“Failure prediction of government funded start-up firms”

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FAILURE PREDICTION OF GOVERNMENT FUNDED START-UP FIRMS

Abstract

This study aims to create a prediction model that would forecast the bankruptcy of government funded start-up firms (GFSUs). Also, the financial development patterns of GFSUs are outlined. The dataset consists of 417 Estonian GFSUs, of which 75 have bankrupted before becoming five years old and 312 have survived for five years. Six financial ratios have been calculated for one (t+1) and two (t+2) years after firms have become active. Weighted logistic regression analysis is applied to create the bankruptcy prediction models and consecutive factor and cluster analyses are applied to outline the financial patterns. Bankruptcy prediction models obtain average classification accuracies, namely 63.8% for t+1 and 67.8% for t+2. The bankrupt firms are distinguished with a higher accuracy than the survived firms, with liquidity and equity ratios being the useful predictors of bankruptcy. Five financial patterns are detected for GFSUs, but bankrupt GFSUs do not follow any distinct patterns that would be characteristic only to them.

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INTRODUCTION

Firm failure prediction has been thoroughly studied for around 50 years starting from the seminal studies by Beaver (1966) and Altman (1968). Since then, a large variety of prediction models have been composed (Balcaen & Ooghe, 2006) and the area has especially flourished recently with the development of different machine learning techniques (Ravi Kumar & Ravi, 2007). Most prediction models focus on older firms, which have overcome post foundation difficulties and experienced several years of normal performance, but, in comparison, a relatively small number of prediction models focus on young or newly founded firms (Laitinen, 2016). Moreover, there is a lack of studies about specific types of start-up firms, for instance, companies funded by government support schemes. Thus, this study aims to mitigate the lack of knowledge in the area of predicting failure of firms that have been funded through a state start-up support program. The failure prediction of such firms might be more difficult compared to other types of firms, as they have normally gone through a thorough pre-selection process, which, in turn, reduces the risk of funding firms with a poor outlook of survival.

This study aims to create a prediction model that would forecast the bankruptcy of government funded start-up firms (GFSUs). Moreover, the financial patterns of GFSUs are outlined to show how the bankrupted GFSUs differ from their non-bankrupted counterparts. For these purposes, the whole population of Estonian firms funded from a government start-up grant program is applied. The study is structured as follows. The literature review section focuses on past achievements in the area of (start-up) firm failure prediction. Also, the failure processes of newly founded firms are considered. The literature review section is followed by data and methods section, which describes the population of firms, variables and statistical analysis methods. This is followed by a section focusing on the results and their discussion in the light of available literature. The study ends with a conclusion section, which also outlines several policy implications.

1. LITERATURE REVIEW

Failure has different notions in the literature, ranging from broad definitions like non-achievement of goals to narrow definitions such as bankruptcy (Cochran, 1981; Cannon & Edmondson, 2005; Pretorius, 2009). The authors of extensive literature reviews about failure prediction note that mainly a legal definition of failure (bankruptcy) has been used, although non-legal definitions such as financial distress are also fairly common (Balcaen & Ooghe, 2006; Sun et al., 2014). Despite applying different definitions, the inability to pay debt has been the central object of research in the failure prediction literature (Dimitras et al., 1996). Still, the usage of bankruptcy (a permanent insolvency declared at court) as the definition should be favored because of its unambiguity (Lukason & Laitinen, 2016) and ease of obtaining and comparing information from different countries (Lukason et al., 2016).

In the stream of failure prediction, a large variety of different methods and variables have been applied (Sun et al., 2014). When the methods range from classical statistical tools (like logistic regression and discriminant analysis) to different machine learning applications (Ravi Kumar & Ravi, 2007), then, in turn, financial ratios have mainly been used as predictor variables (Balcaen & Ooghe, 2006; Bellovary et al., 2007). Although studies indicate that a large variety of different financial ratios have been used in prediction models (Dimitras et al., 1996; Ravi Kumar & Ravi, 2007), the profitability, liquidity, solvency and efficiency ratios have been the most significant predictors in highly-cited models (Lukason et al., 2016).

When predicting the failure of newly founded or very young firms, attention has mostly been paid to non-financial attributes of success or failure of such firms (for instance, Cooper et al., 1994; Bates, 2005; Miettinen & Littunen, 2013; Boyer & Blazy, 2014). Such a tendency is logical, as first performance results are normally publicly available more than a year after each firm's foundation, and, thus, other variables must be applied in prediction. Moreover, firms might not perform well during the first years, making the discrimination of failing and non-failing start-ups based on financial ratios difficult (Huyghebaert et al., 2000). Laitinen (1992) showed that failure prediction of newly founded firms with financial ratios one or two years after foundation is fairly difficult and involves (very) high classification errors. This is interconnected with liability of newness theory stating that all young firms (including those which will eventually survive) have not yet overcome post foundation difficulties (see, for instance, Aldrich & Auster, 1986). Using a large sample of young firms, Wiklund et al. (2010) showed that lower leverage and higher liquidity and profitability play a crucial role in the survival of young firms, serving as a protection against the liability of newness. Altman et al.'s (2017) universal bankruptcy prediction model of European firms also indicated that liquidity, profitability (both annual and accumulated) and capital structure ratios need to be higher for younger firms in comparison to adolescent ones in order to survive. The literature review by Dimitras et al. (1996) focusing mainly on bankruptcy prediction studies about older firms also indicates that liquidity, capital structure and profitability ratios are most commonly used, although cash flow and efficiency (also called productivity) ratios have been quite frequent as well. Thus, this study relies on previous research by implementing financial ratios portraying firms' liquidity, capital structure, profitability and productivity to predict the future failure of GFSUs.

Various studies have focused on the effects of government grants on either firm performance or survival and mostly found out that grants have a positive impact (for instance, Del Monte & Scalera, 2001; Girma et al., 2007; Pergelova & Angulo-Ruiz, 2014; Pellegrini & Muccigrosso, 2016). Some potential explanations for such a phenomenon can include better planning and availability of professional advice (Lussier, 1995; Perry, 2001; Chrisman & McMullan, 2004; Liao & Gartner, 2006) in case of GFSUs. It is a long established fact that not only a large proportion of young firms do not survive (Brüderl et al., 1992), but also many GFSUs are not able to fulfil their initial plans and witness payment defaults already at an early stage in their life cycle (Lukason & Masso, 2010). Still, previous studies do not specifically aim to predict the bankruptcy of government supported start-ups based on financial ratios.

The study by Wiklund et al. (2010) focused on the linkage between single financial ratios and firm survival possibilities. Yet, the survival of firms can be determined by a combination of criteria: for instance, firms with a negative profitability but enough reserves can overcome the liability of newness. Thus, multiple studies have focused on the co-behavior of financial variables for survived and/or failed firms (for instance, Pinches et al., 1973; Laitinen, 1991; Coad et al., 2013; Lukason et al., 2016). Lukason et al. (2016) used the co-behavior of 11 different financial variables to detect different firm failure patterns and found that among European manufacturing firms bankrupting at a very young age (namely, in 3-4 years after foundation), the prevalent type has negative profitability and equity for all years of existence. This is consistent with the failure pattern outlined in several other studies, namely start-up firms never becoming successful (Argenti, 1976; Ooghe & de Prijcker, 2008). Still, there is a small proportion of young firms in a population that do not indicate any signs of failure before bankruptcy is declared (Lukason et al., 2016). Therefore, the prediction accuracy of a model focusing on GFSUs is directly dependent of whether bankrupting and surviving firms follow similar or different financial patterns.

Based on the review of literature, we set four hypotheses concerning the differences in financial ratio values for bankrupted and survived government financed start-ups. In comparison to bankrupting GFSUs, the surviving GFSUs have: a) higher profitability (Hypothesis 1), b) lower leverage (Hypothesis 2), c) higher liquidity (Hypothesis 3), and d) higher productivity (Hypothesis 4). We also propose that despite obtaining a grant, bankrupting GFSUs are not able to overcome post-foundation difficulties and, therefore, follow some distinct financial pattern(s) characteristic only to them (Hypothesis 5).

2. DATA AND METHODS

This study is based on the whole population data of firms funded by a start-up grant by Enterprise Estonia, a government institution created to support entrepreneurship development. The period of grant receipt ranges from January 2004 to December 2013 and the respective whole population obtained for this study is 2855 firms. During the viewed period, the grant application rules have slightly varied. For instance, when the qualifying firm had to be less than a year old, then, the maximum grant amount has varied between 6,391-10,226 Euros and project's maximum support share has been 75%-80%. Firms must use the start-up grant for purchases of some goods or services, mainly machinery and equipment, and they cannot keep it as cash. All funded 2855 firms have gone through a rigorous selection mechanism, within which Enterprise Estonia aims to sort out firms with high likelihood of failure. The exact attributes of this selection mechanism are not known, as they have not been revealed in detail for public by Enterprise Estonia. Thus, at the time of grant provision, firms' business plans submitted with the grant application and further interviews with management have indicated a perspective of overcoming post-foundation difficulties and surviving thereafter.

Several criteria have been used to determine the suitability of firms for this analysis. First, firms must be active (earning sales revenue) for all years of their existence. For bankrupt firms this means all years before bankruptcy is declared, but not less than two years, and for surviving firms at least five years. The period of five years has been noted to be the most crucial in young firm survival (Ooghe & de Prijcker, 2008). Empirical findings have shown that more than a half of micro firms exit in four years (Mata & Portugal, 1994), thus, surviving beyond that time horizon makes it likely that firms have overcome both the liabilities of newness and adolescence (see Henderson, 1999), and will be subject to problems more characteristic to mature firms. Firms surviving only one year can be considered "born dead firms" (Lukason et al., 2016) and in the dataset, such firms almost exclusively have not submitted an annual report or have no sales revenue. The time of survival in this study is calculated by using the grant provision date, not the official registration of a firm, as firms might not start their activities right after foundation. As grants can be provided at a random date throughout the calendar year, but all the analyzed firms have their financial years matching the calendar year, then, the following logic has been applied. When the grant has been provided in the first half of the calendar year, this specific year has been considered the first financial year, but otherwise the next year is applied. This helps to make the dataset more homogenous, as, for instance, comparing firms that have functioned 1 or 11 months could lead to false conclusions.

The criterion of activeness is determined so that firms have to receive at least 16,000 Euros turnover for each of the years, as this is the official limit for a firm to be liable to pay the value added tax in Estonia. All analyzed firms must have annual reports available for the first two years and the survived firms should not have payment defaults after five years, as, in case of defaulted firms, it is not known whether they are already on the course of going out of business. All the restrictions resulted in a final dataset of 417 firms, out of which 75 have bankrupted sometime in between two and five years after becoming active and 342 have survived for five years, also having no payment defaults in the end of the fifth year. All 417 analyzed firms are micro firms, of which the most frequent industry is manufacturing, followed by service firms and a small proportion of construction firms. Due to the small sample size, we do not further distinguish between the industries.

The variable selection is based on previous studies about bankruptcy prediction (see the literature review section). In total, six financial ratios have been calculated to cover the main financial dimensions relevant in failure prediction. These variables have been documented in Table 1. Firm liquidity is measured with two ratios. Variable CCL measures the ability to cover current liabilities with cash and variable CACL the ability to cover current liabilities with current assets. We have excluded the ratio of net working capital to total assets, as its numerator duplicates the content of CACL. Firm profitability is measured with two variables, namely net income to total assets (NITA) and net income to operating revenue (NIS). These variables can also be calculated by using earnings before interest and taxes (EBIT) in the numerator, but due to a very high significant positive correlation between NIS and NITA, they are already initially dropped from analysis. Moreover, for all analyzed firms NI and EBIT reveal the same tendency: when NI is negative, then, EBIT is also negative. Capital structure (portraying also solidity) is measured with a single variable: total equity to total assets (TETA). The final variable applied in the analysis symbolizes firm productivity and is calculated as operating revenue to total assets (STA). All financial ratios have been calculated for two years: one (t+1) and two (t+2) years after becoming active, and they have been presented as percentages by multiplying the ratio with 100. Also, the financial ratios have been winsorized before using in the statistical analysis.

Table 1. Formulae of financial ratios applied in the analysis

Variable code	Variable domain	Formula
STA (%)	Productivity / efficiency	[Operating revenue$_t$ / Total assets$_t$] × 100
CACL (%)	Liquidity	[Current assets$_t$ / Current liabilities$_t$] × 100
CCL (%)	Liquidity	[Cash&equivalents$_t$ / Current liabilities$_t$] × 100
NIS (%)	Profitability	[Net income$_t$ / Operating revenue$_t$] × 100
NITA (%)	Profitability	[Net income$_t$ / Total assets$_t$] × 100
TETA (%)	Capital structure / solidity	[Total equity$_t$ / Total assets$_t$] × 100

In order to predict the bankruptcy of GFSUs, binary logistic regression analysis (LR) with stepwise backward option is applied. Bankrupt firms are coded with 0 and non-bankrupt firms with 1. As the dataset in unbalanced – there are remarkably more non-bankrupt firms than bankrupt firms – a weighted LR is used. The same approach has been practiced in previous bankruptcy prediction studies (for instance, in Altman et al., 2017).

The weight applied for bankrupt firms is calculated as 0.5/(the share of bankrupt firms in the sample) and for non-bankrupt firms as 0.5/(the share of non-bankrupt firms in the sample). This procedure makes the two groups in the analysis to be equal: 209 bankrupt and non-bankrupt firms. It should be noted that such a procedure alters the p-values in the LR model. An alternative would be to select 75 non-bankrupt firms randomly, but this method does not enable to use all non-bankrupt firms simultaneously in the analysis. LR is applied on t+1 and t+2 data separately to disclose, which are the predictors of bankruptcy one and two years after a firm becomes active.

In addition, the financial patterns of the firms have been studied with the aim to find out whether the analyzed firms can be grouped into a meaningful taxonomy based on the simultaneous behavior of financial ratios. For this purpose, a methodology frequently used to detect financial failure processes has been applied (see, for instance, Lukason et al., 2016; Lukason & Laitinen, 2016). First, the 12 financial ratios (6 financial ratios from periods t+1 and t+2) are reduced to latent dimensions by using the maximum likelihood factor analysis with Varimax rotation. This procedure is necessary, as original financial ratios might not be suitable for classical clustering methods because of being skewed and correlated (Lukason & Laitinen, 2016). Then, the resulting regression based factor scores are clustered with k-means clustering algorithm. The cluster solution is chosen based on the first local maximum of pseudo-F cluster distinctiveness measure. The k-means clustering results in each of the 417 firms assigned to a specific cluster and each of these clusters is considered to represent a distinct type of financial pattern. Then, a Chi-square contingency test is applied to find out whether there is an association between firm status (bankrupt or survived) and the financial pattern it follows. The study of these financial patterns also helps to disclose why the logistic regression models are not accurate in discriminating between bankrupt and non-bankrupt firms.

3. RESULTS AND DISCUSSION

The descriptive statistics (means, standard deviations and medians) of the sample have been documented in Table 2. The statistical tests indicate that bankrupt and non-bankrupt firms mainly differ in respect to t+1 and t+2 liquidity, but there are some differences in profitability and capital structure as well. Specifically, non-bankrupt firms are

Table 2. Descriptive statistics of financial ratios for the whole sample and two types of firms, %

Variable	Bankrupt (N = 75)			Non-bankrupt (N = 342)			Total (N = 417)		
	Mean	Std. Deviation	Median	Mean	Std. Deviation	Median	Mean	Std. Deviation	Median
CCL_1^{xw}	40	75	11	116	213	32	102	198	24
$CACL_1^{xw}$	110	100	81	229	354	109	207	327	100
STA_1	246	173	222	227	161	186	230	163	188
$TETA_1^{xw}$	29	25	21	42	28	38	39	28	35
$NITA_1^{xw}$	19	22	8	25	22	19	24	22	18
NIS_1^{x}	11	16	5	15	16	10	14	16	10
CCL_2^{xw}	23	44	6	137	252	31	117	233	22
$CACL_2^{xw}$	84	66	67	255	332	126	224	309	111
STA_2	255	188	200	217	146	181	224	155	181
$TETA_2^{xw}$	26	23	22	45	29	43	42	29	36
$NITA_2$	19	21	12	21	21	15	21	21	15
NIS_2^{w}	9	10	5	14	15	8	13	14	7

Notes: ^{x} Independent samples median test p-value < 0.05, ^{w} Brown-Forsyth ANOVA test p-value < 0.05. 1 is t+1, 2 is t+2.

Table 3. Results of weighted logistic regression (LR) analysis for periods t+1 and t+2

LR model for period t+1				
Variable	**Coefficient**	**Standard error**	**Wald statistic**	**p-value**
CCL_1	0.328	0.117	7.831	0.005
$TETA_1$	1.000	0.452	4.907	0.027
Constant	–0.562	0.168	11.156	0.001
LR model for period t+2				
Variable	**Coefficient**	**Standard error**	**Wald statistic**	**p-value**
$CACL_2$	0.553	0.132	17.631	0.000
STA_2	–0.131	0.065	4.029	0.045
$TETA_2$	1.674	0.490	11.679	0.001
Constant	–0.952	0.241	15.561	0.000

not only more liquid and profitable, but also use less leverage. The statistical tests do not indicate differences in productivity. Thus, the descriptive statistics already provide some indication, which might be the best predictors in discriminating between bankrupt and non-bankrupt firms in further LR analysis.

The LR analysis conducted separately for periods t+1 and t+2 reveals (see Table 3) that for both periods lower liquidity and higher leverage increase the probability to belong to bankrupt firms' group. The LR model is free from multicollinearity, as VIF values are close to one. Different liquidity ratios are important predictors for periods t+1 and t+2. While in t+1 the quick ratio (CCL) is a significant predictor, then, in turn, the current ratio (CACL) is in t+2. This indicates that shortly after becoming active, either the availability of sufficient cash reserves and/or financing operations with less current liabilities is crucial for survival. In both periods, the higher leverage (a lower share of equity) increases the probability of failure. The lower equity ratio can indeed be caused by either or both, increased leverage and accumulated losses. Still, as the descriptive statistics indicate positive profitability in both groups of firms, the lower value of equity ratio for bankrupt firms could still mainly be explained by increased leverage. An interesting feature is that the t+2 LR model also includes STA variable, although a rise in its value increases the probability of failure. Still, the p-val-

Table 4. Classification accuracies of logistic regression models for periods t+1 and t+2

Period t+1				
Grouping		**Classified group**		**Accuracy (%)**
		Bankrupt	**Non-bankrupt**	
Observed group	Bankrupt	167	42	80.0
	Non-bankrupt	109	99	47.7
Overall		63.8		
Period t+2				
Grouping		**Classified group**		**Accuracy (%)**
		Bankrupt	**Non-bankrupt**	
Observed group	Bankrupt	167	42	80.0
	Non-bankrupt	93	116	55.6
Overall		67.8		

Table 5. Median values of financial ratios through five detected patterns, %

Variable	Pattern 1 (N = 26) median	Pattern 2 (N = 11) median	Pattern 3 (N = 82) median	Pattern 4 (N = 219) median	Pattern 5 (N = 79) median	Total (N = 417) median
CCL_1	489	834	67	13	33	24
$CACL_1$	557	1702	166	73	105	100
STA_1	187	114	191	141	470	188
$TETA_1$	81	85	58	21	42	35
$NITA_1$	41	24	49	9	24	18
NIS_1	21	28	29	6	4	10
CCL_2	961	21	41	13	28	22
$CACL_2$	1246	576	124	96	112	111
STA_2	177	76	179	147	431	181
$TETA_2$	92	65	57	25	42	36
$NITA_2$	41	16	23	8	23	15
NIS_2	24	20	15	6	5	7

ue for this variable is very close to 0.05 and the usage of a lower threshold would exclude it from the model. Also, the removal of this variable from the model reduces prediction abilities marginally, thus, it is not as important as other variables in the LR model. Still, such a contra-theory anomaly (a lower productivity of assets increases survival chances) can sometimes be caused by the fact that nearer to insolvency, bankrupt firms are rapidly exhausting their (liquid) assets and the denominator of the ratio becomes quite small, not because they would actually be more productive. The results concerning the proposed hypotheses about financial ratios can be followed in Table 7.

The overall classification accuracies of the models (63.8% for t+1 and 67.8% t+2) are expectedly on an average level (see Table 4), as all the analyzed firms have been considered suitable for the grant provision and their future bankruptcy might, therefore, be expectedly difficult to predict. A similar result was documented in Laitinen (1992), where model errors varied between 25%-40%. The LR models are more efficient in detecting future bankrupt firms, namely with an accuracy of 80% for both periods t+1 and t+2. The models are not efficient in predicting the survived firms, which follows the findings in Laitinen's (1992) study. In turn, this is a clear indication that many firms that have not bankrupted during the five first years of existence were still at high risk of failure during the first two years after foundation, therefore, being in the post-foundation "valley of death" (Stam et al., 2008). This argument can be well illustrated by studying GFSUs' financial patterns.

The conducted maximum likelihood factor analysis reveals four factors with initial eigenvalues explaining 80.6% of variance (for the factor matrix, see Table 8). Thus, the established factor solution explains a sufficiently high amount of variance. The cluster analysis of factor scores reveals that the

Table 6. Contingency between detected patterns and firm statuses

Status	Pattern 1	Pattern 2	Pattern 3	Pattern 4	Pattern 5	Total
Bankrupt	0	0	13	43	19	75
Non-bankrupt	26	11	69	176	60	342
Total	26	11	82	219	79	417

Note: Chi-square p-value 0.030, likelihood ratio p-value 0.002.

Table 7. Results of hypotheses testing

Hypothesis	Result
H1. Higher profitability increases GFSU survival likelihood	Rejected for both t+1 and t+2
H2. Lower leverage increases GFSU survival likelihood	Accepted for both t+1 and t+2
H3. Higher liquidity increases GFSU survival likelihood	Accepted for both t+1 and t+2
H4. Higher productivity increases GFSU survival likelihood	Rejected for both t+1 and t+2
H5. Bankrupting GFSUs follow distinct financial patterns	Rejected, no financial patterns specifically characteristic to bankrupting firms were found

Table 8. Rotated factor matrix

Variable	Factor			
	1	2	3	4
CCL_1	0.434	0.220	0.767	–0.061
$CACL_1$	0.263	0.157	0.949	–0.075
STA_1	0.036	0.039	–0.010	0.941
$TETA_1$	0.329	0.530	0.314	0.185
$NITA_1$	0.175	0.887	0.153	0.159
NIS_1	0.076	0.785	0.077	–0.359
CCL_2	0.938	0.139	0.276	–0.048
$CACL_2$	0.830	0.123	0.395	–0.071
STA_2	–0.011	–0.019	–0.044	0.783
$TETA_2$	0.537	0.386	0.190	0.073
$NITA_2$	0.287	0.262	0.011	0.241
NIS_2	0.219	0.261	0.129	–0.253

first local maximum of pseudo-F statistic in the value of 183 is achieved with a five-cluster solution. The frequencies of observations in different clusters can be followed in Table 5, which also documents the median values of six financial ratios for t+1 and t+2 in these clusters. Pattern 4 accounts for more than a half (52%) of the observations. Firms following Pattern 4 have lower values for most financial ratios when compared with other patterns. In turn, the contingency provided in Table 6 indicates that the majority of firms from both groups (bankrupt and non-bankrupt) follow Pattern 4. Thus, when the financial development of most bankrupt and non-bankrupt firms is very similar, it is logical that they are very difficult to discriminate from each other. The presence of Pattern 4 is mainly responsible for the Type II error of LR analysis: poorly performing surviving firms that cannot be distinguished from bankrupting firms. The nature of Pattern 4 is very similar to patterns found in Lukason et al. (2016), which also indicated poor performance throughout all years of existence.

Firms following Patterns 3 and 5 have very similar shares (19% and 20%, respectively). These two patterns indicate a remarkably better performance compared to firms following Pattern 4. Firms following Pattern 3 are much more liquid and profitable at t+1, but less productive in both years when compared with Pattern 5 firms. Patterns 3 and 5 are responsible for the Type I error of LR, as, in total, 43% of bankrupted firms follow these patterns, and due to their good performance, cannot be distinguished from non-bankrupt firms. Patterns 1 and 2 with small shares and indicating extremely good performance during t+1 and t+2, are solely characteristic to non-bankrupt firms. These two patterns do not produce any errors to LR, as firms following them can be easily distinguished from firms bankrupting in the future. The hypothesis about the existence of specific financial pattern(s) for failed firms is rejected (see also Table 7), as no patterns were detected that would be exclusively characteristic to bankrupt firms.

CONCLUSION

This study aimed to compose a prediction model for government funded start-up firms (GFSUs) and also outline such firms' financial patterns. The following main conclusions can be drawn from the empirical analysis. The future bankruptcy of GFSUs cannot be predicted with high accuracy by using binary logistic regression and a set of well-known financial ratios as predictors. Still, likewise to many known bankruptcy prediction models, the ratios portraying liquidity (quick and current ratios) and capital structure/solvency (equity ratio) serve as the best predictors. The moderate prediction abilities are caused by a large proportion of surviving firms following the same financial patterns as the bankrupting firms.

There are several ways government agencies providing start-up grants can benefit from this study. First, the results indicate that bankrupted GFSUs are more leveraged and less liquid than their survived counterparts. Thus, the grants meant for purchasing goods or services should be accompanied by additional start-up loans or loan guarantees. This would enhance the liquidity of the firms during the start-up phase. Second, as the prediction accuracies of the models are modest, the financial performance during the first years might not be a suitable instrument to decide whether to provide different follow-up grants to such firms. We suggest combining financial information with additional non-financial information (for instance, information about managerial characteristics or firms' business plans), in case it is available. This also links to a suggested future research domain, namely research could be conducted by studying the prediction abilities of a wider range of variables, in order to determine which GFSUs bankrupt. As the financial development processes of GFSUs indicate that there are distinct types of them characteristic only to surviving GFSUs, this processual context can be taken into account in future bankruptcy prediction studies, for instance by applying machine learning techniques (see, for instance, du Jardin, 2015; du Jardin, 2017).

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REFERENCES

1. Aldrich, H. E., & Auster, E. R. (1986). Even dwarfs started small: Liabilities of age and size and their strategic implications. *Research in Organizational Behavior, 8*, 165-198.
2. Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., & Suvas, A. (2017). Financial distress prediction in an international context: A review and empirical analysis of Altman's *Z*-Score model. *Journal of International Financial Management & Accounting, 28*(2), 131-171. http://dx.doi.org/10.1111/jifm.12053
3. Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance, 23*(4), 589-609. http://dx.doi.org/10.1111/j.1540-6261.1968.tb00843.x
4. Argenti, J. (1976). *Corporate collapse: the causes and symptoms*. McGraw-Hill, New York, NY.
5. Balcaen, S., & Ooghe, H. (2006). 35 years of studies on business failure: an overview of classic statistical methodologies and their related problems. *British Accounting Review, 38*(1), 63-93. https://doi.org/10.1016/j.bar.2005.09.001
6. Bates, T. (2005). Analysis of young, small firms that have closed: delineating successful from unsuccessful closures. *Journal of Business Venturing 20*(3), 343-358. https://doi.org/10.1016/j.jbusvent.2004.01.003
7. Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research, 4*, 71-111. http://dx.doi.org/10.2307/2490171
8. Bellovary, J. L., Giacomino, D. E., & Akers, M. D. (2007). A review of bankruptcy prediction studies: 1930 to present. *Journal of Financial Education, 33*(4), 3-41. Retrieved from http://www.jstor.org/stable/41948574
9. Boyer, T., & Blazy, R. (2014). Born to be alive? The survival of innovative and non-innovative French micro start-ups. *Small Business Economics, 42*(4), 669-683. https://doi.org/10.1007/s11187-013-9522-8
10. Brüderl, J., Preisendörfer, P., & Ziegler, R. (1992). Survival chances of newly founded business organizations. *American Sociological Review, 57*(2), 227-242. Retrieved from http://www.jstor.org/stable/2096207
11. Cannon, M. D., & Edmondson, A. C. (2005). Failing to learn and learning to fail (intelligently): How great organizations put failure to work to innovate and improve. *Long Range Planning, 38*(3), 299-319. https://doi.org/10.1016/j.lrp.2005.04.005
12. Chrisman, J. J., & McMullan, W. E. (2004). Outsider assistance as a knowledge resource for new venture survival. *Journal of Small Business Management, 42*(3), 229-244. http://dx.doi.org/10.1111/j.1540-627X.2004.00109.x
13. Coad, A., Frankish, J., Roberts, R. G., & Storey, D. J. (2013). Growths paths and survival chances: An application of Gambler's Ruin theory. *Journal of Business Venturing, 28*(5), 615-632. https://doi.org/10.1016/j.jbusvent.2012.06.002

14. Cochran, A. B. (1981). Small business mortality rates: a review of the literature. *Journal of Small Business Management, 19*(4), 50-59.

15. Cooper, A. C., Gimeno-Gascon, J. F., & Woo, C. Y. (1994). Initial human and financial capital as predictors of new venture performance. *Journal of Business Venturing, 9*(5), 371-395. https://doi.org/10.1016/0883-9026(94)90013-2

16. Del Monte, A., & Scalera, D. (2001). The life duration of small firms born within a start-up programme: Evidence from Italy. *Regional Studies, 35*(1), 11-21. http://dx.doi.org/10.1080/00343400120025646

17. Dimitras, A. I., Zanakis, S. H., & Zopounidis, C. (1996). A survey of business failures with an emphasis on prediction methods and industrial applications. *European Journal of Operational Research, 90*(6), 487-513. https://doi.org/10.1016/0377-2217(95)00070-4

18. du Jardin. (2015). Bankruptcy prediction using terminal failure processes. *European Journal of Operational Research, 242*(1), 286-303. https://doi.org/10.1016/j.ejor.2014.09.059

19. du Jardin. (2017). Dynamics of firm financial evolution and bankruptcy prediction. *Expert Systems with Applications, 75*(1), 25-43. https://doi.org/10.1016/j.eswa.2017.01.016

20. Girma, S., Görg, H., & Strobl, E. (2007). The effects of government grants on plant survival: A micro-econometric analysis. *International Journal of Industrial Organization, 25*(4), 701-720. https://doi.org/10.1016/j.ijindorg.2006.08.001

21. 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), 281-314. https://doi.org/10.2307/2666997

22. Huyghebaert, N., Gaeremynck, A., Roodhooft, F., & van de Gucht, L. M. (2000). New firm survival: The effects of start-up characteristics. *Journal of Business Finance & Accounting, 27*(5-6), 627-651. http://dx.doi.org/10.1111/1468-5957.00328

23. Laitinen, E. K. (1991). Financial ratios and different failure processes. *Journal of Business Finance & Accounting, 18*(5), 649-673. http://dx.doi.org/10.1111/j.1468-5957.1991.tb00231.x

24. Laitinen, E. K. (1992). Prediction of failure of a newly founded firm. *Journal of Business Venturing, 7*(4), 323-340. https://doi.org/10.1016/0883-9026(92)90005-C

25. Laitinen, E. K. (2016). Financial failure of a startup: a simulation approach. *International Journal of Management and Enterprise Development, 15*(4), 282-307. https://doi.org/10.1504/IJMED.2016.079851

26. Liao, J., & Gartner, W. B. (2006). The effects of pre-venture plan timing and perceived environmental uncertainty on the persistence of emerging firms. *Small Business Economics, 27*(1), 23-40. https://doi.org/10.1007/s11187-006-0020-0

27. Lukason, O., & Laitinen, E. K. (2016). Failure processes of old manufacturing firms in different European countries. *Investment Management and Financial Innovations, 13*(2), 310-321. http://dx.doi.org/10.21511/imfi.13(2-2).2016.06

28. Lukason, O., Laitinen, E. K., Suvas, A. (2016). Failure processes of young manufacturing micro firms in Europe. *Management Decision, 54*(8), 1966-1985. https://doi.org/10.1108/MD-07-2015-0294

29. Lukason, O., & Masso, J. (2010). Performance of selected Estonian firms financed with start-up grant: Ability to follow plans and grant usage efficiency. *Discussions on Estonian Economic Policy, 18,* 253-265. https://doi.org/10.15157/tpep.v18i0.883

30. Lussier, R. N. (1995). A nonfinancial business success versus failure prediction model for young firms. *Journal of Small Business Management, 33*(1), 8-20.

31. Mata, J., & Portugal, P. (1994). Life duration of new firms. *Journal of Industrial Economics, 42*(3), 227-245. http://dx.doi.org/10.2307/2950567

32. Miettinen, M. R., & Littunen, H. (2013). Factors contributing to the success of start-up firms using two-point or multiple-point scale models. *Entrepreneurship Research Journal, 3*(4), 449-481. https://doi.org/10.1515/erj-2012-0012

33. Ooghe, H., & de Prijcker, S. (2008). Failure processes and causes of company bankruptcy: a typology. *Management Decision, 46*(2), 223-242. https://doi.org/10.1108/00251740810854131

34. Pellegrini, G., & Muccigrosso, T. (2016). Do subsidized new firms survive longer? Evidence from a counterfactual approach. *Regional Studies* (early view article). http://dx.doi.org/10.1080/00343404.2016.1190814

35. Pergelova, A., & Angulo-Ruiz, F. (2014). The impact of government financial support on the performance of new firms: the role of competitive advantage as an intermediate outcome. *Entrepreneurship and Regional Development, 26*(9-10), 663-705. http://dx.doi.org/10.1080/08985626.2014.980757

36. Perry, S. C. (2001). The relationship between written business plans and the failure of small businesses in the U.S. *Journal of Small Business Management, 39*(3), 201-208. http://dx.doi.org/10.1111/1540-627X.00019

37. Pinches, G. E., Mingo, K. A., & Caruthers, J. K. (1973). The stability of financial patterns in industrial organizations. *Journal of Finance, 28*(2), 389-396. http://dx.doi.org/10.1111/j.1540-6261.1973.tb01782.x

38. Pretorius, M. (2009). Defining business decline, failure and turnaround: a content analysis. *Southern African Journal of Entrepreneurship and Small Business Management, 2*(1), 1-16. https://dx.doi.org/10.4102/sajesbm.v2i1.15

39. Ravi Kumar, P., & Ravi, V. (2007). Bankruptcy prediction in banks and firms via statistical and intelligent techniques – a review. *European Journal of Operational Research, 180*(1), 1-28. https://doi.org/10.1016/j.ejor.2006.08.043

40. Stam, E., Audretsch, D., & Meijaard, J. (2008). Renascent entrepreneurship. *Journal of Evolutionary Economics, 18*(3), 493-507. https://doi.org/10.1007/s00191-008-0095-7

41. Sun, J., Li, H., Huang, Q.-H., & He, K.-Y. (2014). Predicting financial distress and corporate failure: A review from state-of-art definitions, modelling, sampling, and featuring approaches. *Knowledge-Based Systems, 57,* 41-56. https://doi.org/10.1016/j.knosys.2013.12.006

42. Wiklund, J., Baker, T., & Shepherd, D. (2010). The age-effect of financial indicators as buffers against the liability of newness. *Journal of Business Venturing, 25*(4), 423-437. https://doi.org/10.1016/j.jbusvent.2008.10.011