profitability ratio more negative on an annual basis, then purely in a financial mathematical sense it can become more/most important contributor closer to the bankruptcy declaration. Also, even when earning losses, LFFP firms manage to stay liquid, thus we expect that liquidity is not an important contributor to the failure risk until t-1.

3. Data and methods

The empirical data for the analysis include 1234 bankrupt firms from different European countries obtained from Bureau van Dijk Amadeus database and the specific country breakdown can be followed in Table 5. Out of 1234 firms, 32% resemble former Eastern European countries, Romania and Hungary being the most represented ones with respective frequencies of 198 and 128 firms. Out of the remaining 68%, Italy, France and Spain have the largest frequencies, respectively 340, 290 and 166 cases. Observations from only these countries were included, in case of which the exact bankruptcy time is known in Amadeus database. Data from different countries are needed, as this guarantees that some specific environment does not affect the obtained results. In case of studying firm bankruptcies there is some risk for the latter, as for instance insolvency legislations (and their implementation in practice) can be to a certain extent country-specific (Blazy, Chopard & Fimayer, 2008). All firms are private limited companies and no firms listed at the stock market are included. Both, exporting and non-exporting firms are included in the sample.

Based on values of the last year's turnover and assets, all firms in the dataset are SMEs with the following shares: 65% micro-, 28% small- and 7% medium-sized. All firms are manufacturing firms in order to avoid sectoral impact on the results. In the multi-sector studies of D'Aveni (1989) and Laitinen (1991), more than half of the firms were also manufacturing firms. Also, as the FFPs in D'Aveni (1989) and Laitinen (1991) concerned adolescent and old firms, in this study the bankrupt firms' age is required to be at least 10 years from their foundation to bankruptcy declaration.

For each firm, a five-year long consecutive time series of financial statement information before bankruptcy declaration is used. Starting from the earlier studies (e.g. Sharma & Mahajan, 1980; D'Aveni, 1989; Moulton, Thomas & Pruett, 1996), this has been the most usual time span applied. For all firms, the exact bankruptcy declaration date is known and the last available annual report is dated between 0.75 to 1.25 years before bankruptcy declaration. On the average, the last financial statement depicts the economic situation of a failing firm one year before the bankruptcy declaration in year t. For each firm, a theoretical FFP is identified by using the time series of financial statement information from t-1 to t-5. Then, the correspondence between the theoretical FFPs and empirically detected FFPs is investigated. Empirically, FFPs are found by using a much larger variety of clustering methods than in prior empirical research on FFPs.

3.1. Detection of theoretical FFPs

Unlike in the previous studies detecting FFPs, this research uses the highest resemblance to theoretical FFPs to select the best empirical solution. For that purpose, each firm in the dataset is assigned to follow one theoretical FFP. In the theoretical assignment, we use the (logistic bankruptcy prediction) Model 2 developed in Altman et al. (2017: 154) for a large number of bankrupt and non-bankrupt firms from a large set of European countries.

In their prediction model, Altman et al. (2017) weighted the observations in order to make the weights of bankrupt and non-bankrupt firms equal. Therefore, the critical probability of bankruptcy used to best discriminate between bankrupt and non-bankrupt firms was 0.5. Following Altman et al. (2017), the (weighted) probability is in this study calculated for each firm from the linear logit score using the logistic transformation.

In this study, we use the Altman et al.'s (2017) Model 2 to detect theoretical FFPs as follows:

1. When the Altman et al.'s (2017) Model 2 transformed logit score of a firm (i.e. weighted probability) does not become > 0.5 earlier than in t-1, it is considered to be SFFP.
2. When the Altman et al.'s (2017) Model 2 transformed logit score of a firm becomes > 0.5 either in t-2 or t-3 and remains > 0.5 for all following years, it is considered MFFP.
3. When the Altman et al.'s (2017) Model 2 transformed logit score of a firm becomes > 0.5 earlier than in t-3 and remains > 0.5 for all following years, it is considered LFFP.

Such an approach is of course not free from limitations. First, it could lead to some bias in further comparison of clustering results with theoretical assignments, as the latter has been achieved with a transformed logit score. Still, as Altman et al.'s (2017) discriminant and logit models have almost the same AUCs (respectively, 0.743 and 0.745), such a threat could be minimal. Second, such an approach accounts for the fact in which specific year before bankruptcy is declared, the risk of bankruptcy becomes over 50% and remains so for the following years, thus excluding other scenarios. For instance, a firm can be at high risk in t-2 and t-3, but not in t-1, thus being classified as SFFP – such a scenario can for instance point to a successful intermediate turnaround. Still, we do not aim to account for such risk fluctuations in this study, and moreover, the applied approach is in accordance with the theoretical FFPs in D'Aveni (1989).

3.2. Detection of empirical FFPs

For the empirical detection of FFPs, four different clustering methods are applied on different sets of variables over the last five years before bankruptcy. The clustering methods include two popular classical methods, namely k-means (KMN) and k-medians (KMD), and two popular more novel methods, namely expectation maximization (EM) and canopy (CA) clustering. In the studies outlined in section 2.2, KMN and KMD have been frequently used for the extraction of FFPs. EM was for the same purpose applied by Wu (2010), while we are not aware of scholarly articles, where CA has been used for the detection of FFPs. The KMN and KMD clusterings are done in Stata 14 statistical package, while EM and CA clusterings in WEKA 3.8.0 software. A certain limitation is that as there are thousands of different clustering algorithms available (Jain, 2010), the results of this study might not be generalizable over the abundance of different options. In case of all clustering methods, the number of clusters is set to be three, as three theoretical FFPs should exist.

[insert Table 2 about here]

Each of those four clustering methods is applied on eight different sets of variables brought out in Table 2, thus resulting in 32 different clustering strategies, each with a unique cluster solution. The eight different sets of variables used in the analysis are based on the bankruptcy prediction study by Altman et al. (2017). From Altman et al.'s (2017) study, either the initial four financial ratios, discriminant bankruptcy model scores (Model 1), logistic regression bankruptcy model scores (i.e. the linear logit scores; see Model 2) or transformed logistic regression bankruptcy model scores (i.e. the linear logit scores transformed with sigmoid function; see Model 2) are used. As these four types of inputs are used directly or by treating them with maximum likelihood factor analysis before clustering, the total amount of input variable sets equals eight. Multiple previous studies (e.g. Laitinen, Lukason & Suvas 2014; Lukason, Laitinen & Suvas 2016; Lukason and Laitinen 2016) have treated financial variables with factor analysis before clustering. The purpose of such action has been to standardize the variables and make them independent from each other, as otherwise the clustering methods might not perform well with financial variables, the distributions of which are originally (very) skewed and many outliers exist.

3.3. Matching theoretical and empirical FFPs

Each clustering strategy leads to a cluster solution where all firms have been assigned to one of the three clusters (see section 3.2). Also, for each firm it is known which of the theoretical FFPs it follows (see section 3.1). Thus, each of the three empirically detected clusters should symbolize only one of three: SFFP, MFFP or LFFP. Ideally (i.e. in case theory proves to be correct), the empirically detected clusters (see section 3.2) and the theoretical assignments (see section 3.1) should exactly match, but the reality of course diverges from this. Thus, an algorithm is needed, how to match the three clusters in all of the 32 cluster solutions with theoretical FFPs. The best option to achieve this would be to search for such an assignment in case of each cluster solution, which maximizes the weighted average correct classification into theoretical FFPs. Another option would be to try to achieve as equal accuracies for the three theoretical FFPs as possible, but such an approach can result in a dramatic misclassification, namely all detected clusters having less than half of cases of the theoretical FFP it is labelled to be. Finally, the cluster solution with the highest weighted average correct classification rate and all clusters with more than 50% of theoretically correct cases, will be chosen as the best one to be analysed further.

It should be noted that theoretical FFPs outlined in section 3.1 could be solely implemented for this study, but such an approach is limited. Namely, when considering only theoretical FFPs, the assignment is dependent on how large failure risk is used as a breakeven, which in this study is the theoretically most correct >50%. In turn, this can lead to a distortion of reality, as for instance a firm having 51% failure risk from t-5 to t-2 and 99% failure risk in t-1, would be classified as LFFP. Thus, using the most theory-resembling empirical solution allows to analyse a "real-life situation", which is in accordance with an "ideal-life" situation. The latter also means that the theoretical assignment in this study serves as a replacement of statistical cluster distinctiveness measures.

3.4. Detection of the contribution of different failure risk components

The analysis of the components of the failure risk is carried out as follows. After the detection of the theoretically most correct empirical cluster solution, the behaviour of four financial ratios in that cluster solution will be studied in order to find out, which of the variables contributes the most to the failure risk development. For outlining the contribution, for each firm in the sample, the value of each of the four financial ratios from Altman et al.'s (2017) Model 2 has been multiplied by its respective coefficient in Model 2, and then, the median values of these multiplied financial ratios have been calculated for each cluster (i.e. FFP). Then, the values of these medians are compared and the largest value is considered to be the most important contributor in determining the failure risk, as mathematically it has the largest effect on the value of transformed logit score (see also the notes section of Table 4). Finally, the prevalence of different failure processes in European countries will be brought out.

4. Results and discussion

4.1. Theoretical and empirical FFPs

The assignment of 1234 firms into theoretical FFPs results in the following classification: 604 firms (49.0%) as SFFP, 352 (28.5%) as MFFP and 278 (22.5%) as LFFP. Such shares of FFPs contradict the findings in D'Aveni (1989), where the SFFP had a very small share, namely one tenth of the sample studied, but that study analysed very large firms, for which problems have been noted to emerge many years before bankruptcy is declared (see Hambrick & D'Aveni, 1988). There is more resemblance with Laitinen's (1991) study, where the SFFP was also dominant. Thus, such a result may to some extent be subject to the size distribution of firms, which is more consistent with Laitinen (1991) than D'Aveni (1989).

Appendix 1 documents the results by 32 clustering strategies used. Expectedly, different clustering strategies lead to a high variation in the number of firms in the three clusters, and thus, their ability to detect FFPs varies largely. For instance, the size of the smallest cluster (theoretically 22.5%) varies from 4.4% to 25.9% from the total sample, the same figures for the largest cluster (theoretically 49.0%) being from 42.6% to 89.8%. In Appendix 1, all empirically detected clusters have been assigned to be one of the three theoretical FFPs (SFFP, MFFP, LFFP), so that the overall weighted average misclassification rate to theoretical FFPs is minimal.

It can be seen from Appendix 1 that the highest weighted average accuracy of classification is achieved with a solution C8, namely 67.6%. The total accuracy varies between the cluster solutions from 40.6% (C9) to 67.6% (C8). Solution C8 refers to k-means clustering (KMN) based on the factored transformed logit model scores from Altman et al.'s (2017) Model 2, while the worst clustering strategy C9 is obtained with k-medians clustering (KMD) using the four financial ratios from Altman et al. (2017) as input variables. Of the previous studies documented in the literature review, one study (Laitinen, Lukason & Suvas, 2014) also applied KMN with factored financial ratios as input variables. In solution C8, all clusters include more than 50% of the theoretically correct assignments, making it a valid solution for further analysis (see Appendix 2). As can be seen from Appendix 2, there are only 7 solutions (C4, C6, C8, C20, C22, C28, C30 – all bolded and underlined), where each of the detected clusters includes more than 50% of the theoretically correct classifications. Also, in Appendix 3 it can be followed what is the contingency between theoretical and empirical FFPs for the chosen solution C8.

It can be concluded that different clustering strategies can lead to a very high variation in the shares of different FFPs. Empirical evidence shows that KMN clustering leads to the best matches with theoretical FPPs, followed by EM and CA. However, KMD is not efficient in matching with theoretical FFPs. Additionally, of the input variables, either the transformed logit model scores or factored discriminant model scores are the most useful in clustering. Still, for the most accurate solution C8, the input variables are factored transformed logit model scores.

4.2. Description of the best empirical solution

Table 3 presents the medians of the four Altman et al. (2017) financial ratios, discriminant scores, logit scores, and transformed logit scores (weighted probability of bankruptcy) over the five years prior to bankruptcy for the most accurate cluster solution C8. The medians of all financial ratios, logit scores, and transformed logit scores are in accordance with the theoretical FFPs postulated by D'Aveni (1989). Namely, in the solution C8, in Cluster 1 they point to MFFP (16%), in Cluster 2 to SFFP (73%) and in Cluster 3 to LFFP (11%). In SFFP, bankruptcy risk becomes higher than 50% one year before bankruptcy, in MFFP three years before and in LFFP it is higher than 50% for all five years studied. The financial ratios from Altman et al.'s (2017) study used in the following discussion are: WCTA (i.e. working capital to total assets ratio, the former calculated as current assets minus current liabilities) portraying liquidity, EBITTA (i.e. earnings before interest and taxes to total assets ratio) portraying annual profitability, RETA (i.e. retained earnings to total assets ratio) portraying accumulated profitability, and BVETD (i.e. book value of equity to total debt ratio) portraying leverage.

[insert Table 3 about here]

In SFFP, liquidity (WCTA) is stable at 0.07-0.10 level from t-2 to t-5, but obtains a negative value in t-1. This is associated with earning high losses (negative EBITTA) during t-1, which also makes accumulated profitability (RETA) negative in t-1. From t-2 to t-5, EBITTA, RETA and BVETD also remain positive and on a sustainable level. Still, a drop of EBITTA is observable from t-3 to t-2. In Altman et al.'s (2017) study WCTA, EBITTA and RETA had very small negative values and BVETD a very small positive value for t-1, therefore being almost identical to the findings about SFFP in this study. Thus, as Altman et al. (2017) used around 31 times larger population of failed firms, it could be presumed that SFFP is also the most common process among firms and countries not included in this study. Firms following

SFFP are probably subject to abrupt changes in environment and/or serious mismanagement, which makes such firms collapse very quickly (Thornhill & Amit, 2003).

In MFFP, firms start earning losses (negative EBITTA) already in t-3, and in addition, losses become especially large in t-1 and t-2. This has also a considerable negative effect on firms' liquidity (WCTA), which also becomes negative in t-3, and on accumulated profitability (RETA), which obtains a very low positive value in t-3, before becoming substantially negative in t-2. BVETD obtains a large negative value in t-2. As such firms have exhausted their accumulated profit to cover losses (i.e. negative RETA in t-2), they must engage either additional share capital or debt to finance their business strategy. Such type of firms could be tackled in revenue financing problems (Laitinen 1991), but a separate question is, whether their attempted turnaround is unsuccessful (Trahms, Ndofor & Sirmon, 2013) or they are apathetic and fade away by relying on their initial strategy (Ooghe & de Prijcker, 2008).

In LFFP, firms are poorly functioning during the whole viewed period. The ratio values for such firms, which are negative for all periods from t-1 to t-5, clearly point to lingering (D'Aveni, 1989) and chronic failure (Laitinen, 1991). Such firms must involve extensive additional capital to finance losses for the whole five-year period. Probably many of these firms should have started insolvency proceedings or voluntary dissolving several years before their bankruptcy was declared.

The conducted median test results (see Table 3) indicate that financial ratios have significantly different median values for FFPs. The largest number of differences is observable between the median values of ratios for SFFP and LFFP, namely on 19 occasions out of 20. When comparing SFFP with MFFP or MFFP with LFFP, there are less differences, but still for more than half of the tests ran. Ratio values of SFFP and MFFP tend to differ more shortly before failure, and in turn, ratio values of MFFP and LFFP for years further from failure. Thus, firms following SFFP and MFFP are very similar many years before failure, but differ from firms following LFFP. In turn, shortly before failure, firms following MFFP are different from those following SFFP and LFFP. Thus, firms following MFFP have accumulated their problems to a shorter time horizon, when compared with those following LFFP. As in case of all three FFPs WCTA and RETA are negative for t-1, the collapse of all firms is subject to both liquidity and solidity bankruptcy as indicated in Laitinen (1995).

4.3. Contribution of the components of failure risk

For studying the components of the failure risk, for each observation each of the four financial ratios from t-1 and t-5 has been multiplied by its respective coefficient from Altman et al.'s (2017) Model 2. Table 4 documents the median values of the resulting multiplied ratios for each of the FFPs from t-1 to t-5.

In case of SFFP, the failure risk is >50% only for t-1 and for that year, negative EBITTA is the most important contributor to the failure risk. Such a finding meets the assumption set in Table 1 and is also consistent with literature (see e.g. Laitinen, 1991; Lukason, Laitinen & Suvas, 2016), as in case of SFFP, the signs of failure do not emerge before t-1 and firms can witness extensive losses during t-1, thus making the EBITTA logically the most important contributor to the failure risk. SFFP is generally in accordance with Scott's (1981) probabilistic theory of bankruptcy (i.e. negative profitability makes a firm's equity negative), although the accumulation of losses occurs in a very short time. In the context of studied SMEs, it is not surprising, as such firms are often focused on a small number of clients and specific niches, making them especially vulnerable to environmental pressures (Crutzen & van Caillie, 2010). Of internal conditions, these firms might be especially subject to a "one man rule" problem (Argenti, 1976).

In case of MFFP, for the years failure risk is >50%, i.e. in t-3 and t-2, EBITTA is the most important failure risk contributor. Still, already in t-2, the accumulated losses are large enough, and thus, RETA obtains a high contribution as well. In t-1, RETA surpasses EBITTA as a contributor, as accumulated losses have become very large. Also, in t-1 due to earning constant losses, firms have drained from liquidity and WCTA contributes substantially to the failure risk as well. Generally, the findings follow the proposed concept in Table 1, although the exact trade-off between different contributors was not proposed for t-1. MFFP is a better portrayal of Scott's (1981) theory than SFFP. Namely, firms sustain the first setback (negative profitability) in t-3, maintaining positive retained earnings, but the "death-blow" evidently occurs in t-2, when large losses drive the retained earnings negative.

[insert Table 4 about here]

In case of LFFP, there is a clear tendency that RETA is the most important contributor during all years, but when a firm becomes closer to bankruptcy, the second important contributor EBITTA is replaced by WCTA. This means that due to constantly earning losses, a firm becomes over-indebted and during the final years of its life struggles with constant liquidity problems. An exact theoretical ranking of financial domains was not proposed for LFFP in Table 1, as which and how large problems exist in different financial domains for this FFP, is more an empirical question. As noted in D'Aveni (1989), LFFP firms might delay bankruptcy filing for too long, and also, such firms might undertake several unsuccessful reorganization attempts (Ooghe & de Prijcker, 2008).

The analysis of the failure risk contributors for different FFPs indicates that the probabilistic theory of bankruptcy by Scott (1981) is useful in explaining the content of FFPs. Namely, his model set the positivity of equity and profit as its impactor in the central place in modelling firm failure. This study indicates that for the stages of different FFPs, when the failure risk is >50%, EBITTA reflecting annual profitability and RETA reflecting accumulated profitability are the most important contributors. The SMEs studied in this paper normally pay in a small amount of capital at the foundation, thus a large proportion of equity is composed of retained earnings.

Also, when studying the stages of SFFP and MFFP, for which the failure risk is not >50%, the median values of financial ratios are very similar (as also indicated with statistical tests in section 4.2). Thus, we could provide some empirical support to Laitinen's (1993) theoretical assumption, that in respect to the failure risk development, only one FFP could exist, when we consider the *de facto* moment of failure (i.e. the moment when the failure risk becomes and remains >50%). Still, the exact proving of such a postulate would demand knowledge about what happened in these firms during the last years, including whether the start of insolvency proceedings was artificially delayed. Also, in case of LFFP, a longer time frame should be applied in the analysis, as already in t-5, the risk is >50%, and thus, we would need information about more further years when these firms were performing normally.

The results also provide a certain contribution to the liabilities of age and size theories. Concerning these theories, since Aldrich and Auster (1986), the common setting has been to view either old and large or young and small organizations. This study indicates that old and small firms follow mainly SFFP, thus we can hypothesize that the coexistence of liabilities of smallness and obsolescence mainly leads to very abrupt termination of businesses.

4.4. FFPs by countries

Lastly, the frequencies of the three FFPs through studied countries will be considered (see Table 5). There is a certain tendency that in more developed economies (e.g. Italy, Spain), the SFFP is more frequent compared to less advanced economies (e.g. Hungary, Romania). Such a tendency occurs mainly in the expense of less advanced economies having a larger share of LFFP, whereas the MFFP shares are very similar. Thus, it can at least partly point to the fact that in countries with a higher development level, the insolvency legislation and its implementation guarantees that firms unable to pay outstanding debt are eliminated from the market quickly. This is supported by Doing Business (2017) country rankings of insolvency procedures, where Romania and Hungary hold respectively places 49 and 63, whereas the same figures for Italy and Spain are 25 and 18.

[insert Table 5 about here]

Although the inter-country differences of FFPs have been studied before, previous research (e.g. Lukason, Laitinen & Suvas, 2016; Lukason and Laitinen, 2016) has not found evidence that countries with different development levels would remarkably differ in respect to shares of FFPs. In Laitinen, Lukason & Suvas (2014) various inter-country differences were found, but in that study some less advanced countries (e.g. Estonia, Czech Republic, Russia) were characterized more by acute failure processes than more developed (e.g. Belgium, United Kingdom). Still, the FFPs in this study are detected based on a different empirical logic, which could partly explain such divergence from the results in previous studies. Namely, the usage of the failure risk calculated based on Altman et al.'s (2017) Model 2 accounts for the fact how failed firms perform in comparison to survived firms, but previous multi-country studies detecting FFPs have all been concentrated on finding clusters only among failed firms and have been based on financial variables, not the failure risk, as an input.

Although FFPs can be differently represented through countries, the failure risk contributors are not altered by country-specifics. Namely, when calculating the rankings of failure contributors for high failure risk (i.e. >50%) years for the three FFPs in five countries with the highest representation (i.e., France, Italy, Romania, Spain, Hungary), the ranking of main contributors outlined in Table 4 is not altered. Thus, the inclusion of different countries does not affect the main results of this study.

5. Implications for bankruptcy prediction

We herewith provide important implications for the bankruptcy prediction domain, as this area of research is currently very important, with hundreds of papers appearing annually. Bankruptcy prediction is also one of the academic areas having the largest intersection with business practice, as relevant tools are needed by all creditors. Some of the findings in this study well explain the existence of (large) misclassification errors of bankruptcy prediction models and suggest some improvement measures.

The dominant process for SMEs is short-range firm failure process (SFFP). First, when firms follow SFFP, their failure is very difficult to predict, as even the last annual report (which is available at least several months after the end of the financial year) might not indicate worsening of financial situation. This study indicates that negative profitability is the most powerful indicator of future bankruptcy in case of SFFP. Moreover, the profitability drops to a very low positive level from t-3 to t-2 in case of such firms. Already for earlier years, the latter tendencies are observable for firms following MFFP. Thus, when profitability turns negative, it can be the first sign that the firm is entering some stage of some FFP. Moreover, multiple years of negative profitability indicate that the firm is already following MFFP or LFFP. Still, in order to predict the future demise of firms with (high) confidence, it should be accounted that firms witnessing negative profitability should simultaneously witness negative retained earnings. Although survived firms were not studied in this paper, it is reasonable to assume that their one or few years of (accidental) bad performance (i.e. negative profitability) is not accompanied by negative values for retained earnings. Another important take away for bankruptcy prediction domain is that liquidity drop to a non-sustainable level is lagged in comparison to profitability, thus despite the high usage of liquidity ratios in bankruptcy prediction studies, profitability should be preferred as an early indicator of potential future collapse. Analysts should account that in more developed countries, SFFP is a more frequent process, accounting for more than 80% of firms. Thus, in these countries the future failure of firms is more difficult to detect when compared with less advanced countries.

Due to the large proportion of SFFP firms, we would urge researchers to additionally use variables other than financial ratios in the SME failure prediction models. As the abrupt decline in profitability would point to some environmental shock or serious managerial mistake as its triggers, probably incorporating variables portraying the specific market the firm is functioning in or managerial characteristics would enhance prediction abilities. Also, the detection of FFPs by various clustering strategies leads to an important methodological implication for the composers of bankruptcy prediction models. Namely, in recent years the trajectory based prediction of corporate bankruptcy has gained popularity (e.g. du Jardin 2015, du Jardin 2017). This study clearly indicates that different trajectory detection algorithms can produce remarkably varying results, either when financial ratios or bankruptcy probabilities are used as input variables. Thus, reliance on one or a few methods should be considered with caution and validation through a large variety of tools should be "a must" for a researcher in order to produce reliable results.

6. Conclusion

This study focused on outlining the failure risk contributors for different stages of firm failure processes (FFPs). Using data of 1234 bankrupted manufacturing firms from different European countries, three theory-driven FFPs are detected using bankruptcy probabilities from Altman et al.'s (2017) model as an input. These FFPs are respectively named short- (SFFP), medium- (MFFP) and long-range (LFFP) firm failure processes based on the failure risk emergence time. The most frequent FFP in the studied sample is SFFP (73%), in case of which the failure risk is not observable until one year before bankruptcy is declared.

We find that the overwhelmingly largest contributor to the failure risk in case of SFFP in period t-1 is negative annual profitability. For MFFP, both annual and accumulated profitability are the most important contributors depending on which period before bankruptcy declaration is viewed. In case of LFFP, accumulated profitability is the overwhelmingly most important contributor. These findings are in line with the probabilistic bankruptcy prediction theory by Scott (1981). In turn, liquidity and leverage do not have a major role in determining the failure risk for different stages of FFPs.

As the actionable implications for bankruptcy prediction model composers, we would suggest the following. The forthcoming failure is portrayed best with profitability. Due to the existence of different FFPs, annual and accumulated profitability should both be accounted, and additionally, annual profitability also dynamically (i.e. the change in between two years). These three variables can capture the potentially emergent future problems in the best way. In addition, as around three quarters of the firms follow a process, where the bankruptcy prediction model's applicability directly depends on when the last annual report becomes available, either quarterly or semi-annual reports or even (non-)financial information outside of financial reports could help to improve prediction accuracies and early warning.

Several limitations of this study should be pointed out. As the focus in this study is on private unlisted adolescent manufacturing SMEs, the results should be especially viewed in this context and might not be transferrable to all other types of firms, especially large listed companies (in other sectors). Large firms are subjected to more control and their annual reports are audited, thus misreporting is less likely to occur in that firm group. Manufacturing firms normally use a larger amount of (fixed) assets than for instance firms is service and sales sectors (e.g. fixed assets as machinery and equipment or current assets as materials), and thus, all ratios in Altman et al.'s (2017) model except for leverage could be affected by that sectoral peculiarity. Also, this study relies on a conceptual model created based on D'Aveni (1989) and Scott (1981), and it was further validated by using Altman et al.'s (2017) model and a limited number of clustering strategies. In case of such a research strategy, the question remains, how would more enhanced theoretical and empirical settings complement the obtained results. In case of the former, for instance the number of theoretical processes could be extended to portray all different mathematical combinations and various other financial domains, like firm productivity or the ability to create cash flows. Still, when considering the scope of theoretical approaches and empirical settings applied in this study, a reasonably robust solution was reached.

There are many ways this paper could be developed further. First, this paper relied on the assumption of the existence of three specific theoretical FFPs, but the pathways to bankruptcy could be more diversified. For instance, in future studies the presence and measures of pre-bankruptcy informal or court supervised reorganization could be accounted. Second, this paper could be extended by viewing the failure risk development in time for both, firms bankrupting and surviving. Among other benefits, this would enable to outline more specific implications for the bankruptcy prediction domain. Third, the variables could be more diversified, namely by not looking only at the bankruptcy risk, but also at managerial actions and environmental developments, as suggested by Amankwah-Amoah (2016).

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Table 1. A conceptual model of interconnections of FFP stages with different financial domains and failure risk.

Period	Financial domain	SFFP		MFFP		LFFP	
		Level of specific financial domain	Failure risk (FR) and its contributors	Level of specific financial domain	Failure risk (FR) and its contributors	Level of specific financial domain	Failure risk (FR) and its contributors
In the long-range (LR, i.e. before t-3)	Liquidity	High/average	FR is not observable	High/average	FR is not observable	Average	FR is observable. Annual & accumulated profitability and leverage contribute, but their exact importance is unknown. Liquidity contributes less.
	Profitability	High/average		High/average		Low	
	Leverage	Low/average/high		Low/average/high		High	
In the mid-range (MR, i.e. during t-2 and/or t-3)	Liquidity	High/average	FR is not observable	Average	FR is observable. The most important contributor is negative annual profitability, which could be followed by high leverage.	Average	FR is observable. Annual & accumulated profitability and leverage contribute, but their exact importance is unknown. Liquidity contributes less.
	Profitability	High/average		Low		Low	
	Leverage	Low/average/high		Average/high		High	
In the short-range (SR, i.e. during t-1)	Liquidity	Average/low	FR might be observable. The most important contributor is negative annual profitability.	Low	FR is observable. All financial domains contribute, but their exact importance is unknown.	Low	FR is observable. All financial domains contribute, but their exact importance is unknown.
	Profitability	Average/low		Low		Low	
	Leverage	Average/high		High		High	

Note: we consider “leverage” in this table in a general meaning, i.e. higher leverage means using more debt. In Altman et al.’s (2017) model book value of equity to debt ratio was applied and that should be interpreted the other way around, i.e. higher ratio value points to lower leverage.

Table 2. The content of 32 clustering strategies based on eight different sets of variables and four clustering methods.

Variable sets used in clustering \ Clustering method	KMN	KMD	EM	CA
1. Four financial ratios from Altman et al.'s (2017) study	C1	C9	C17	C25
2. Discriminant model scores from Altman et al.'s (2017) Model 1	C2	C10	C18	C26
3. Logit model scores from Altman et al.'s (2017) Model 2	C3	C11	C19	C27
4. Transformed logit model scores from Altman et al.'s (2017) Model 2	C4	C12	C20	C28
5. Factored four financial ratios from Altman et al.'s (2017) study	C5	C13	C21	C29
6. Factored discriminant model scores from Altman et al.'s (2017) Model 1	C6	C14	C22	C30
7. Factored logit model scores from Altman et al.'s (2017) Model 2	C7	C15	C23	C31
8. Factored transformed logit model scores from Altman et al.'s (2017) Model 2	C8	C16	C24	C32

Note: C*n* denotes the specific cluster solutions resulting from a clustering strategy (i.e. a combination of input variables and the clustering method). In case of variable sets 1-4, the input variables range from t-1 to t-5. In case of variable sets 5-8, the input variables are factor scores obtained from the maximum likelihood factor analysis with Varimax rotation of the specific input variables from t-1 to t-5.

Table 3. Median values of variables through three FFPs.

Variable	SFFP	MFFP	LFFP	Total	Variable	SFFP	MFFP	LFFP	Total
WCTA1^{13}	-0.08	-0.84	-0.67	-0.19	Z1^{13}	0.22	1.73	1.81	0.51
WCTA2^{13}	0.07	-0.39	-0.43	0.00	Z2^{13}	-0.16	1.12	0.97	-0.02
WCTA3^{123}	0.09	-0.05	-0.49	0.05	Z3^{123}	-0.23	0.09	0.90	-0.16
WCTA4^{23}	0.09	0.07	-0.44	0.06	Z4^{123}	-0.25	-0.18	0.97	-0.21
WCTA5^{23}	0.10	0.09	-0.27	0.07	Z5^{23}	-0.27	-0.24	0.49	-0.23
RETA1^{13}	-0.02	-0.88	-1.23	-0.15	LOG1^{13}	0.28	1.87	2.00	0.58
RETA2^{123}	0.09	-0.47	-0.75	0.03	LOG2^{13}	-0.09	1.22	1.12	0.04
RETA3^{123}	0.11	0.01	-0.59	0.07	LOG3^{123}	-0.16	0.15	0.99	-0.09
RETA4^{123}	0.13	0.08	-0.51	0.09	LOG4^{123}	-0.18	-0.12	1.08	-0.14
RETA5^{23}	0.14	0.11	-0.31	0.11	LOG5^{23}	-0.21	-0.16	0.65	-0.16
EBITTA1^{12}	-0.12	-0.36	-0.16	-0.15	LOGT1^{13}	0.57	0.87	0.88	0.64
EBITTA2^{123}	0.01	-0.35	-0.08	-0.02	LOGT2^{13}	0.48	0.77	0.75	0.51
EBITTA3^{13}	0.03	-0.08	-0.09	0.02	LOGT3^{123}	0.46	0.54	0.73	0.48
EBITTA4^{23}	0.04	0.03	-0.20	0.03	LOGT4^{123}	0.45	0.47	0.75	0.47
EBITTA5^{23}	0.04	0.03	-0.07	0.03	LOGT5^{23}	0.45	0.46	0.66	0.46
BVETD1^{13}	0.06	-0.43	-0.48	-0.01					
BVETD2^{13}	0.23	-0.26	-0.33	0.12					
BVETD3^{123}	0.25	0.07	-0.30	0.19					
BVETD4^{23}	0.27	0.22	-0.25	0.22					
BVETD5^{23}	0.29	0.27	-0.08	0.25					

Notes: WCTA – working capital (i.e. current assets minus current liabilities) to total assets ratio, RETA – retained earnings to total assets ratio, EBITTA – earnings before interest and taxes to total assets ratio, BVETD – book value of equity to total debt ratio; D – Altman et al.'s (2017) discriminant model's (i.e. Model 1) score, LOG – Altman et al.'s (2017) logit model's (i.e. Model 2) linear score, LOGT – Altman et al.'s (2017) logit model's (i.e. Model 2) transformed score (i.e. $0 \leq \text{LOGT} \leq 1$). The number behind each variable denotes the pre-bankruptcy year, e.g. 1 means one year before bankruptcy (i.e. t-1). Superscripts 1, 2, 3 indicate pairwise median test p-values < 0.05 as follows: ^{1} – SFFP versus MFFP, ^{2} – MFFP versus LFFP, ^{3} – SFFP versus LFFP.

Table 4. The rankings of variables in the FFPs of the best cluster solution C8 based on the median values of ratios multiplied by their coefficients.

Variable multiplied by relevant coefficient	Median	Ranking	Median	Ranking	Median	Ranking	Median	Ranking
	SFFP		MFFP		LFFP		Total	
WCTA1	-0.039	2	-0.417	3	-0.330	2	-0.094	3
RETA1	-0.014	3	-0.758	1	-1.059	1	-0.132	2
EBITTA1	-0.210	1	-0.616	2	-0.269	3	-0.257	1
BVETD1	0.001	4	-0.007	4	-0.008	4	0.000	4
WCTA2	0.036	2	-0.193	3	-0.213	2	0.000	4
RETA2	0.082	1	-0.402	2	-0.642	1	0.025	2
EBITTA2	0.009	3	-0.606	1	-0.140	3	-0.033	1
BVETD2	0.004	4	-0.004	4	-0.006	4	0.002	3
WCTA3	0.043	3	-0.025	2	-0.245	2	0.022	3
RETA3	0.099	1	0.005	3	-0.513	1	0.059	1
EBITTA3	0.046	2	-0.134	1	-0.152	3	0.030	2
BVETD3	0.004	4	0.001	4	-0.005	4	0.003	4
WCTA4	0.045	3	0.036	3	-0.217	3	0.030	3
RETA4	0.112	1	0.068	1	-0.437	1	0.079	1
EBITTA4	0.065	2	0.049	2	-0.346	2	0.050	2
BVETD4	0.005	4	0.004	4	-0.004	4	0.004	4
WCTA5	0.049	3	0.043	3	-0.132	2	0.033	3
RETA5	0.118	1	0.095	1	-0.265	1	0.095	1
EBITTA5	0.067	2	0.052	2	-0.120	3	0.058	2
BVETD5	0.005	4	0.005	4	-0.001	4	0.004	4

Note: Each financial ratio of each firm has been multiplied by the absolute value of the coefficient in Altman et al.'s (2017) Model 2 and the table presents the median values of such new variables (i.e. coefficient-weighted ratios) through the clusters of C8. Although all coefficients in Altman et al. (2017) Model 2 are negative (i.e. theoretically correct), the multiplication has been achieved with absolute values of coefficients to enhance comparison of Tables 3 and 4. The latter is a mere technical aspect, not altering the content anyhow. In the ranking column, the smaller the number, the higher the importance of a specific variable, i.e. "1" indicates the highest contribution. The ranking has been obtained by comparing absolute values of medians. For some years of some FFPs, when the failure risk is >50%, the medians of some coefficient-weighted ratios are positive (i.e. they are decreasing the failure risk), but their contribution is very low compared to those ratios, which have (high) negative values and therefore (substantially) increasing the failure risk.

Table 5. The frequencies of FFPs through different European countries.

Country	SFFP	MFFP	LFFP	Total
Belgium	6	1	0	7
Bulgaria	1	0	0	1
Czech Republic	24	6	5	35
Spain	137	16	13	166
Finland	17	0	6	23
France	202	45	43	290
United Kingdom	4	0	1	5
Croatia	14	4	3	21
Hungary	91	21	16	128
Italy	273	54	13	340
Latvia	1	1	0	2
Portugal	5	2	1	8
Romania	119	45	34	198
Sweden	1	0	0	1
Slovakia	6	3	0	9
Total	901	198	135	1234

Note: Chi-square test statistic was 65 and p-value 0.000. These indicators for only 5 countries with over 100 observations included were respectively 49 and 0.000.

Appendixes

Appendix 1. Cluster sizes in 32 cluster solutions and classification of each cluster to a theoretical firm failure process.

Solution	Cluster 1 size	TFFP	Cluster 2 size	TFFP	Cluster 3 size	TFFP	Smallest cluster share	Largest cluster share	Median cluster share	Clustering accuracy
C1	164	M	115	L	955	S	9.3%	77.4%	13.3%	45.0%
C2	305	M	109	L	820	S	8.8%	66.5%	24.7%	47.5%
C3	130	L	707	S	397	M	10.5%	57.3%	32.2%	62.8%
C4	187	M	943	S	104	L	8.4%	76.4%	15.2%	63.1%
C5	409	M	705	S	120	L	9.7%	57.1%	33.1%	63.5%
C6	184	M	938	S	112	L	9.1%	76.0%	14.9%	63.9%
C7	477	M	616	S	141	L	11.4%	49.9%	38.7%	64.7%
C8	198	M	901	S	135	L	10.9%	73.0%	16.0%	67.6%
C9	232	L	280	M	722	S	18.8%	58.5%	22.7%	40.6%
C10	316	M	386	L	532	S	25.6%	43.1%	31.3%	54.0%
C11	388	L	320	S	526	M	25.9%	42.6%	31.4%	53.1%
C12	385	S	627	M	222	L	18.0%	50.8%	31.2%	49.3%
C13	399	L	300	S	535	M	24.3%	43.4%	32.3%	51.9%
C14	392	S	604	M	238	L	19.3%	48.9%	31.8%	49.0%
C15	192	L	535	S	507	M	15.6%	43.4%	41.1%	62.7%
C16	245	L	602	M	387	S	19.9%	48.8%	31.4%	47.9%
C17	374	S	553	M	307	L	24.9%	44.8%	30.3%	52.0%
C18	226	L	387	M	621	S	18.3%	50.3%	31.4%	46.1%
C19	625	M	267	S	342	L	21.6%	50.6%	27.7%	52.6%
C20	223	M	901	S	110	L	8.9%	73.0%	18.1%	65.2%
C21	604	M	279	S	351	L	22.6%	48.9%	28.4%	53.0%
C22	847	S	263	M	124	L	10.0%	68.6%	21.3%	65.1%
C23	279	S	582	M	373	L	22.6%	47.2%	30.2%	53.0%
C24	800	S	307	M	127	L	10.3%	64.8%	24.9%	64.1%
C25	1045	S	105	M	84	L	6.8%	84.7%	8.5%	49.4%
C26	1108	S	72	M	54	L	4.4%	89.8%	5.8%	46.2%
C27	803	M	337	S	94	L	7.6%	65.1%	27.3%	60.7%
C28	1059	S	106	M	69	L	5.6%	85.8%	8.6%	58.8%
C29	773	M	367	S	94	L	7.6%	62.6%	29.7%	61.5%
C30	1051	S	109	M	74	L	6.0%	85.2%	8.8%	59.3%
C31	883	M	257	S	94	L	7.6%	71.6%	20.8%	54.9%
C32	972	S	108	M	154	L	8.8%	78.8%	12.5%	41.7%

Note: Theoretical firm failure process (TFFP) which the specific cluster represents is noted as follows: S – SFFP, M – MFFP, L – LFFP. Clustering accuracy column indicates with what weighted average precision the theoretical FFPs have been detected.

Appendix 2. Shares of theoretically correct processes by clusters in 32 cluster solutions.

Solution	Accuracy in Cluster 1	Accuracy in Cluster 2	Accuracy in Cluster 3	Solution	Accuracy in Cluster 1	Accuracy in Cluster 2	Accuracy in Cluster 3
C1	14.6%	63.5%	48.0%	C17	77.0%	32.9%	56.0%
C2	22.6%	72.5%	53.4%	C18	51.3%	27.9%	55.6%
C3	86.9%	67.6%	46.3%	C19	34.9%	89.5%	56.1%
<u>C4</u>	**<u>57.8%</u>**	**<u>62.1%</u>**	**<u>81.7%</u>**	**<u>C20</u>**	**<u>61.4%</u>**	**<u>64.2%</u>**	**<u>81.8%</u>**
C5	47.2%	68.5%	90.0%	C21	34.9%	88.5%	55.8%
<u>C6</u>	**<u>60.3%</u>**	**<u>62.4%</u>**	**<u>82.1%</u>**	**<u>C22</u>**	**<u>64.8%</u>**	**<u>57.4%</u>**	**<u>83.1%</u>**
C7	46.1%	74.5%	85.1%	C23	88.5%	35.1%	54.4%
<u>C8</u>	**<u>68.7%</u>**	**<u>64.8%</u>**	**<u>84.4%</u>**	C24	65.8%	53.4%	79.5%
C9	51.7%	14.6%	47.1%	C25	49.4%	16.2%	90.5%
C10	47.5%	40.7%	67.5%	C26	48.5%	16.7%	38.9%
C11	39.4%	95.9%	37.1%	C27	41.8%	96.4%	93.6%
C12	82.3%	28.5%	50.5%	**<u>C28</u>**	**<u>56.5%</u>**	**<u>59.4%</u>**	**<u>92.8%</u>**
C13	40.1%	96.0%	35.9%	C29	42.2%	94.0%	93.6%
C14	81.1%	27.5%	50.8%	**<u>C30</u>**	**<u>56.9%</u>**	**<u>59.6%</u>**	**<u>93.2%</u>**
C15	71.9%	79.1%	42.0%	C31	38.5%	96.9%	93.6%
C16	46.1%	26.2%	82.7%	C32	46.2%	60.2%	0.0%

Note: The percentage in the cell shows the share of the assigned theoretical FFP in the cluster. For the assignment of theoretical FFPs to the detected clusters, see Appendix 1. Bolded and underlined are the cluster solutions in which each of the clusters includes more than 50% of theoretically correct cases.

Appendix 3. Contingency between theoretical and empirical FFPs in the solution C8.

	Empirical SFFP	Empirical MFFP	Empirical LFFP	Total
Theoretical SFFP	**584**	4	16	604
Theoretical MFFP	211	**136**	5	352
Theoretical LFFP	106	58	**114**	278
Total	901	198	135	1234

Note: correctly clustered theoretical FFPs are bolded and underlined.