Oliver Lukason (Estonia), Erkki K. Laitinen (Finland)

Failure processes of old manufacturing firms in different European countries

Abstract

This study aims to detect failure processes on the example of old bankrupted European manufacturing firms. Two study designs are applied, namely the original six variables from Laitinen's (1991) model and an extended dataset with eleven variables for a five-year timespan before declared bankruptcy. On both occasions, two different failure processes are detected which indicate elements of either quickly or gradually failing firms. Clear contingencies between detected processes and firms' countries of origin exist. There is some evidence that firms of different sizes follow varying failure processes, but this does not apply when discriminating between exporters and non-exporters.

Keywords: firm failure processes, bankruptcy, old manufacturing firms, European countries.
JEL Classification: G33, M10, M21, O57.

Introduction

In recent years, research about firm failure has flourished. This is especially observable in the domain of failure prediction studies, where dozens of papers appear annually, both applying classical statistical and novel machine learning techniques. When a myriad of different prediction models have been created since the piloting multivariate study by Altman (1968), another close research domain – firm failure processes – has received episodic attention since the piloting monograph by Argenti (1976). Studies focusing on firm failure processes offer an insight in which different ways firms collapse. Both causal and symptomatic domains have been elaborated in this research stream. In a few past years, the topic has re-emerged and multiple recent studies are available (e.g., Laitinen and Lukason, 2014; Laitinen et al., 2014; du Jardin, 2015), some of which also provide first evidence of inter-country comparison of failure processes. Recent studies also carry several limitations like small and multi-sector datasets. Therefore, this study aims to provide single-sectoral evidence from a large set of European countries relying on multiple different study designs.

From a more theoretical perspective, this study contributes to the liability of obsolescence concept explaining the failure of old firms. The main foundation of this approach is that firms become inert to changes in environment and therefore start to decline (Barron et al., 1994; Henderson, 1999; Thornhill and Amit, 2003). Still, the timing of such a decline and its characteristics depicted through different financial variables remain understudied in the available research focusing on the liability of obsolescence concept. The topic of failure processes has also been neglected in bankruptcy prediction studies and only a few of them (e.g., Pompe and Bilderbeek, 2005) have outlined the large dispersion in the pre-bankruptcy values of firms' financial ratios, therefore, offering some indication of the possible presence of different failure processes.

The general objective of the paper is to create a taxonomy of failure processes on the example of old European manufacturing firms. This will be achieved by applying two different study designs on a dataset of manufacturing firms from all size categories from 15 European countries. The paper is focused on manufacturing firms that were at least 10 years old by the moment of bankruptcy declaration.

The paper is structured as follows. The literature review focuses on past studies about failure processes. In the literature review part, also key terminology is outlined and hypotheses are set to guide the research. The overview of past studies is followed by the section describing the sample, variables and methods of the analysis. After that, the results of the study are presented and discussed. The paper ends with a conclusion also encompassing implications.

1. A review of literature

1.1. Context of failure and failure process. Failure has been defined differently through studies, but researchers focusing on failure prediction and failure processes have almost univocally used court-declared permanent insolvency (i.e., bankruptcy) as the definition of a failed firm (Mellahi and Wilkinson, 2004; Balcaen and Ooghe, 2006; Laitinen et al., 2014). The popularity of bankruptcy as a definition is obviously connected to the fact that such firms are deleted from business registers and are therefore "dead". In case of other possible definitions (see, e.g., Mellahi and Wilkinson, 2004, p. 22) it is always arguable, what situation to consider as failure. For instance, during economic downturn, a majority of firms can witness temporary liquidity problems or even temporary payment defaults. As another example, a firm can deliberately earn losses when applying a strategy of out-marketing competitors.

Oliver Lukason, Researcher of Finance, School of Economics and Business Administration, University of Tartu, Estonia.
Erkki K. Laitinen, Professor of Accounting and Finance, Department of Accounting and Finance, University of Vaasa, Finland.

There is more terminological and content-related variation when considering firm failure processes (Laitinen and Lukason, 2014, p. 811). When several studies follow the example of Laitinen's (1991) study by applying the term "failure process" (e.g., Laitinen and Lukason, 2014; du Jardin, 2015), then, others apply completely different terms (e.g., "trajectories" in Argenti, 1976 and "patterns" in D'Aveni, 1989) for a very similar concept. Using different terms is often merely a linguistic issue. More variety arises when considering the variables different authors have applied for modelling the failure process. Such diversity can be aggregated as whether studies apply "why", "how" or both of them for depicting the failure process. Thus, there are studies focusing only on failure causes (e.g. Crutzen and van Caillie, 2010), financial indicators (e.g., Laitinen, 1991) and on both of them (Laitinen and Lukason, 2014). This study focuses solely on financial variables to model the failure process and failure is defined as bankruptcy (i.e., permanent insolvency declared at court).

1.2. Failure processes detected in previous studies. Empirical detection of failure processes is a rather scarce topic in available literature. Most of the available studies have focused on the example of old firms, whereas study designs have been diverse. Studies can be divided between those providing case study evidence (e.g., Argenti, 1976; Sheppard and Chowdhury, 2005; Ooghe and de Prijcker, 2008), and those applying statistical analysis on samples (e.g., D'Aveni, 1989; Laitinen, 1991; Laitinen et al., 2014). Sample sizes have varied, being below 100 firms in earlier studies and remarkably larger in recent ones (e.g., 558 firms in Laitinen et al., 2014). Available research has almost exclusively applied multi-sector approach and only a scant amount of studies (e.g., Lukason, 2014) are focusing on a single sector. In multi-sector studies, the manufacturing sector has mostly been included, although analysis results might not include sectoral breakdown. Process extraction methods have mostly included classical statistical tools like factor and/or cluster analysis (e.g., D'Aveni, 1989; Laitinen, 1991; Laitinen et al., 2014), but there are examples of more sophisticated novel tools as well (e.g., du Jardin, 2015). Thus, the set of applied methods has been rather constrained, unlike in the connected research stream of bankruptcy prediction, where novel methods are introduced almost annually (see e.g., Ravi Kumar and Ravi, 2007; Kirkos, 2012). In case of old firms, the modelling focus has been set on the last years of existence, which can for instance include only two years (e.g., Laitinen and Lukason, 2014), four to six years (e.g., D'Aveni, 1989; Laitinen, 1991; Laitinen et al., 2014) or even ten years (e.g., Hambrick and D'Aveni, 1988) before bankruptcy. The considered time span has some connections to firm size, as, for instance, in Hambrick and D'Aveni (1988), the focus was on large US corporations, whereas in Laitinen and Lukason (2014) mostly on micro-firms.

Most of the studies have detected a small number (three or four) of different processes, which represent the chronically unsuccessful firm (i.e., financial ratios indicate poor performance long before bankruptcy is declared), gradually deteriorating firm (i.e., performance becomes worse step by step until bankruptcy is declared) and suddenly collapsing firm (i.e., forthcoming bankruptcy might not be indicated through financial ratios not earlier than just before bankruptcy) (e.g., D'Aveni, 1989; Laitinen, 1991; Laitinen et al., 2014). In Laitinen's (1991) study, process extraction was based on a theoretical model outlining which variables and how could be interconnected in the failure process. These variables were (Laitinen, 1991, p. 656): return on investment ratio, rate of growth in total assets, net sales to total assets ratio, traditional cash flow to net sales ratio, capital assets ratio and current ratio. In Laitinen et al. (2014) study that applied similar variables as Laitinen (1991), manufacturing firms were pooled together with mining and quarrying firms, accounting for 30.7% of the applied sample. The representation of processes in Laitinen et al. (2014) study was as follows: a) acute failure 23% (two different acute failure sub-processes detected), b) gradual failure 62%, and c) chronic failure 15%.

In Laitinen's (1991) model, liquidity and solvency were captured by three variables: traditional cash flow ratio (dynamic liquidity, but this variable also portrays cash flow based profitability), current ratio (static liquidity) and capital assets ratio (i.e., 1 – equity ratio; static solvency). In a model specifically focusing on firm liquidity and solidity (see Laitinen, 1995), a larger set of variables was used to portray the static and dynamic concepts of liquidity and solidity. Namely, dynamic liquidity was measured by two variables (traditional cash flow and operating cash flow ratios), static liquidity by two variables (quick ratio and average payment period of accounts receivables), dynamic and static solvency were both measured by one variable (respectively shareholder's capital to total capital and cash flow to total debt ratios) (Laitinen, 1995, p. 441). In Laitinen (1995), it was demonstrated that failing firms can face various combinations of liquidity and solvency problems.

In the model proposed for old firm failure by Ooghe and de Prijcker (2008, p. 233), some important contributors to failure have been noted to be declining sales, high expenses (operational costs) and inappropriate capital expenditures (excess leverage). In Moulton et al. (1996), different failure processes have been described with the development in total assets, total debt and total sales. All different failure processes are characterized by debt growth exceeding assets growth, whereas sales growth has varied from negative to positive (Moulton et al., 1996, p. 585). Also, changes in firms' total assets and costs during downfall have been well documented in another stream of literature, namely turnaround studies (e.g., Robbins and Pearce, 1992; Barker and Duhaime, 1997; Smith and Graves, 2005).

Thus, a failure process can be modelled in a narrower classical approach, but also in an extended framework by incorporating additional variables. This has been depicted on Figure 1. The development of total debt, sales and operating costs links well to the variables applied in Laitinen (1991), as these variables are statically included in the denominators and nominators of different ratios applied in that study.

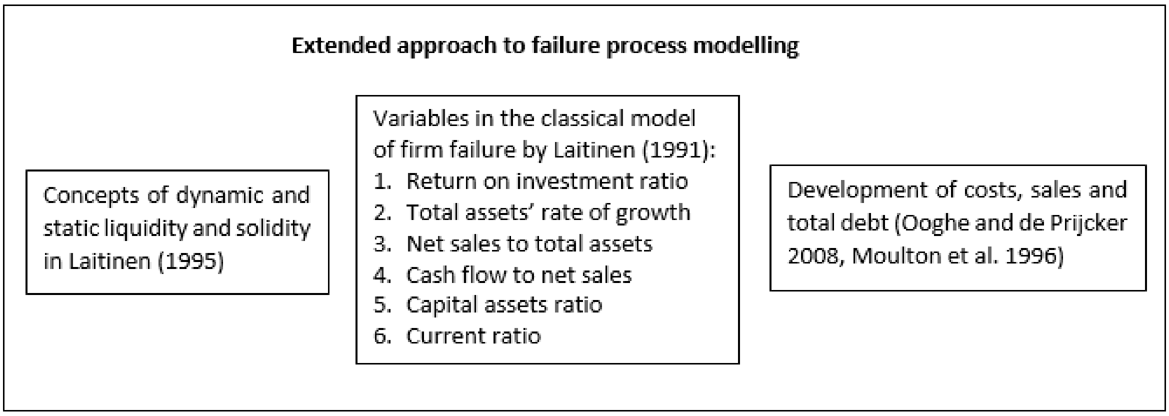

Fig. 1. Classical and extended framework for modelling failure processes

Although past studies have found that (at least three) different failure processes exist reflecting the chronically, gradually and acutely failing firms, this finding needs confirmation in case of old manufacturing firms. Therefore, we set the first general hypothesis as follows.

Hypothesis 1. Different failure processes exist for old manufacturing firms.

We will incorporate two stages in the empirical analysis, namely, in the first stage, we will use the variables from the classical Laitinen (1991) model and, thereafter, we will apply the extended approach portrayed on Figure 1.

1.3. Contingencies of failure processes. There is very little evidence whether failure processes vary through different types of manufacturing firms. From Laitinen (1991, p. 661), it can be only concluded that different industries are characterized by varying failure processes. Still, the sample in Laitinen (1991) was very small, thus, from some sectors, only one or a few observations were available. In the follow-up study by Laitinen et al. (2014) applying the similar variables as in Laitinen (1991) on a larger dataset from multiple European countries, clear evidence was found about the dissimilarity of failure processes through countries. In that study, the general and paired comparison of countries revealed abundance of inter-country differences (Laitinen et al., 2014, pp. 218-219). Namely, although the gradual failure process was dominating in all studied countries, the shares in specific countries could vary from 44%-82%, whereas in case of other processes, the dispersion was even higher (e.g. some detected processes were practically non-existent in specific countries) (Laitinen et al., 2014, p. 218). This will ground the following hypothesis concerning the representation of different failure processes through countries.

Hypothesis 2a. Old manufacturing firms in different countries are characterized by different failure processes.

Past studies detecting failure processes have mostly relied on either specific size categories while in some others, the sizes of included firms have been dispersed without providing further evidence about the interaction of size and processes. For instance, in Hambrick and D'Aveni (1988), only large firms were studied, whereas Laitinen (1991) and Laitinen et al. (2014) focused on small- and medium-sized firms. Although there can be small differences in the formulas of ratios, then when comparing the return on assets and equity ratios through the samples of failed firms in Hambrick and D'Aveni (1988) and Laitinen (1991), it can be concluded that they behave differently in the pre-bankruptcy years. Only in a study by Laitinen and Lukason (2014), it can be observed that some processes are specifically characteristic to firms in a certain size category. From a more theoretical perspective, the theories about the liability of size would suggest that larger firms are more likely to survive, but that might not apply when the industry has reached a mature stage (Mellahi and Wilkinson, 2004). Smaller firms have been noted to have more problems with raising capital and higher interest rates, but also being more reluctant or incapable of making necessary operational or strategic changes (Aldrich and Auster, 1986). Thus, there is some ground to assume that manufacturing firms in different size categories (especially when comparing very small and large firms) can follow different failure processes and therefore we set the following hypothesis.

Hypothesis 2b. Old manufacturing firms in different size categories are characterized by different failure processes.

The interconnection of firm failure processes and firms' international commitment by means of exporting is a neglected topic in the available literature. There is a multitude of evidence about the process of withdrawal from foreign markets (e.g., Pauwels and Mathyssens, 1999; Turcan, 2003; Crick, 2004), but such studies do not rely emphasis on failure. Still, de-internationalization cannot be automatically considered a failure (Vissak et al., 2012; Vissak and Francioni, 2013) and it has been shown that nonlinear internationalization (i.e., multiple consecutive enters and full or partial retreats from foreign markets) can be a highly frequent phenomenon among firms (Vissak and Masso, 2015). Vissak and Masso (2015) showed on the whole population of Estonian firms that full deinternationalization is a rare process among all exporters, thus it can be deduced that de-internationalization ending with bankruptcy is even more rare among the population of all firms. Although without general consensus, there is more evidence that exporting firms have higher likelihood of survival (Wagner, 2013). Still, the multitude of evidence concerning the interconnection of survival opportunities and exporting does not answer the question whether exporting and non-exporting old firms arrive to bankruptcy similarly or not. The literature review by Wagner (2012) demonstrated that when exporting firms are generally more productive, then the relevant studies about profitability do not indicate homogenous results. As there is no univocal basis to hypothesize about the relationship between the involvement in exporting and failure processes, we simply make use of the fact of probable discrepancies in the values of financial ratios between exporting and non-exporting firms, therefore, setting the last hypothesis as follows.

Hypothesis 2c. Old exporting and non-exporting manufacturing firms are characterized by different failure processes.

The testing of Hypotheses 2a, 2b and 2c is evidently dependent of the fact that different failure processes emerge from the preceding analysis. Still, based on the review of past literature, this is obviously a reasonable expectation to be set.

2. Data, variables and methods

2.1. Data of bankrupted firms. In line with past studies, financial data are applied for extracting failure processes in this research. Financial data are obtained from Amadeus database incorporating the balance sheets and income statements of European firms. The following criteria will be applied for all firms to be included in the analysis. Firstly, all firms must have all relevant information listed in Amadeus. This means not only financial information needed to calculate variables, but also firm foundation and bankruptcy dates. Secondly, all included firms should be at least ten years old to be classified as "old". A similar age criterion has been applied, for instance, in Moulton et al. (1996). The age of a firm is determined by deducting exact foundation time (year, month, day) from bankruptcy time (year, month, day). Thirdly, each included firm should have six consecutive pre-bankruptcy annual reports available. This enables calculation of five consecutive variables, as for some variables information from two consecutive years has to be applied. Fourthly, the main industry of all firms included should be NACE Rev. 2 section C, i.e., the manufacturing industry. Fifthly, the last annual report of each firm should be in the interval of 0.75 to 1.25 years before bankruptcy declaration. This makes the dataset homogenous, as in case of using just the last available annual report, it is not known whether some annual reports are missing from the in-between period. It is impossible to obtain sufficient number of cases having data exactly one year before bankruptcy declaration. Still, it must be noted that the mean and median interval between bankruptcy declaration and the last available report is exactly one year in the applied sample.

The application of previous restrictions results in 1235 valid cases from 15 different European countries (see Appendix 1). Still, many countries are represented only with a few cases, but they will not be excluded from analysis. The five countries with the largest number of cases are: Italy (340 cases), France (290), Romania (198), Spain (166), and Hungary (129). In the analysis, another taxonomy will be also applied, which indicates whether the country belongs to a former socialist or capitalist countries' group. The regional dispersion can be followed in Appendixes 1 and 2. Based on median operating revenue of five last years of action and using the EU official size criteria, firms are grouped as follows: 797 micro firms, 346 small firms, 92 medium- and large-sized firms. Medium- and large-sized firms are not distinguished herewith, as there are only a few large firms having median turnover over 50 million euros. In the sample, for 337 firms export revenue has been noted for last five years and out of them, 43% are non-exporters and 57% had been exporting during at least one year out of five.

2.2. Financial variables. The financial variables are chosen for the analysis exactly based on the model brought out on Figure 1. For extracting the First Set of Processes (also referred to as Analysis Stage 1), six variables from Laitinen's (1991) study will be applied. The Second Set of Processes (also referred to as Analysis Stage 2) is extracted by using five variables in addition to those given in Laitinen's (1991) study as depicted on Figure 1. Two additional variables (traditional cash flow to total debt, i.e., CFTD, and cash and equivalents to current liabilities, i.e., CCL) reflect dynamic solidity and static liquidity as given in Laitinen's (1995) study. In this study, terms "debt" and "liabilities" are applied synonymously, e.g., "total debt" includes all short-term (i.e., current) and long-term liabilities no matter of their type. Two variables (*DeltaTD* and *DeltaS*) reflect the development of total debt and total sales as given in Moulton et al. (1996) study and one variable (*DeltaOC*) reflects the development of operating costs as given in Ooghe and de Prijcker's (2008) study. In this study, terms "sales" and "operating revenue" are used as synonyms reflecting all revenue obtained from operating activities. The operating costs' variable does not include amortization and depreciation, as the latter can be subject to different accounting practices and therefore not portray the incurred costs correctly. The formulas of all variables are shown in Table 1. Some variables have been presented in a form of a ratio and others in a %, the latter to make it easier to follow results. All variables have been calculated for five consecutive pre-bankruptcy years, whereas the number behind the variable in Tables 3 and 4 denotes the respective pre-bankruptcy year (e.g., 1 denotes one year before the bankruptcy was declared). The specific processes detected in the Analysis Stage 1 will be denoted as 1.n (e.g., first process among the First Set of Processes is denoted 1.1) and among the Second Set of Processes as 2.m. In Laitinen's (1991) study, four periods ($t-1$, $t-2$, $t-4$, $t-6$) were applied, but herewith the aim is to portray the exact step-by-step financial development, thus five consecutive years have been chosen.

Table 1. Applied variables in different analysis stages

Variable code	Formula	Analysis stage	
		1	2
DeltaTA (%)	$[(\textit{Total assets}_t - \textit{Total assets}_{t-1})/\textit{Total assets}_{t-1} - 1] \times 100$	X	X
STA	$\textit{Operating revenue}_t / \textit{Total assets}_{t-1}$	X	X
CACL	$\textit{Current assets}_t / \textit{Current liabilities}_t$	X	X
ROA (%)	$[\textit{EBIT}_t / \textit{Total assets}_{t-1}] \times 100$	X	X
TETA	$\textit{Total equity}_t / \textit{Total assets}_t$	X	X
CFS (%)	$[(\textit{Net income}_t + \textit{amortization and depreciation}_t) / \textit{Operating revenue}_t] \times 100$	X	X
CFTD (%)	$[(\textit{Net income}_t + \textit{amortization and depreciation}_t)/\textit{Total liabilities}_t] \times 100$		X
CCL (%)	$[\textit{Cash and equivalents}_t/\textit{Current liabilities}_t] \times 100$		X
DeltaTD (%)	$[\textit{Total liabilities}_t / \textit{Total liabilities}_{t-1} - 1] \times 100$		X
DeltaS (%)	$[\textit{Operating revenue}_t / \textit{Operating revenue}_{t-1} - 1] \times 100$		X
DeltaOC (%)	$[(\textit{Operating costs}_t + \textit{Amortization and depreciation}_t) / (\textit{Operating costs}_{t-1} + \textit{amortization and depreciation}_{t-1}) - 1] \times 100$		X

2.3. Process extraction method. The failure processes in this study are detected with a two-stage method, namely the consecutive application of factor and cluster analysis. This "factor-cluster analysis" method has been applied in multiple areas, also outside the field of social sciences. It has proven to be very efficient for the extraction of failure processes (see, e.g., Laitinen et al., 2014). In both Analysis Stages, the set of applied variables from five pre-bankruptcy years is firstly reduced with factor analysis. Factor analysis helps to reduce a large amount of initial variables to a smaller amount of uncorrelated latent variables and also reveals the interconnections between different initial variables. Factor analysis could itself be used for classification by assigning firms to groups based on the largest factor score (e.g., Laitinen, 1991; Laitinen and Lukason, 2014). Still, such an approach, especially in case of a large number of variables, could be limited. Namely, past failure process studies have indicated that factors have normally high loadings by only a few variables (see, e.g., Laitinen, 1991). Thus, specific factor score obtains a high value when specific highly loading variable(s) have high value(s). This can lead to situations, in which processes are characterized by (extreme) behavior by only a few variables, but attention is not paid to the concurrent behavior of other factor scores. As noted, in case of a small number of factors, such an approach can prove to be useful. In this study, unweighted least squares extraction with Varimax rotation is applied and the number of factors is chosen by using the Eigen value exceeding one rule. The Eigen value exceeding one rule is the most classical approach, although like other methods for the choice of the number of factors, it has limitations as well (Costello and Osborne, 2005).

Secondly, the obtained factor scores are clustered. Clustering enables to detect homogenous groups based on factor scores. Different clustering algorithms are available, but of the classical ones, *k*-means and *k*-medians methods are very useful, as they enable easy comparison of solutions in case of different *k* values. The preliminary screening of the data showed that *k*-means clustering almost exclusively resulted in cluster solutions in which one cluster included most of the cases. Thus, *k*-medians clustering is herewith preferred. The best cluster solution from different *k* values can be chosen based on various statistics, for instance, based on the highest value of pseudo-*F* statistic (Chiang and Mirkin, 2010). In past studies, the local maximum of pseudo-*F* has been applied, meaning that pseudo-*F* values have been calculated starting from $k = 2$ and the first *k* after which pseudo-*F* drops will be chosen as the local maximum (see, e.g., Laitinen et al., 2014). By searching for the first local maximum value, the best solution among low values of *k* will be determined, and thus, it resembles the most efficient highly aggregated cluster solution. For checking the robustness of the results, pseudo-*F* values should be calculated for cluster solutions in which the number of clusters exceeds $K + 1$, where *K* reflects the chosen solution. This enables to study whether other local maximums of pseudo-*F* could indicate a more efficient clustering.

The interpretation of established cluster solutions can be achieved by comparing the median values of the variables applied through different clusters. Median values are less affected by extreme observations when compared to mean values. The median values of ratios reflect the general tendency of their development in the cluster, although it must be noted that, in case of some variables, the first/last decile/quartile can obviously differ from the median values. This is logical, as firms in the analysis are not fully identical in respect to financial variable values. Independent Samples Median Test will be also applied to indicate which financial variables have significantly different median values through established clusters. As the objective is also to study whether detected processes are differently associated with firms' country of origin, size and export behavior, a simple statistical tool, Chi-Square Test, will be applied. Also, the shares of detected processes in different countries, size categories and export behavior groups have been calculated and discussed.

3. Results and discussion

3.1. Analysis Stage 1 – the First Set of Processes. In Analysis Stage 1, the variables from Laitinen's (1991) study have been applied to extract failure processes. For Analysis Stages, the factor and cluster analysis characteristics have been documented in Table 2. Factor analysis results in 80% of variance explained by the initial variables with 11 factors, which is higher than the 52% in Laitinen's (1991) study. Still, in Laitinen's (1991) study such an explained variance was obtained with three factors, but, in this study, with five factors. The results have more similarity with Laitinen et al. (2014) study in which an eight-factor solution explained 69% of total variance. When clustering the factor scores with *k*-medians tool, the local maximum of pseudo-*F* of 64.2 is achieved already with a 2 cluster solution. The robustness of the result is checked up to $k = 20$, but none of the cluster solutions has a higher pseudo-*F* value. Thus, the $k = 2$ solution could probably hold the maximum pseudo-*F* through all possible values of *k*. In Laitinen et al. (2014), in which *k*-means clustering was applied, a pseudo-*F* of 41 was reached with a 5 cluster solution, although one cluster was an outlier later joined with another cluster. Thus, the current solution has several improved features when compared to the past calculations using a similar setting.

Table 2. Characteristics of factor and cluster solutions in Analysis Stages 1 and 2

Taxonomy	Number of factors	Variance explained	Number of clusters	pseudo-*F*
First Set of Processes	11	80%	2	64
Second Set of Processes	19	84%	2	36

The results indicate two different failure processes (see Table 3): Process 1.1 with 444 cases (i.e., 36%) and Process 1.2 with 791 cases (64%). Both processes share the elements of acute and gradual failure, as indicated by the median values in Table 3. The accrual (*ROA*) and cash flow based (*CFS*) profitability develop quite similarly in both processes, although for Process 1.1, *ROA* values are lower and *CFS* is negative already in $t – 2$, whereas in Process 1.2, *CFS* obtains negative value (-16.3%) only in $t – 1$. The median values do not indicate the dominant presence of chronic failure firms among the studied population, as in Laitinen (1991), for such firms both *ROA* and *CFA* were negative already four years before failure. Contrary to profitability, Process 1.1 firms use less leverage and *TETA* remains positive even for year $t – 1$, when for Process 1.2 firms, the share of total debt is constantly high and accumulating losses make *TETA* negative at $t – 1$. In most countries, firms with negative *TETA* must file for bankruptcy, start a voluntary liquidation process or reorganize. In Laitinen's (1991) study, the medians for *TETA* $t – 1$ values through three processes were, respectively:

-12% (chronic), 10% (gradual), -2% (acute). Firms following Process 1.1 are remarkably more productive and in $t-1$, the *STA* is about 3.4 times higher than for Process 1.2 firms. The liquidity (*CACL*) of Process 1.1 firms is higher, but both processes indicate a drop to a non-sustainable level below 1.00 for $t-1$. The change in total assets (*DeltaTA*) shows negative development for Process 1.1 throughout all studied years, whereas for Process 1.2 the total assets' growth turns negative in $t-2$. In both processes, firms witness remarkable drop in $t-1$, evidently because of quickly accumulating losses. Unlike in Laitinen et al. (2014) study, firms seem not to undertake remarkable investments or divestments during the viewed five-year cycle.

There is weak evidence that the detected failure processes are associated with different firm size groups (Chi-Square Test statistic 13 with *p*-value 0.002). With a growth in firm size, Process 1.2 becomes more prominent (see Appendix 3). This is in line with findings from other studies, which indicate that larger firms might witness lengthier poor performance before failure occurs (e.g., Hambrick and D'Aveni, 1988). Still, for groups of small-sized firms and medium-large sized firms the shares of processes are very similar.

The countries can be divided into three categories (see Appendix 1) in the analysis, as the Chi-Square Test with a value 321 (*p*-value 0.000) indicates a high contingency between countries and processes. In some (e.g., France) Process 1.1 is clearly dominating, in some (e.g., Italy and Romania), in turn, Process 1.2 is more frequent and there are those (e.g., Hungary and Spain) where both of these processes have a similar representation. Thus, it can be concluded that detected processes can be very country-specific. When countries are grouped as former capitalist and socialist countries (see Appendix 2), the Chi-Square Test value 6.5 (*p*-value 0.011) indicates weak association between processes and country groups. Namely, when in both country groups Process 1.2 dominates, then, it has a higher share in former socialist countries (69.1%) than in former capitalist countries (61.7%).

What concerns exporting and non-exporting firms, then in both groups Process 1.1 accounts for about two thirds of cases, thus, there is clearly no contingency between exporting behavior and detected failure processes (see Appendix 4). All aforementioned results of Chi-Square Tests can be followed in Table 5.

Table 3. Median values of variables for First Set of Processes

Variable	Process 1.1 (*N* = 444)	Process 1.2. (*N* = 791)	Total (*N* = 1235)	Variable	Process 1.1. (*N* = 444)	Process 1.2. (*N* = 791)	Total (*N* = 1235)
*DeltaTA*1	-14.9%	-14.0%	-14.4%	*ROA*1	-18.0%	-10.8%	-13.1%*
*DeltaTA*2	-9.7%	-2.4%	-4.8%*	*ROA*2	-5.5%	-0.5%	-1.8%*
*DeltaTA*3	-3.5%	0.0%	-1.0%*	*ROA*3	0.5%	2.3%	1.8%*
*DeltaTA*4	-5.2%	2.3%	-0.9%*	*ROA*4	1.9%	3.5%	3.1%*
*DeltaTA*5	-2.4%	2.1%	0.3%*	*ROA*5	2.8%	3.6%	3.4%
*STA*1	1.58	0.47	0.70*	*TETA*1	0.11	-0.10	-0.01*
*STA*2	1.74	0.75	0.98*	*TETA*2	0.23	0.07	0.11*
*STA*3	1.95	0.88	1.13*	*TETA*3	0.29	0.10	0.16*
*STA*4	1.79	0.97	1.21*	*TETA*4	0.36	0.11	0.18*
*STA*5	1.94	1.08	1.32*	*TETA*5	0.34	0.13	0.20*
*CACL*1	0.91	0.66	0.73*	*CFS*1	-8.2%	-16.3%	-12.4%*
*CACL*2	1.16	0.92	1.00*	*CFS*2	-0.8%	0.7%	0.1%
*CACL*3	1.27	1.01	1.07*	*CFS*3	1.2%	2.1%	1.7%*
*CACL*4	1.40	1.01	1.09*	*CFS*4	2.0%	2.6%	2.4%
*CACL*5	1.39	1.03	1.11*	*CFS*5	2.4%	2.9%	2.7%

Note: * Independent samples median test *p*-value ≤ 0.01.

3.2. Analysis Stage 2 – the Second Set of Processes. The inclusion of five additional variables in the analysis results in 84% explained variance by the initial variables with 19 factors. Clustering with *k*-medians provides the highest pseudo-*F* similarly to Analysis Stage 1 in case of $k = 2$. Still, the pseudo-*F* value is lower, namely 36.3. The robustness of the result is similarly to Analysis Stage 1 checked up to $k = 20$, but none of the cluster solutions obtains higher pseudo-*F* value, thus, the $k = 2$ solution in Analysis Stage 2 could also hold the maximum pseudo-*F* value over all possible values of *k*.

The results indicate two different failure processes (see Table 4): Process 2.1 with 698 cases (i.e., 56.5%) and Process 2.2 with 537 cases (43.5%). The behavior of the variables applied in Analysis Stage 1 is very similar in case of Analysis Stage 2. This is logical, as Pearson Chi-Square test value 257 (*p*-value 0.000) indicates high contingency between the cluster solutions of Analysis Stages 1 and 2. Still, the five additional variables offer additional interesting insight into the processes. Similarly to higher *CACL*, Process 2.1 firms have also higher *CCL* figures. Still, the difference in the median values of *CACL* is not as large as in case of comparing Processes 1.1 and 1.2. Also, the *CACL* $t - 1$ median value is lower for Process 2.1 than for 2.2. In case of both processes, the dynamic solidity reflected by total debt coverage with traditional cash flow (*CFTD*) is very poor throughout the five years and turns negative during one or two last years of existence. In both processes, total debt (*DeltaTD*) is constantly growing throughout the five years, whereas with quicker rate for Process 2.2 (except for year $t - 1$) than for Process 2.1. In both processes, operating revenue (*DeltaS*) is constantly dropping throughout the five years, whereas for years $t - 1$ and $t - 2$, the drops are very large (e.g., -25.8% for Process 2.1 and -22% for Process 2.2 in $t - 1$). The reduction of operating costs (*DeltaOC*) goes in line with dropping sales, but with a slower pace. Thus, in both processes, the inability to retrench operating costs quickly in the condition of dropping sales seems to be an important issue. Such a phenomenon has been also portrayed in Ooghe and de Prijcker's (2008) model.

Likewise with Analysis Stage 1, the two detected processes are differently distributed through countries (Chi-Square Test value 273 (p-value 0.000), also see Appendix 1). For instance, Process 2.1 is dominant in France, Hungary and Spain, Process 2.2 in Romania, but, in Italy, two processes have almost equal shares. The largest change in the representation of processes is clearly in Italy, where in Analysis Stage 1, Process 1.2 had a representation of 91%, but, in Stage 2, both processes have an almost equal representation. The Chi-Square Test value 10.4 (p-value 0.001) offers a weak indication that former capitalist countries are more characterized by Process 2.1 (namely 59.6%) than their former socialist counterparts (namely 49.9%).

Table 4. Median values of variables for Second Set of Processes

Variable	Process 1 (*N* = 698)	Process 2 (*N* = 537)	Total (*N* = 1235)	Variable	Process 1 (*N* = 698)	Process 2 (*N* = 537)	Total (*N* = 1235)
*DeltaTA*1	-24.9%	-6.0%	-14.4%*	*CFTD*1	-21.7%	-2.6%	-10.1%*
*DeltaTA*2	-8.2%	-1.3%	-4.8%*	*CFTD*2	-3.6%	1.4%	0.1%*
*DeltaTA*3	-2.6%	1.2%	-1.0%*	*CFTD*3	2.4%	2.1%	2.3%
*DeltaTA*4	-1.2%	-0.5%	-0.9%	*CFTD*4	4.5%	2.8%	3.6%*
*DeltaTA*5	0.3%	0.4%	0.3%	*CFTD*5	5.5%	3.7%	4.4%*
*STA*1	0.95	0.52	0.70*	*CCL*1	1.6%	1.1%	1.3%
*STA*2	1.17	0.77	0.98*	*CCL*2	2.8%	1.6%	2.1%*
*STA*3	1.45	0.87	1.13*	*CCL*3	4.0%	1.7%	2.8%*
*STA*4	1.52	0.89	1.21*	*CCL*4	4.8%	2.0%	3.3%*
*STA*5	1.59	1.03	1.32*	*CCL*5	6.4%	2.4%	4.1%*
*CACL*1	0.65	0.84	0.73*	*DeltaTD*1	1.3%	0.9%	1.2%
*CACL*2	1.01	0.99	1.00	*DeltaTD*2	0.6%	2.2%	1.4%
*CACL*3	1.11	1.02	1.07*	*DeltaTD*3	2.4%	4.6%	3.6%
*CACL*4	1.17	1.02	1.09*	*DeltaTD*4	1.9%	3.7%	2.7%
*CACL*5	1.19	1.03	1.11*	*DeltaTD*5	2.6%	2.9%	2.7%
*ROA*1	-23.4%	-4.3%	-13.1%*	*DeltaS*1	-25.8%	-22.0%	-23.9%
*ROA*2	-6.5%	0.7%	-1.8%*	*DeltaS*2	-12.5%	-9.2%	-11.2%
*ROA*3	1.6%	2.2%	1.8%	*DeltaS*3	-3.6%	-1.8%	-3.4%
*ROA*4	3.4%	2.4%	3.1%	*DeltaS*4	-2.7%	-4.7%	-3.3%
*ROA*5	3.7%	3.3%	3.4%	*DeltaS*5	-1.3%	-6.0%	-3.3%*
*TETA*1	-0.18	0.04	-0.01*	*DeltaOC*1	-11.9%	-11.6%	-11.6%
*TETA*2	0.13	0.09	0.11	*DeltaOC*2	-8.5%	-7.6%	-8.2%
*TETA*3	0.21	0.11	0.16*	*DeltaOC*3	-2.8%	-2.3%	-2.5%
*TETA*4	0.24	0.12	0.18*	*DeltaOC*4	-2.9%	-3.8%	-3.5%
*TETA*5	0.25	0.14	0.20*	*DeltaOC*5	-0.2%	-4.0%	-1.9%*
*CFS*1	-19.3%	-5.2%	-12.4%*				
*CFS*2	-2.3%	1.5%	0.1%*				
*CFS*3	1.5%	2.1%	1.7%				
*CFS*4	2.4%	2.5%	2.4%				
*CFS*5	2.6%	2.9%	2.7%				

Note: * Independent samples median test p-value ≤ 0.01.

In respect to firms' size, the Chi-Square Test also indicates some association between firm size and processes. Namely, Process 2.1 has the highest share in case of small firms and the smallest in case of medium-large firms (see Appendix 3). What concerns firms' export behavior, the Chi-Square

Test likewise to the Analysis Stage 1 does not indicate a relationship (when *p*-level 0.01 is applied) between detected processes and whether a firm belongs to an exporting or non-exporting group (see Appendix 4). All the above-described Chi-Square Test results can be followed in Table 5.

Table 5. Contingencies of processes with firms' country of origin, size and export behavior

Taxonomy	Countries (Chi-square statistic and p-value)	Country groups (Chi-square statistic and p-value)	Size (Chi-square statistic and p-value)	Exporting (Chi-square statistic and p-value)
First Set of Processes	321; 0.000	6.5; 0.011	13; 0.002	0.4; 0.523
Second Set of Processes	273; 0.000	10.4; 0.001	23; 0.000	6.5; 0.038

Note: The Chi-Square Test indicates clear contingency between the detected processes and countries also in case only countries with more than 100 observations have been applied.

3.3. Comparison of First and Second Set of Processes. As indicated in Table 3, for the First Set of Processes, the medians of 25 initial variables out of 30 (six variables for five pre-bankruptcy years) were significantly different through two established processes (i.e., Processes 1.1 and 1.2). When focusing on same 30 variables in case of the Second Set of Processes, this result is 20 variables from 30. For the detection of the Second Set of Processes, 25 additional variables were applied (five additional variables for five pre-bankruptcy years), but only 10 out of 25 have significantly different medians through two established processes (i.e., Process 2.1 and 2.2). Out of the five additional variables (*CFTD*, *CCL*, *DeltaTD*, *DeltaS*, *DeltaOC*) in Analysis Stage 2, only *CFTD* and *CCL* have remarkable differences through two detected failure processes. This is an expected result, as the medians of other measures of liquidity and solvency also indicate remarkable differences for the two extracted processes.

The Chi-Square Test indicates high contingency of First and Second Set of Processes (see also Table 6 for contingency), the relevant test statistic being 257 (*p*-value 0.000). From Table 5 it can be concluded that 86.7% of Process 1.1 cases follow Process 2.1 and 60.4% of Process 1.2 cases follow Process 2.2. It is also noteworthy that 89.0% of cases following Process 2.2 also follow Process 1.2.

Table 6. Contingency of First and Second Set of Processes

		Second Set of Processes		Total
		Process 2.1	Process 2.2	
First Set of Processes	Process 1.1	385	59	444
	Process 1.2	313	478	791
Total		698	537	1235

When comparing First and Second Set of Processes, the behavior of variables remains similar. The latter holds for 25 variables out of 30 variables used in both Analysis Stages. Namely, when a variable has a higher median value in case of Process 1.1 when compared to Process 1.2, this holds also when comparing Processes 2.1 and 2.2. For the five variables, in case of which this does not hold, it mainly concerns financial ratios of year $t-1$, in which they obtain poor values for all processes detected in Analysis Stages 1 and 2. Thus, the behavior of variables from Laitinen's (1991) model through specific detected processes remains very similar in both Analysis Stages.

Thus, when focusing on the high contingency of First and Second Set of Processes, but also on the differences in the medians of applied variables, it can be concluded that the variables applied in Laitinen's (1991) model are already very efficient in creating a taxonomy of failure processes. Still, the inclusion of additional variables into the model based on available literature about failure processes helps to offer some additional insight into those processes, especially in respect of dynamic solidity (CFTD) and static liquidity (CCL) development.

Table 7. Results of hypotheses testing

Hypothesis	Result
Hypothesis 1. Different failure processes exist for old manufacturing firms.	Accepted in case of First and Second Set of Processes. Namely, in both Sets, two different failure processes were detected. Past studies have detected more different processes, namely at least three.
Hypothesis 2a. Old manufacturing firms in different countries are characterized by different failure processes.	Accepted in case of First and Second Set of Processes. When individual countries in analysis are characterized by remarkably different shares of processes, then the same evidence in case of country groups (former socialist and capitalist) remains weaker.
Hypothesis 2b. Old manufacturing firms in different size categories are characterized by different failure processes.	Accepted in case of First and Second Set of Processes. The evidence that firms in different size groups follow different failure processes is existent, but weak.
Hypothesis 2c. Old exporting and non-exporting manufacturing firms are characterized by different failure processes.	Rejected in case of First and Second Set of Processes. There is clear evidence that exporting and non-exporting firms are not characterized by different failure processes.

Note: the two sets of failure processes referred to are: a) the First set is based only on variables from Laitinen's (1991) model, b) the Second set is based on refined Laitinen's (1991) model by supplementing additional five variables. For Hypotheses 2a, 2b and 2c the Chi-Square Test *p*-level 0.01 has been applied to accept or reject each of the specific hypotheses.

3.4. Summary of Analysis Stages. The findings of this study provide some important new evidence to failure literature. They have been summarized in Table 7. Namely, in case of both study designs, two different failure processes emerged. These different processes are mostly discriminated by the speed of failure, namely how quickly financial ratios start to decline before failure. Unlike in Laitinen's (1991) study, none of these processes symbolizes a chronic failure – a firm that would have very poor performance through many years before failure. As also established in past studies (Laitinen and Lukason, 2014; Laitinen et al., 2014), failure processes can differ through countries. While the differences of failure processes also hold for different size categories, then, in turn, the shares of different failure processes are very similar for exporting and non-exporting firms.

Conclusion

This paper aimed to detect the presence of different failure processes for bankrupted manufacturing firms. For that purpose, factor and cluster analyses were applied on a dataset of 1235 bankrupted companies from 15 different European countries, although only five countries had a representation of over 100 cases. The focus was on five consecutive pre-bankruptcy years. Different financial variables (financial ratios and changes in balance sheet and profit statement accounts) were applied. The study incorporated two different study designs: namely, an initial model incorporating six variables from Laitinen's (1991) study and an extended model with five additional variables.

Both study designs resulted in two different failure processes. The processes extracted in case of both study designs have elements of acute and gradual failure (see D'Aveni, 1989; Laitinen, 1991), but unlike in past studies on the same topic (e.g. Laitinen, 1991; Laitinen et al., 2014), the chronic failure process does not emerge among the extracted processes. The two extracted processes can be very differently associated with firms' country of origin: namely, in some countries one of the extracted processes is clearly dominating and in others, their frequencies can be very similar. There is no strong association between firm size and the process it follows. Also, there is no difference in the representation of processes for exporting and non-exporting firms.

There are several limitations in this study that could be taken into account in the future research. Namely, the dataset included a smaller number of medium-sized firms than in two size categories for smaller firms. Also, there are only a few large-sized firms in the analysis, which have therefore been consolidated with the group of medium-sized firms. As past studies (e.g., Hambrick and D'Aveni, 1988) have noted the failure process for large corporation to span over a lengthy time, it could be interesting to pay specific attention to large-sized firms. Also, currently the internationalization context of firms is captured by a single variable, namely whether a firm has been engaged in exporting during the last five years of existence. As numerous different internationalization patterns exist (e.g., Vissak and Masso, 2015), such a diversity could be taken into account in further analysis. Still, as in the current analysis, there is a relatively small number of exporting firms (namely 192; see Appendix 4), the dataset is too small to take such internationalization differences into account. The study aimed to extract the main processes existing in the data, but as the main processes could be disaggregated into sub-processes, future studies can be focused on them as well. As different process detection methods can have their specific peculiarities, future studies can be extended by using a larger set of extraction methods: for instance, novel machine learning techniques. Finally, although this study encompassed more than 1000 applicable observations, the further analysis would benefit from a larger sample, in which, for instance, the countries currently represented with only a few cases would have a proportional amount of observations.

Several implications for practice can be drawn from this study. The median values of financial ratios indicate that the collapse of old manufacturing firms could be forecastable with bankruptcy prediction models. Namely, for all failure processes detected in this study, it can be observed that for instance profitability, capital structure and liquidity ratios obtain low values for the last years before collapse. Those dimensions have been common predictors of collapse (see, e.g., Dimitras et al. (1996) overview of prediction studies), thus, bankruptcy prediction models could easily capture such failure signals. Such a downturn could also be observable for managers, who can thus implement different turnaround strategies for vitalizing firms. As the majority of firms are following processes in case of which failure signals are observable years ahead of failure, policy measures could be implemented to address the low values of financial ratios of failing firms. For instance, many bankrupted firms witness very low total equity to total assets ratios, which could lead to more strict capital requirements.

Acknowledgements

We acknowledge financial support from Jenny and Antti Wihuri Foundation in Finland and Estonian Research Council grants PUT20-49 "A holistic process perspective of export patterns: theory development and empirical evidence" and IUT20-49 "Structural Change as the Factor of Productivity Growth in the Case of Catching up Economies". We would like to thank the anonymous referee and Tiia Vissak for valuable comments.

References

1. Aldrich, H.E. and Auster, E.R. (1986). Even dwarfs started small: liabilities of age and size and their strategic implications, *Research in Organizational Behavior*, 8, pp. 165-198.
2. Altman, E.I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *Journal of Finance*, 23(4), pp. 589-609.
3. Argenti, J. (1976). *Corporate collapse: the causes and symptoms*. McGraw-Hill, New York, NY.
4. Balcaen, S. and Ooghe, H. (2006). 35 years of studies on business failure: an overview of classic statistical methodologies and their related problems, *The British Accounting Review*, 38(1), pp. 63-93.
5. Barker III, V.L. and Duhaime, I.M. (1997). Strategic choice in the turnaround process. *Strategic Management Journal*, 18(1), pp. 13-38.
6. Barron, D.N., West., E. and Hannan, M.T. (1994). A time to grow and a time to die: growth and mortality of credit unions in New York City: 1914-1990, *American Journal of Sociology*, 100(2), pp. 381-421.
7. Chiang, M.M.-T. and Mirkin, B. (2010). Intelligent choice of the number of clusters in *k*-means clustering: an experimental study with different cluster spreads, *Journal of Classification*, 27(1), pp. 3-40.
8. Costello, A.B. and Osborne, J.W. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis, *Practical Assessment, Research and Evaluation*, 10(7), pp. 1-9.
9. Crick, D. (2004). U.K. SMEs' decision to discontinue exporting: an exploratory investigation into practices within the clothing industry, *Journal of Business Venturing*, 19(4), pp. 561-587.
10. Crutzen, N. and Van Caillie, D. (2010). Towards a taxonomy of explanatory failure patterns for small firms: a quantitative research, *Review of Business and Economics*, 55(4), pp. 438-462.
11. D'Aveni, R.A. (1989). The aftermath of organizational decline: a longitudinal study of the strategic and managerial characteristics of declining firms, *Academy of Management Journal*, 32(3), pp. 577-605.
12. Dimitras, A.I., Zanakis, S.H. and Zopounidis, C. (1996). A survey of business failures with an emphasis on prediction methods and industrial applications, *European Journal of Operational Research*, 90(3), pp. 487-513.
13. Du Jardin, P. (2015). Bankruptcy prediction using terminal failure processes, *European Journal of Operational Research*, 242(1), pp. 286-303.
14. Hambrick, D.C. and D'Aveni, R. (1988). Large corporate failures as downward spirals, *Administrative Science Quarterly*, 33(1), pp. 1-23.
15. Henderson, A.D. (1999). Firm strategy and age dependence: a contingent view of the liability of newness, adolescence and obsolescence, *Administrative Science Quarterly*, 44(2), pp. 281-314.
16. Kirkos, E. (2012). Assessing methodologies for intelligent bankruptcy prediction, *Aritificial Intelligence Review*, 43(1), pp. 83-123.
17. Laitinen, E.K. (1991). Financial ratios and different failure processes, *Journal of Business Finance and Accounting*, 18(5), pp. 649-673.
18. Laitinen, E.K. (1995). The duality of bankruptcy process in Finland, *European Accounting Review*, 4(3), pp. 433-454.
19. Laitinen, E.K. and Lukason, O. (2014). Do firm failure processes differ across countries: evidence from Finland and Estonia, *Journal of Business Economics and Management*, 15(5), pp. 810-832.
20. Laitinen, E.K., Lukason, O. and Suvas, A. (2014). Are firm failure processes different? Evidence from seven countries, *Investment Management and Financial Innovations*, 11(4), pp. 212-222.
21. Lukason, O. (2014). Why and how agricultural firms fail: evidence from Estonia, *Bulgarian Journal of Agricultural Science*, 20(1), pp. 5-11.
22. Mellahi, K. and Wilkinson, A. (2004). Organizational failure: a critique of recent research and a proposed integrative framework, *International Journal of Management Reviews*, 5(1), pp. 21-41.
23. Moulton, W.N., Thomas, H. and Pruett, M. (1996). Business failure pathways: environmental stress and organizational response, *Journal of Management*, 22(4), pp. 571-595.
24. Ooghe, H. and de Prijcker, S. (2008). Failure processes and causes of company bankruptcy: a typology, *Management Decision*, 46(2), pp. 223-242.
25. Pauwels, P. and Matthyssens, P. (1999). A strategy process perspective of export withdrawal, *Journal of International Marketing*, 7(9), pp. 10-37.
26. Pompe, P.P.M. and Bilderbeek, J. (2005). The prediction of bankruptcy of small- and medium-sized industrial firms, *Journal of Business Venturing*, 20(6), pp. 847-868.
27. Ravi Kumar, P. and Ravi, V. (2007). Bankruptcy prediction in banks and firms via statistical and intelligent techniques – a review, *European Journal of Operational Research*, 180(1), pp. 1-28.
28. Robbins, D.K. and Pearce II, J.A. (1992). Turnaround: retrenchment and recovery, *Strategic Management Journal*, 13(4), pp. 287-309.
29. Sheppard, J.P. and Chowdhury, S.D. (2005). Riding the wrong wave: organizational failure as failed turnaround, *Long Range Planning*, 38(3), pp. 239-260.
30. Smith, M. and Graves, C. (2005). Corporate turnaround and financial distress, *Managerial Auditing Journal*, 20(3), pp. 304-320.
31. Thornhill, S. and Amit, R. (2003). Learning about failure: bankruptcy, firm age, and the resource-based view, *Organization Science*, 14(5), pp. 497-509.

32. Turcan, R.V. (2003). De-internationalization and the small firm. In *Internationalization. Firm Strategies and Management*, ed. C. Wheeler, F. McDonald and Greaves, I., pp. 208-222.
33. Vissak, T. and Francioni, B. (2013). Serial nonlinear internationalization in practice: a case study, *International Business Review*, 22(6), pp. 951-962.
34. Vissak, T., Francioni, B. and Musso, F. (2012). MVM's nonlinear internationalization: a case study, *Journal of East-West Business*, 18(4), pp. 275-300.
35. Vissak, T. and Masso, J. (2015). Export patterns: typology development and application to Estonian data, *International Business Review*, 24(4), pp. 652-664.
36. Wagner, J. (2012). International trade and firm performance, *Review of World Economics*, 148(2), pp. 235-267.
37. Wagner, J. (2013). Export, imports and firm survival: first evidence for manufacturing enterprises in Germany, *Review of World Economics*, 149(1), pp. 113-130.

Appendices

Appendix 1. Country breakdown through different Sets of Processes

Country	Number of cases	First Set of Processes		Second Set of Processes	
		Process 1.1	Process 1.2	Process 2.1	Process 2.2
Belgium	7	71.4%	28.6%	71.4%	28.6%
Bulgaria	1	0.0%	100.0%	0.0%	100.0%
Czech Republic	35	37.1%	62.9%	62.9%	37.1%
Spain	166	46.4%	53.6%	60.2%	39.8%
Finland	23	52.2%	47.8%	47.8%	52.2%
France	290	70.0%	30.0%	73.8%	26.2%
United Kingdom	5	60.0%	40.0%	40.0%	60.0%
Croatia	21	23.8%	76.2%	33.3%	66.7%
Hungary	129	41.1%	58.9%	63.6%	36.4%
Italy	340	5.6%	94.4%	48.2%	51.8%
Latvia	2	100.0%	0.0%	50.0%	50.0%
Portugal	8	25.0%	75.0%	50.0%	50.0%
Romania	198	23.2%	76.8%	39.9%	60.1%
Sweden	1	100.0%	0.0%	100.0%	0.0%
Slovakia	9	33.3%	66.7%	66.7%	33.3%
Total	1235	36.0%	64.0%	56.5%	43.5%

Appendix 2. Country group breakdown through different Sets of Processes

Country group	Number of cases	First Set of Processes		Second Set of Processes	
		Process 1.1	Process 1.2	Process 2.1	Process 2.2
Former capitalist	840	38.3%	61.7%	59.6%	40.4%
Former socialist	395	30.9%	69.1%	49.9%	50.1%
Total	1235	36.0%	64.0%	56.5%	43.5%

Appendix 3. Size breakdown through different Sets of Processes

Size	Number of cases	First Set of Processes		Second Set of Processes	
		Process 1.1	Process 1.2	Process 2.1	Process 2.2
Microfirms	797	39.5%	60.5%	55.6%	44.4%
Small firms	346	29.8%	70.2%	60.1%	39.9%
Medium-sized and large firms	92	28.3%	71.7%	51.1%	48.9%
Total	1235	36.0%	64.0%	56.5%	43.5%

Appendix 4. Export behavior breakdown through different Sets of Processes

Export behavior	Number of cases	First Set of Processes		Second Set of Processes	
		Process 1.1	Process 1.2	Process 2.1	Process 2.2
Non-exporting	145	66.9%	33.1%	72.4%	27.6%
Exporting	192	63.5%	36.5%	69.3%	30.7%
Total	337	65.0%	35.0%	70.6%	29.4%