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WHAT DISTINGUISHES SURVIVORS FROM FAILURES AMONG DEFAULTED FIRMS?

Literature on firm failure prediction is extensive, but it lacks research directed to analyse which defaulted firms will survive. Current study applies a dataset of 496 Estonian firms for determining which financial ratios discriminate between failing and surviving firms with defaults (i.e. having payment default and not submitting annual report). The study indicates that lower leverage, higher profitability, solvency and liquidity are common to surviving firms. The results obtained are dependent on a default year used in analysis, the varying of which can alter specific ratios discriminating between 2 groups of firms.

Keywords: firm failure, payment default, non-submission of accounts, failure prediction, financial ratios.

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ЧИМ ВІДРІЗНЯЮТЬСЯ ПІДПРИЄМСТВА З ПОТЕНЦІАЛОМ ВИЖИВАННЯ ВІД ПОТЕНЦІЙНИХ БАНКРОТІВ?

У статті визначено, які фінансові показники по 496 естонських фірмах відрізняють потенційних банкрутів від фірм із потенціалом виживання з невиконаними зобов'язаннями (тобто тих, що мають неплатежі і не здали річний звіт). Дослідження показало, що нижчий леверідж, підвищена прибутковість, платоспроможність і ліквідність характерні для виживаючих фірм. Отримані результати залежать від року, за який узяті дані, і їх перебір дозволив визначити співвідношення характеристик між двома групами фірм.

Ключові слова: банкрутство, неплатіж, ненадання бухгалтерської звітності, прогнозування збоїв, фінансові показники.
Таб. 2. Літ. 29.

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ЧЕМ ОТЛИЧАЮТСЯ ПРЕДПРИЯТИЯ С ПОТЕНЦИАЛОМ ВЫЖИВАНИЯ ОТ ПОТЕНЦИАЛЬНЫХ БАНКРОТОВ?

В статье определены финансовые показатели по 496 эстонским фирмам, которые отличают потенциальных банкротов от фирм с потенциалом выживания с невыполненными обязательствами (т.е. имеющие неплатежи и не предоставившие годовой отчет). Исследование показало, что более низкий леверидж, повышенная прибыльность, платежеспособность и ликвидность характерны для выживающих фирм. Полученные результаты зависят от года, за который взяты данные, и их перебор позволил определить соотношения характеристик между двумя группами фирм.

Ключевые слова: банкротство, неплатеж, непредоставление бухгалтерской отчетности, прогнозирования сбоев, финансовые показатели.

Introduction. Since 1930-1940s the topic of firm failure has received growing attention in academia. When viewing different subsets of available literature (e.g., Pretorius, 2008), the one receiving highest attention is failure prediction. After the creation of first well-known models in 1960s (Beaver, 1966; Altman, 1968) the topic

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has been extensively researched. The main aim of failure prediction studies is by using financial data of failed (mostly bankrupted) firms and their non-failed (successful or survived) counterparts to find discriminators, which would allow forecasting failures. Although studies have shown elaboration in data and methodology used (Balcaen and Ooghe, 2006), such innovation has not resulted in remarkable growth of forecast accuracy. Mostly this is because of the ex post nature of models and given limitation has been addressed since their creation (Johnson, 1970). There are multitude of other problems, for instance the necessity to have data from several consecutive years (Edmister, 1972; El Hennawy and Morris, 1983), the importance of not including only successful firms among the survived group (Peel and Peel, 1987), the role of economic downturn in decreasing the predictive performance of models (Pompe and Bilderbeek, 2005) and the relevance of having data from shorter period than annual for improving predictive abilities (Baldwin and Glezen, 1992) have been emphasised. A problem to be addressed is also the reliability of financial statement data (Staubus, 2005), especially for small firms.

Another important body of research distinguishing failures from non-failures is credit scoring, where the main difference lies in the definition of failure. Namely, credit scoring models aim to discriminate those firms that will default with loan payments and those that will not (Thomas et al., 2002). Payment default is a symptom of earlier stage in firm decline, which sometimes is succeeded by permanent insolvency and in other cases firms are able to overcome difficulties and restore their vitality. The limitations concerning credit scoring models are mostly the same as for bankruptcy models. Namely, being based on historical data, their predictive abilities can be questioned in the case of substantial changes in economic environment or firms' characteristics. Leaving given limitations aside, the literature of credit scoring models offers good insight to the range of default predictors.

Literature lacks studies focusing only on problematic firms. A subset of literature dealing with given domain considers firms under reorganization, more specifically outlining what distinguishes surviving and failing firms in court supervised turn-around process (Casey et al., 1986; Laitinen, 2009; Karkinen, 2010). Beside previously given set of literature, empirical studies directed to finding healthy and unhealthy firms among a set of defaulted firms are rather scarce.

Derived from previous, the objective of current paper is to find indicators that would help to discriminate which defaulted firms will survive and which will fail. The discrimination will be performed with the help of financial ratios, which have been the most traditional way of comparing healthy and unhealthy firms (Dimitras et al., 1996). The paper is structured classically. The introductory part is followed by a theoretical overview elaborating the topics discussed in the introduction and listing relevant achievements from available studies. The next section describes the data and the methodology for empirical analysis, being followed by main results accompanied with their discussion. The paper traditionally finalizes with conclusive remarks from the analysis, but also some practical implications and suggestions for further studies are offered.

Literature review. A general consensus has been established on the ability of financial ratios to distinguish surviving and failing firms. Researchers focusing on past

accomplishments in the field of failure prediction (Chen and Shimerda, 1981; Dimitras et al., 1996; Altman and Narayanan, 1997; Bellovary et al., 2007) noted the similarity of predictors through the studies. Namely, the given studies outline profitability, liquidity, solidity and solvency ratios being widely applied in prediction models. An extensive research by Dimitras et al. (1996) reviewed methods and variables used in 47 previous failure studies. As a conclusion they found the 10 most widely used financial ratios to be $\frac{WC}{TA}, \frac{TD}{TA}, \frac{CA}{CL}, \frac{EBIT}{TA}, \frac{NI}{TA}, \frac{CF}{TD}, \frac{QA}{CL}, \frac{CF}{S}, \frac{S}{TA}$, the abbreviations for variables being as follows: WC — working capital, TA — total assets, TD — total debt, CA — current assets, CL - current liabilities, EBIT - earnings before interest and taxes, NI - net income, CF - cash flow, QA - quick assets, S - sales. Still, Gilbert et al. (1990) have found that ratios traditionally discriminating well between bankrupt and non-bankrupt firms might not work when applied to a set of only defaulted firms.

Beside the fact that past performance does not necessarily reflect situation in future, the usage of accounting statement data and ratios calculated based on them has several other deficiencies, like the inability of accrual data to show firms' financial situation correctly and frequent manipulation of accounting information in declining firms (Keasey and Watson, 1991; Gentry et al., 1985). Barnes (1987) noted that financial ratios are often used for failure prediction without theoretical background explaining why specific variables should signal decline. Also, some financial ratios (ROA and ROE) might in specific circumstances fail to capture economic phenomena they are designed to measure.

A variety of non-financial predictors of bankruptcy have been applied in studies. Several measures connected to firm's accounting have been used for failure prediction, for instance non-submission of accounts (Argenti, 1976; Whittred and Zimmer, 19844 Keasey and Watson, 1988), which can mean the non-submission of annual/quarterly reports and/or tax declarations, and the content of audit qualifications (Keasey and Watson, 1987). Previous payment behaviour, more specifically the presence of payment defaults, is also a classical failure predictor (Back, 2005). Still, in many cases the causality between used predictors and failure remains weak.

The hypothesis of the current study is developed based on the literature review. Previous studies have indicated that non-submission of accounts and previous payment behaviour are important non-financial predictors of bankruptcy, but still not all firms witnessing those deficiencies will collapse. In addition, literature has shown that financial ratios are efficient in discriminating between bankrupt and non-bankrupt firms. When integrating these 2 aspects it can be hypothesized that out of a set of firms not submitting annual reports and also having payment defaults, those that become permanently insolvent and those that survive have different predefault values of financial ratios.

Data and methodology. The current study applies a dataset of firms which have not timely submitted annual report and have been fined for that. As all firms in the analysis have defaulted to pay fines, executive proceedings have been started to collect claims. Each firm in the dataset is therefore characterized by 2 bankruptcy pre-

dictors (i.e. defaults) - payment default and default in timely submission of annual report. Under Estonian legal station, bailiff is the official who enforces claims through executive proceedings. There are different types of claims, of which some need to be court approved and some not (including fines). For current study, information on 496 claims in executive proceeding process was obtained from a bailiff's office. The start of official collection period ranges from 2005 to 2010. The fine collection start periods distribute as follows: 2005 - 2 cases, 2006 - 12, 2007 - 189, 2008 - 116, 2009 - 168, 2010 - 9. Due to low number of cases in 2005, 2006 and 2010 the results of the empirical analysis will also be calculated when the years with low representation are excluded. As discussed in more detail below, there are 3 types of firms in the dataset: a) firms that do not overcome either of the defaults and become permanently insolvent, b) firms that overcome the defaults but still become permanently insolvent after some time, c) firms that overcome both defaults and remain vital.

Each firm must submit annual report to Estonian Commercial Register (ECR) in maximum half a year after its business year ends. Timely non-submission will at first hand result in warning by ECR, which is followed by a fine in an amount of approximately 200 euros. In case the fine is not paid, executive proceeding will be started and bailiff enforces the fine claim. The time from non-submission to enforcement can vary, being among others dependent of the ECRs work practice and explanations for non-submission given by entrepreneur. After the fine has been paid, the executive proceeding will be ended. As relevant information from bailiffs office, the enforcement start and end time has been provided. This is accompanied by ECR data on the status of a firm, i.e. whether it is a functioning firm without further reporting problems or instead it has gone into bankrupt or been liquidated without bankruptcy proceeding. As for all liquidation cases under analysis, firms have not paid the claim, then they can also be considered permanently insolvent (bankrupt). For the firms that paid fines and survived after the first payment default, their status in the first quarter of 2012 has been checked again, to find out if they have remained vital or not. The current study is limited by the fact that information from bailiffs office is anonymous due to legal requirements (firms' identities are not disclosed), which in turn does not allow procuring data on additional payment defaults from available databases for elaborating the analysis.

Financial ratios widely used in the failure literature have been selected to discriminate between failed and non-failed firms. The financial ratios applied for analysis are as follows: 2 solvency ratios ($\frac{CASSETS}{CLIABIL}$, i.e. $\frac{CA}{CL}$; $\frac{CASH}{CLIABIL}$, i.e. $\frac{C}{CL}$), 3 profitability ratios ($\frac{NI}{SALES}$, i.e. $\frac{NI}{S}$;

$\frac{OPROFIT}{SALES}$, i.e. $\frac{OP}{S}$), 2 solidity, i.e. capital structure ratios ($\frac{EQUITY}{ASSETS}$, i.e. $\frac{E}{A}$; $\frac{CLIABIL}{ASSETS}$, i.e. $\frac{CL}{A}$) and one measuring liquidity ($\frac{CASSETS}{ASSETS}$, i.e. $\frac{CA}{A}$).

From the balance sheet and profit statement the following variables have been used (with abbreviations in brackets) to calculate the ratios: assets (ASSETS), liabilities (LIABIL), equity (EQUITY), current assets (CASSETS), cash and cash equivalents (CASH), current liabilities (CLIABIL), sales revenue (SALES), operating

profit (OPROFIT), net income (i.e. net profit, NI). The selection of financial ratios does not include some common variables (e.g., ROE and ROA), as their application can bring misleading results. Values of the ratios will be calculated for 3 years before the claim enforcement year. Subscript one (i.e., Ratio1) denotes the value of specific ratio for the year previous to claim enforcement year, 2 and 3 (Ratio2 and Ratio3) for 2 or 3 years before claim enforcement year.

In the current study the focus is to test whether and how firms with defaults eventually failing or surviving differ from each other through predefault financial ratios. For those purposes a nonparametric test, independent samples median test (ISMT), will be used. Nonparametric test is applied instead of ANOVA, because for most ratios in the analysis Kolmogorov-Smirnov test and Shapiro-Wilk test indicate violation of normality in the data. The ISMT views, whether there is at least one sample among k samples, that has different median than others (H_0: $\theta_0 = \theta_1 = \theta_2 = ... = \theta_k$; H_1: the median of at least one population is different). H1 will be accepted when asymptotic significance of the test is < 0.05 and significance will be denoted in the following tables as Sig., where additionally test statistic values have been shown. The calculation mechanism of ISMT can be followed in Green and Salkind (2005).

As noted previously, the study uses 2 classifications. The first of them divides firms as failed and survived basing on the fact, whether it managed to submit the annual report and pay fines. This breaks the database of 496 firms into 221 failed and 275 survived firms. The second classification views firms in the first quarter of year 2012, more specifically cuts the database to those firms that have eventually survived and those that have not (bankrupted or liquidated). The second classification divides the dataset into 379 bad and 117 good firms. As a limitation it must be stated that it is not known what will happen to 117 survived firms in future, i.e. some of them might change their status and be members of the failed group. Still, this is a limitation common to most failure studies discriminating between failed and non-failed companies.

Empirical results and discussion. The application of ISMT shows that the number of variables discriminating between failed and non-failed firms is rather small. Out of 7 different ratios for 3 predefault years (in total 21 variables) only 3 are significantly different through firm groups for the first classification and only 1 for the second classification (see Table 1).

The results are in accordance with theoretical considerations of firm failure. The first classification shows that firms failing after defaults show higher leverage (share of current liabilities from total assets), about 10 times lower profitability (the ratio of net income and net sales) and more than 2 times lower solvency (immediate payment ability measured with the ratio of cash to current liabilities). When survived firms in Classification 1 witness growth in solvency between the second and the third pre-bankruptcy year, then failing firms show steady decline, clearly indicating a temporary insolvency for one firm type and gradual decline to permanent insolvency for other type. About the same phenomena concerns profitability, as for surviving firms it remains almost steady and failing firms show more than twofold drop. Classification 2 is not as good in discriminating between two sets of firms, as only one solvency measure is significantly different. This is probably connected to the fact that negative

events occurring after defaults have been overcome are not signalled through the pre first default financial reporting.

Table 1. **Variables significantly different in the groups of failed and survived firms.**

Variable	ISMT test statistic; Sig.	Median for survived firms	Median for failed firms
Classification 1			
$\dfrac{CL_3}{A_3}$	4.730; 0.030	0.413	0.655
$\dfrac{C_2}{CL_2}$	7.449; 0.006	0.466	0.185
$\dfrac{NI_2}{S_2}$	5.947; 0.015	0.058	0.005
Classification 2			
$\dfrac{C_2}{CL_2}$	5.396; 0.019	0.466	0.226

Source: Author's calculations.

The exclusion of the years 2005, 2006 and 2010 with low number of cases from the analysis practically does not change the results given in Table 1. More specifically, the ratio of current liabilities and assets is no more significant, but the values of all other significantly different variables remain about the same, although median values are slightly altered. All years with high representation of cases (2007, 2008, 2009) were also tested individually and the results are given in Table 2. It can be seen, that in case of different years under analysis are viewed separately, the number of significantly different variables is reduced and there are some changes compared to those given in Table 1, e.g. liquidity (share of current assets from total assets) before the first default is predictor of the second default.

Table 2. **Variables significantly different in the of failed and survived firms for the years 2007, 2008 and 2009**

Variable	ISMT test statistic; Sig.	Median for survived firms	Median for failed firms
Classification 1 —year 2007			
$\dfrac{NI_2}{S_2}$	8.159; 0.004	0.069	0.005
Classification 1 —year 2008			
$\dfrac{OP_2}{S_2}$	6.902; 0.009	0.064	-0.002
Classification 2 —year 2009			
$\dfrac{CA_1}{A_1}$	6.107; 0.033	0.864	0.110

Source: Author's calculations.

As the previous results indicated the usage of different (narrower) time period under analysis can alter the results, then it can be concluded that the stability of the

results is affected by time (and situation in economic environment). In the current analysis this can be logical, as Estonia witnessed high fluctuations in economic growth and other macroeconomic indicators in the considered research period.

Conclusion. The study considers a topic receiving relatively low attention in academia — what distinguishes survivors from non-survivors among the firms with defaults. Literature considering bankruptcy models, credit scoring and firm reorganization outlines different financial ratios to be distinguishers of surviving and non-surviving firms. Specifically, studies list profitability, liquidity, solidity and solvency ratios as widely applied for discriminating between failed and non-failed firms.

Based on the dataset of Estonian firms, it was proven that survival of defaulted firms can be detected by applying financial ratios. Dependent of the data used, lower leverage, higher profitability, solvency and liquidity are common to surviving firms. When there are several predictors indicating the difference between survived and failed firms after the first default, then initial values of financial ratios are not so successful in distinguishing final survivors after consequent defaults. This is probably connected to the fact that the ratios measured before the first default are not connected with the events occurring before the second default. The choice of time period has also impact on the calculated results.

The paper can be developed further by using larger datasets, incorporating more variables to analysis and collecting information on defaults from different sources. The study carries some practical implications, as the results can be helpful for failure forecasting. For instance, creditors and bailiffs can use the results for determining when there might not be rational to start collecting a claim and when to use different setup of executive proceeding methods.

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