Permanent Insolvency Prediction Model in the Example of Estonian Micro-Enterprises Financed with Start-up Grant

Kaspar Käsper

Supervisor:

Oliver Lukason (Research Fellow)

University of Tartu

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Abstract

The objective of this paper is to create a prediction model to distinguish between government supported start-up firms becoming permanently insolvent and surviving. To achieve this, financial ratios from one and two years after foundation are applied for newly founded Estonian firms, all of which received a start-up grant in the period 2004-2009. Data are derived from Enterprise Estonia, Estonian Business Register and Estonian Tax and Customs Board. The results indicate, that financial ratios two years after foundation are most efficient in discriminating between failed and survived firms. Namely, higher profitability and liquidity increase the likelihood of survival. The prediction model composed in this study outperforms known bankruptcy prediction models.

Introduction

One action that helps government boost its economy is handing out governmental start-up grants. This has a positive effect as it helps to create new jobs and increases tax revenue. As Lukason and Masso (2010) noted in their research, the firms that received start-up grant between 2005 and 2008, had paid more labor taxes compared to the sum of the grant, therefore indicating the positive net impact of grants on the state's fiscal position.

Start-up grants are paid out by certain rules that are set with the government regulations. The applicants would have to create a business plan and among other documents a prediction of its future cash flows. Most of the applicants plan a lot of secured revenues and leave no room for error. Laitinen (1992) wrote, that newly founded firms are typically highly indebted already in the first stages of business operations. Thus, they have to plan a lot of revenues to pay their financial obligations, when the availability of share capital is limited. Unfortunately, there are always some failures, which appear in the form of insolvency (Lukason, Masso 2010) and are followed by declaring the ending of business.

The ability to identify or predict that firm is heading towards failure is important for bankers, investors, creditors and even for the distressed firms themselves, whether in the beginning of handing out loan and making an investment or in case of purchasing an operating firm. It has been an important research topic in accounting, auditing and finance for the last four decades (Cheng *et al.* 2006; Lee *et al.* 1996).

Insolvency could be the result of different causes and it strikes companies temporarily as a common occurrence. In some cases, it persists and becomes permanent. Permanent insolvency will finally bankrupt the company.

Literature regards insolvency as a specific type of corporate failure. One of the first definition of corporate failure was provided by Altman (1968), who declared it to be in relation to ceased operations, bankruptcy claiming and above all going out of business. The reason for failure lies in different aspects, but it all comes down to the lack of existent cash inflows. Bariatti and van Galen (2014) suggest that insolvency would occur in two different forms:

a) Cash flow insolvency – a debtor does not manage to pay all of its liabilities in fixed term and will not be able to do that in the future;
b) Balance sheet insolvency – excess of liabilities over assets, which refers to financial distress.

Permanent insolvency could be predicted by the same way as bankruptcy and there are plenty of prediction models that have been created and have been applied in practice (for literature reviews, see e.g. Altman 1968; Laitinen 1991; Gaeremynck, Willekens 2003; Altman et al. 2014). Unfortunately, they are based on and applicable to only a certain region, because of differences in legislation, taxation and distribution of subsidies.

Failure process, which ends with bankruptcy could be a time consuming process (Laitinen *et al.* 2014). The whole trial, including insolvency proceeding, could take more than five years, which is longer than the period observed in this paper. As written in Estonian bankruptcy law, bankruptcy means the insolvency of a debtor declared by a court ruling. In other words, a debtor is insolvent, if the debtor is unable to satisfy the claims of creditors and such inability, due to the debtor's financial situation, is not temporary (Eesti Vabariigi pankrotiseadus 2003).

This research includes court declared permanent insolvencies as well as insolvency proceedings. The phases of failure by Crutzen and van Caillie (2008), list permanent insolvency as the phase number three, prior to and a presumption of bankruptcy. Furthermore, Mackevicius *et al.* (2010) conclude that considering the legal and economic aspects of insolvency, the terms *enterprise insolvency* or *bankruptcy* are used, and that models for bankruptcy prediction also serve as a forecasting models of a possible insolvency.

Literature about start-up firms mainly focuses on its ability to survive. Different quantitative and qualitative variables have been applied to evaluate firms' survival prospects. Earlier studies regarding start-up firms' performance started to emerge in 1990's and focused on both, the quantitative and qualitative factors, like financial and human capital (Cooper *et al.* 1994; Honig 1998). On the other hand, the latest academic research on this matter are focused more on the qualitative factors. For example, some (Hyytinen *et al.* 2015; BarNir 2012) used innovativeness as a variable, while others

(Driga, Prior 2010; BarNir 2012) used gender of the start-up entrepreneur to assess the firms' ability to survive.

The goal of this research is to create a model that is capable of predicting permanent insolvency in the example of start-up enterprises financed with start-up grant in Estonia.

The author creates a pool of data based on firms, which have received governmental start-up grant in the first year of its existence during the period of 2004-2009. The initial pool consists of 2855 start-up firms and will be reduced after applying different criteria, which will be explained in the data and methodology section.

The rest of the paper is structured as follows. The next section will cover a brief literature review on the topic and it is divided into three major subjects: start-up grants and their effect, start-up enterprise and its failure process and finally a review of different prediction models. Section three presents the regulations behind governmental start-up grants as well as introduces the data that is used in the empirical analysis. In addition to previous, the methodology of the statistical analysis is covered in the same section. Section four presents the results from statistical analysis and the article ends with conclusive remarks in section five.

Literature Review

Start-up Grants and Their Effect

The effect of start-up grant on firms' financial performance would help to indicate which ratios should be used. Unfortunately, there is not an abundance of papers about the effect of start-up grants. For instance, foreign researchers Girma *et al.* (2010) proved, that start-up grants have a positive effect on the initial size of the manufacturing plants. The grant receipt encourages plants to start-up with more employment than otherwise. Caliendo *et al.* (2010) concluded with their research, that governmental start-up grants have positive effect on self-employment and increases the percentage of its occurrence.

Estonian researchers, Lukason and Masso (2010), examined local enterprises, after receiving a start-up grant, how would they manage to follow the plans they compiled prior to receiving grants. The results indicated, that many firms could not meet their reported goals and more than half of them had tax arrears. Another paper on start-up grants was composed by Vildo and Masso (2009), where they studied the impact of local start-up grants on firm performance. The results showed that the grants tend to positively affect the number of employed people and turnover.

Start-up Enterprise and Its Failure Process

Financing is a key concern for start-up firms, but they must also create a long-term growth instead of focusing merely on survival (Tanrisever *et al.* 2012). An increasing amount of literature focuses on the decision models involving the financing and operations of start-up firms (Erzurumlu *et al.* 2011; Joglekar, Levesque 2009). This should guide young entrepreneurs through the decisions increasing start-up's survival and ultimately prevent the young firm from defaulting.

The entrepreneurship literature has long recognized the fact that start-up firms have an unequal chance of getting adequate finance at their inception due to the fact, that capital markets are favoring larger and older firms, which are recognized as generally financially transparent (Girma *et al.* 2010). Laitinen (1992) has said, that the rate of mortality among newly founded firms is very high and more than half of them will fail during their first five years of business in the form of insolvency or bankruptcy.

Thornhill and Amit (2003) found that the reasons behind start-up's and an older company's bankruptcy may differ. Younger entrepreneurs lack of resources and capabilities, while older entrepreneurs tend to fail in adjusting with the ever-changing business environment and competitive situation. Henderson (1999), who also studied the relations between company's bankruptcy and its newness, came to a conclusion that the liability of newness is the result of lacking an established relationship with customers, vendors, creditors and other companies, while they still have limited funding.

In addition, the possibility to default is also affected by the size of the company. Aldrich and Auster (1986) stated that small size makes survival problematic. The liability of smallness is caused by the lack of financial resources and reserves, which makes these companies to default whenever the economy or the market falls (Strotmann 2007). On the other hand, it has an upside, as a small company is more innovative and can react faster on the changes of the market.

The liability of smallness is often coupled with the liability of newness. Start-up companies have to face both of these liabilities. From the two of them, the effect of newness has more impact on the company's performance (Halliday *et al.* 1987), because entrepreneurs lack of experience in optimizing the operative and strategic business processes (Kale, Arditi 1998).

Permanent Insolvency Prediction Models

There have not been previous studies in the field of predicting permanent insolvency among start-up firms that received governmental start-up grant. Furthermore, there is none in the example of newly founded Estonian micro-enterprises.

Insolvency in current assessment tends to be as scarce topic in academic literature as the effects of governmental start-up grants. The closest research to Estonian market about insolvency and its prediction model was composed by Altman *et al.* (2014), where they assess the classification performance of Altman's Z´´-Score using logistic regression analysis. What makes this research valuable for this paper, is the fact that the study used Estonian companies in its large international sample. Second research worth mentioning was carried out by Mackevicius in collaboration with Sneidere (2010), where they concluded the research with recommending to test the insolvency symptoms every year after preparation of the financial report. In addition, they stated that Altman's Z`` model can be used for analyzing financial reports of Latvian enterprises.

Balcean and Ooghe (2006) reviewed 43 different models of business failure prediction and classified these models into four categories: univariate, risk index, multivariate discriminant analysis (MDA) and conditional probability models. The most popular model was MDA, which was used in 21 different prediction studies. Gissel, *et al.* (2006), Jackson and Wood (2013) and Makeeva and Neretina (2013) got the same results in their review of frequently occurred forecasting techniques in prior literature. The second most common technique was the logit model.

According to Megan and Circa (2014), all these models are potentially able to identify the financial variables, that are statistically significant in distinguishing entities that will file for insolvency from the entities that will not file for insolvency.

Dimitras *et al.* (1996) note that methods for predicting business failure commonly use three inputs: sampling and data collection; method selection and specification of variables. Variables and sample determine the method that should be used. Therefore, logit-model has its advantages over MDA as it does not require normally distributed predictors, nor the variance-covariance matrices of the predictors to be the same for both groups (failed and survived firms) (Ohlson 1980; Laitinen *et al.* 2014). This is confirmed by Lennox (1999), who's paper argued, that well-specified logit model can identify failing companies more accurately than discriminant analysis.

Bankruptcy prediction has been a field of research for many decades by now and multiple models have been conducted over time (Lensberg *et al.* 2006; Balcean, Ooghe 2006; Berzkalne, Zelgalve 2013). The composition of bankruptcy prediction models started to develop after Beaver's (1966) univariate study, as he compared 30 ratios of 158 firms that were divided into two equal groups of failed and survived businesses. Outcome of the research stated that the highest predictive ability (78% accuracy one year prior to failure) was secured by the factor of cash flow to total debt (Beaver 1966). Nevertheless, his univariate method to predict bankruptcy was seldom followed, because while one variable would imply for failure another could imply survival (Sharma 2001).

The necessity of bankruptcy prediction models and their application potential is justified as follows:

1) Bankruptcy prediction models are important for the various parties related to the company:
    a. Banks use bankruptcy prediction models to assess the credit risk (Hol 2007).
    b. Institutional investors and business angels use bankruptcy prediction models in investing and lending (Dimitras *et al.* 1996).
    c. Bankruptcy of a company may affect employees, customers, vendors and consumers. It could lead to a bankruptcy of a related enterprise (Wu 2010; Jackson, Wood 2013).
    d. Prediction models give an early warning and leave a substantial amount of time for the management to address the situation (Dimitras *et al.* 1996).

2) The statistical methods of bankruptcy prediction models enable to analyze, which financial ratios are the most efficient to classify enterprises as “bankrupt” and “non-bankrupt” (Altman, 1968).

The first scientist to create bankruptcy prediction model using multiple variables was Edward Altman (1968), who later conducted more than 150 studies over the period of 30 years (Berzkalne, Zelgalve 2013). His Z-score is still widely used and proven to be quite accurate in different industries and countries. Nevertheless, higher model accuracy is not assured with a greater number of factors, because a model with just two factors could predict failure as accurately as a model with 21 factors (Gissel *et al*. 2006).

Altman’s Models

The best known bankruptcy model is a MDA model called Altman’s Z′-score. The model analyzed financial data of 33 distressed US companies and 33 sound US enterprises. At the beginning, Altman considered 22 financial ratios, but only five were included in the model: working capital/total assets (X_1), measuring the company’s ability to cover its short term financial obligations; retained earnings/total assets (X_2), measuring profitability that reflects the company’s age and earning power; earnings before interest and taxes/total assets (X_3), as a measure of the asset productivity; market value of equity/book value of total liabilities (X_4), measuring the maximum decline of the asset value, before the liabilities exceed the assets and the company becomes insolvent; sales/total assets (X_5), i.e. the capital turnover ratio, showing the ability of the company’s assets to generate sales (Altman, 1968):

(1) $$\mathrm{Z} = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5$$

Altman’s (1968) model has a specified range from 1.89 to 2.99. All firms having Z-score of greater than 2.99 are considered in a group of “non-bankrupt”, while those having a Z-score below 1.81 are in a group of “bankrupt”. The area in between is defined as “zone of ignorance” or “gray area”, because of the sensibility for error classification. Fulmer *et al.* (1984) later pointed out, that Altman considered only large firms in his research, with average total assets of 100 million dollars. In addition, Eidleman (1995) cautioned that the sales/total asset ratio varies significantly by industry. Considering the remarks of his colleagues, Altman recommended a correction in the model that eliminates the Sales/total assets ratio (Huo 2006):

$$(2) \qquad Z = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$

It also establishes new range for Z-score. All firms having Z-score greater than 2.6 are considered in a group of “non-bankrupt”, while those having a Z-score below 1.1 are in a group of “bankrupt”. The “zone of ignorance” is in range 1.1 – 2.6 (Eidelman 1995).

Although, there are several new bankruptcy prediction models nowadays, the Z-score is still frequently used. For example, Mark Uebergang (2006) applied it in 2006, on a sample of 84 ASX (Australian Securities Exchange) listed companies, which had experienced insolvency. The outcome was that Altman’s Z-score is still adequate and is able to detect financial distress not only in US entities, but even in Australian entities.

In 2014, Altman conducted another paper on bankruptcy prediction, where he reviewed and altered his Altman Z´´- score. It was improved by the re-estimation, using logistic regression analysis (LRA) instead of MDA, because LRA would perform better on a larger sample. In all, the sample includes financial data from 2 602 563 survived and 38 215 failed firms.

In this case, LRA creates a score (logit) L for every firm. This score will be used later in the equation to determine the conditional probability of failure:

$$(3) \qquad p(Y=1|X) = \frac{1}{1+e^{-L}} = \frac{1}{1+e^{-(b_0+b_1X_1+\ldots+b_4X_4)}}$$

$$L = 0.035 - 0.495X_1 - 0.862X_2 - 1.721X_3 - 0.017X_4$$

where b_i (i =0,…, 4) are the coefficients and X_i (i =1,…, 4) are the four independent variables of the original Z´´-score model. The model was named Z´´-Score LR-model.

If the result of this equation should be equal or above 0.5, the firm is considered to be heading towards bankruptcy. If the result should be below 0.5, then the firm is not heading for bankruptcy.

Stahlman’s Model

Stahlman (2015) created a manufacturing industry bankruptcy prediction model, based on the financial data of micro and small enterprises all over Europe. He included four variables into his model:

1) X_1 - EBITDA to debt ratio (EBITDA / Total debt);

2) X_2 - Equity ratio (Total equity / Total assets);
3) X_3 - Asset turnover (Turnover / Total assets);
4) X_4 - Cash ratio (Cash / Short-term liabilities).

These variables are used in the bankruptcy prediction model as follows:

(4) $$P(Y_i = 1) = \frac{1}{1+e^{-Z_i}}$$

$$Z = 0.785 - 4.011X_1 - 0.692X_2 - 0.338X_3 - 2.149X_4$$

If the result of this equation should be equal or above 0.5, the firm is considered to be heading towards bankruptcy. If the result should be below 0.5, then the firm is not heading for bankruptcy.

The model came out to be statistically significant and the overall classification accuracy was 78.3%. In most of the European countries, the model proved to be accurate, being in the range of 75.0-89.4%, whereas in Estonia, it was significantly lower at 65.4%.

Variables in Permanent Insolvency Prediction Models

From the beginning, financial ratios have been introduced as characteristics that are able to predict the failure of a firm (Dimitras *et al.* 1996). Analyzing and comparing different prediction models assure, that the range of financial ratios, which are considered for insolvency prediction, is very wide. Therefore, deeper research had to be done to create a more unique set of variables that would be the basis of the model created in this paper.

Laitinen (1992) implies, that the failure for newly founded firms could be predicted with eight financial factors. Additionally, all the financial factors, which have been used over time in different prediction models, can be classified into three commonly used categories (Altman *et al*. 2014; Laitinen 1992; Makeeva, Neretina 2013; Huang *et al.* 2008; Courtis 1978):

1) Profitability;
2) Liquidity;
3) Solvency.

Dimitras *et al.* (1996) summarized 47 articles into one research, creating an overview of 59 models and a detailed listing of the financial ratios included in the models. According to Bellovary *et al.* (2007), the number factors or variables in one study range from one to fifty-seven. They also state that by 2007, there were more than 752 different variables used in the studies, and that 42 of these factors are considered to be most common.

Based on the information from Makeeva and Naretina (2013) and Dimitras *et al.* (1996), the author categorized the factors that were provided by Bellovary *et al.* (2007). The results are presented in table 1, which lists financial ratios that are considered in the highest number of studies and are classified into three categories mentioned earlier.

Table 1. The most popular financial ratios by their classification.

Category	Financial ratio	Number of Studies
Profitability	Net income / Total assets	54
	Retained earnings / Total assets	42
	Earnings before interest and taxes / Total assets	35
	Sales (turnover) / Total assets	32
	Earnings before interest and taxes / Interest	10
Liquidity	Current assets / Current liabilities	51
	Working capital / Total assets	45
	Quick ratio	30
	Cash / Current Liabilities	26
	Current assets / Total assets	23
	Cash / Total assets	18
Solvency	Total debt / Total assets	27
	Total liabilities / Total assets	19
	Market value of equity / Book value of total debt	16
	Current liabilities / Total assets	13

Source: Dimitras *et al.* (1996), Bellovary *et al.* (2007), Makeeva, Neretina (2013). Notes: Financial ratios were categorized according to Makeeva and Neretina (2013:75) and Dimitras *et al.* (1996:493). Information about the financial ratios and the number of studies came from Bellovary et al. (2007:42).

As shown in table 1, the most widely used factor comes from profitability category and is the ratio of Net Income to Total Assets, which is included in 54 studies. Due to the similar nature, many prediction models use EBIT to Total Assets instead of Net Income to Total assets. The best known universal bankruptcy prediction model, which is Altman's Z-score, uses EBIT to Total assets instead of Net income to Total Assets. That said, Altman's Z´´-score model has all of its four ratios listed in the 15 most used factors table, while Stahlman has only its asset ratio listed in the table.

Data and Method

Estonian Star-up Grants

This paper uses governmental start-up grants as the basis of the analysis. The period in this research includes start-up grants that were paid out between 2004 and 2009 by Enterprise Estonia. In this period, there were two different grant programs: Start-up firm's start-grant 2004-2006 and Star-up firm's start-grant and growth grant 2007-2013.

Start-up grants can be used to finance the purchase of fixed assets needed in firm's business process. That includes transportation, set-up and other costs that are directly related to implementation of fixed asset. In recent years, the program will also cover the costs of certain type of software, patents and even marketing costs.

It is worth mentioning that before the 16^{th} of August 2009, only firms that where registered outside of Estonian capital Tallinn, were eligible for applying grants from Enterprise Estonia (Start-up firm's… 2009). This is the main reason why the majority of firms presented in this paper are registered out of Tallinn.

The legal framework for start-up grant is created by the acts of the Ministry of Economic Affairs and Communication (Start-up firm's… 2004; Star-up firm's… 2008; Start-up firm's… 2009). The first act came into force on the 26^{th} of April 2004 and all grants given out until the next act were regulated by these rules. The next act came into force on the 8^{th} of February 2008, and after various changes that eased the preconditions to qualify for the grant, the final act that is adequate for this research came into force on 30^{th} of August 2009.

Table 2 presents prerequisites that were regulated by different acts. All acts stated the same limits for age of applying firm, maximum number of employees and revenue or balance limits. The difference lays in the margin of grant funding limit and the grants amount.

Table 2. Prerequisites of start-up grant acts from 2004 till 2009.

Prerequisite	First act (2004)	Second act (02.2008)	Second act (09.2009)
Age of applying firm, months	< 12	< 12	< 12
Maximum number of employees	50	50	50
Maximum Revenue/balance sheet, mln euros	3.2/1.6	3.2/1.6	3.2/1.6
Limit of grant funding of total investment, %	75	75	80
Maximum grant amount, euros	10 226	3 196	6 391

Source: Start-up firm's… 2004; Star-up firm's… 2008; Start-up firm's… 2009.

Empirical Data

Compilation of the sample used data from three sources: Enterprise Estonia, Estonian Business Register and Estonian Tax and Customs Board. The first input of data came from Enterprise Estonia, where the author could find all firms that had applied and received start-up grant from January 2004 to December 2013. At this time, there was 2855 firms in the sample.

Given the fact that the main purpose of this analysis is to find the difference between survived and permanently insolvent firms during first five years of existence, it was essential to distinguish these two groups of grant recipients. To achieve the main purpose, permanently insolvent firms had to be identified. Permanently insolvent group of firms included companies that declared the ending of the business during the first five years after receiving start-up grant.

The first group of permanently insolvent firms were identified by declared bankruptcy or abatement of bankruptcy proceeding. Secondly, firms that were in liquidation process, already liquidated or deleted, were also added to permanently insolvent group of firms. Deleting entry is a consequence of failing to declare your fiscal year report for multiple years in a row. Deleting entry will be done by Estonian Business Registry without the permission of the owner. Liquidation is carried out with the consent of the owner. The next step was to identify tax arrears among these firms.

Deleting entry and liquidation had to be caused by permanent insolvency. Therefore, having consecutive tax arrears for at least six months before deleting or liquidating the firm, is considered adequate proof of permanent insolvency. The result of this classification was that 2402 firms were still operating five years after receiving start-up grant and 182 that did not. Information about the ending clause was available from Centre of Registers and Information Systems (Estonian Business Register data) and information regarding tax arrears was provided by the Estonian Tax and Customs Board.

The time criterion of the sample declares, that the period being analyzed for each firm consists of five consecutive years starting from the year of receiving the grant. If a firm receives the grant in first three months of 2005, then this would be the start of the five-year period that ends with the year 2009. If the grant is received after the first three months of the year, then the basis of the period would be 2006 and period ends with 2010. This would provide enough financial information for analysis and also makes the sample more homogeneous.

As the critical part of the analysis is the availability of fiscal year report, the author applied this as the third criterion on the sample. The five-year criterion establishes that there should be five consecutive annual reports for all survived firms. The group of permanently insolvent firms would end the business in this five-year period and they should have financial information in their annual reports for at least two years after receiving the grant. These reports were made available by the Center of Registers and Information Systems, who holds annual reports of Estonian firms as publicly available information.

To avoid including inactive firms in analysis a criterion had to be applied. The solution was to add a lower limit for turnover. The lowest bar to meet the criteria was 16 000 euros of turnover during the both first two years. After all these corrections 478 firms were left in the sample in total, which split into 403 survived firms and 75 firms that had gone bankrupt or ended the business due to permanent insolvency.

Some of the survived firms had persistent tax arrears for at least six months before the ending of the five-year period. To be certain, that these firms would not alter the outcome of the analysis, it is necessary to test the model using two different options: group 1, which includes these firms in the group of survived firms and group 2, which excludes these firms entirely.

Statistical Method

Due to the nature of this research, (binary) logistic regression analysis will be applied for the entire sample as to identify the financial variables that are significantly different between two groups of firms. The dependent variable $Y = 0$ when the firm is permanently insolvent and $Y = 1$ when it survived. LRA model presumes, that the two groups must be accurately distinguished (Balcaen, Ooghe 2006).

The strength of association is assessed by the standard tests for LRA such as the R^2 Square and the Nagelkerke adjusted R^2. The number of survived firms is high in comparison with the permanently insolvent firms. However, it is logical to assume that permanently insolvent and survived firms affect the conditional probability of insolvency with equal weights. Therefore, the two groups are weighted in the way that permanently insolvent and survived firms get equal weights in estimation, but the number of firms is set equal to the original sample size. The weighting of observations remarkably affects the statistical tests as was noted by Laitinen and Suvas (2013).

LRA creates a score (logit) L for every firm. This score is used to determine the conditional probability of failure as follows (Altman *et al.* 2014):

(5) $$p(Y = 1|X) = \frac{1}{1+e^{-L}} = \frac{1}{1+e^{-(b_0+b_1X_1+\ldots+b_nX_n)}}$$

where b_i (i =0,…, 6) are the coefficients and X_i (i =1,…, n) are the six independent variables that will be introduced in the next section.

The analysis part of the paper was carried out with the help of statistical software *IBM SPSS Statistics 20*. Considering the fact that there are two first years of operations under examination, both years must be analyzed separately. Moreover, there are two different groups of survived firms, because some of these enterprises had compiling tax arrears in six consecutive months before the end of the five-year term. In the light of previous notes, four separate logistic regression analysis were carried out:

LR analysis 1. 1st years financial variables of survived group of firms, which consists of survived firms with and without tax arrears (Y = 1) and other group consisted of firms that became permanently insolvent (Y = 0).

LR analysis 2. 2nd years financial variables of survived group of firms, which consists of survived firms with and without tax arrears (Y = 1) and other group consisted of firms that became permanently insolvent (Y = 0).

LR analysis 3. 1st years financial variables of survived group of firms, which consists of only survived firms without tax arrears (Y = 1) and other group consisted of firms that became permanently insolvent (Y = 0).

LR analysis 4. 2nd years financial variables of survived group of firms, which consists of only survived firms without tax arrears (Y = 1) and other group consisted of firms that became permanently insolvent (Y = 0).

Financial Ratios Applied in Modelling

The analysis will include only the first two years of financial data for each firm. Financial data is necessary for calculating the variables that will be covariates in the logit model. Including a high number of financial variables in the model may lead to multi-collinearity, so that the model coefficients can be strongly influenced.

In literature review, three categories of variables were listed. For this research, all these categories will be represented at least with one variable. In the light of given data, variables for this model are considered to be as followed:

a. the liquidity (Cash_SL), measured as **cash stock/short-term liabilities**;
b. the ability to pay off its liabilities (CA_SL), measured as **current assets/short-term liabilities**;
c. the business scale of the company (Turn_TA), measured as **turnover/total assets**;
d. the company’s financial leverage (Eq_TA), measured as **equity/total assets**;
e. the asset productivity (NI_TA), measured as **net income/total assets**;
f. the profit margin (NI_Turn), measured as **net income/turnover**.

Results and Discussion

Descriptive Statistics

Table 3 presents first year's descriptive statistics of the six independent variables (X_1-X_6) that were used in this research. The results include survived firms and permanently insolvent firms, which are presented in the table as failed. In case of survived firms two different grouping options are used, where Group 1 consists of survived firms with and without tax arrears and Group 2 consists of only firms that did not have any tax arrears. Failed group represents only permanently insolvent firms. The standard deviation shows that the variation in the ratios is significant. For all the variables, the means significantly exceed the median for both failed and survived firms, indicating a positively skewed distribution.

Table 3. Descriptive statistics for first year.

	Mean			**Median**			**Std. Deviation**		
	Failed	Survived		Failed	Survived		Failed	Survived	
Variable		Group 1	Group 2		Group 1	Group 2		Group 1	Group 2
Cash_SL	0.3959	1.2042	1.3117	0.1081	0.3069	0.3153	0.7469	2.7482	2.9444
CA_SL	1.0949	2.4723	2.6012	0.8068	1.0712	1.0866	0.9962	4.9783	5.2706
Turn_TA	2.4696	2.2632	2.3152	2.2247	1.8122	1.8579	1.7810	1.7917	1.8078
Eq_TA	0.3958	0.4146	0.4200	0.2092	0.3779	0.3819	1.0071	0.2848	0.2911
NI_TA	0.2798	0.2514	0.2590	0.0834	0.1868	0.1870	0.8918	0.2391	0.2479
NI_Turn	0.1213	0.1586	0.1593	0.0513	0.1005	0.1017	0.1981	0.2063	0.2101

Notes: Survived firms with tax arrears consist of 403 companies. Survived firms without tax arrears consist of 342 companies. Failed companies consist of 75 firms.

Table 4 presents second year's descriptive statistics of those six variables. The standard deviation shows that the variation in the ratios is as significant as for the first year. For all the variables, the means significantly exceed the median for both failed and survived firms, indicating a positively skewed distribution.

Table 4. Descriptive statistics for second year.

Variable	Mean			Median			Std. Deviation		
	Failed	Survived		Failed	Survived		Failed	Survived	
		Group 1	Group 2		Group 1	Group 2		Group 1	Group 2
Cash_SL	0.2340	1.6107	1.7960	0.0635	0.2794	0.3134	0.4431	5.6852	6.1400
CA_SL	0.8383	2.9023	3.1337	0.6682	1.2174	1.2641	0.6574	7.7652	8.3771
Turn_TA	2.5834	2.1477	2.2023	2.0029	1.7422	1.8051	1.9939	1.5696	1.5948
Eq_TA	0.3973	0.4431	0.4561	0.2172	0.3938	0.4257	1.2786	0.3001	0.3085
NI_TA	0.1934	0.2125	0.2220	0.1227	0.1468	0.1547	0.2139	0.2340	0.2397
NI_Turn	0.0903	0.1377	0.1424	0.0496	0.0775	0.0784	0.1002	0.1796	0.1846

Notes: Survived firms with tax arrears consist of 403 companies. Survived firms without tax arrears consist of 342 companies. Failed companies consist of 75 firms.

Table 5 presents ANOVA and Independent Samples Median Test (ISMT) results (p-values) through all variables and taxonomies applied in the evaluation. In case of both tests the p-values <0.05 are considered to reflect significant differences in this study. Only ratios Cash_LS and CA_SL are statistically significant for both years on both tests, indicating, that these variables could be important discriminators of failed and survived firms. The means of Cash_SL and CA_SL were significantly higher for survived companies on the second year, whereas it was much higher for failed companies on the first year. The mean and median values of Cash_SL and CA_SL showed several times higher results on survived firms, which is also expected as the surviving firms tend to have more liquid assets. The biggest difference between survived and failed companies showed the liquidity ratio Cash_SL, where the mean values differed more than six times and median values more than four times. The median test (ISMT) showed, that Eq_TA, NI_TA and NI_Turn ratios are statistically significant in the first year. All of them had a median value for survived companies almost twice as high as for failed companies.

Table 5. ANOVA (Brown-Forsyth) and Independent Samples Median Test (ISMT) results (p-values) through all variables and taxonomies applied.

Variables	Year	Test	P-values	
			Group 1	**Group 2**
Cash_SL	1	ANOVA	0.000*	0.000*
		ISMT	0.003⁺	0.002⁺
	2	ANOVA	0.000*	0.000*
		ISMT	0.000⁺	0.000⁺
CA_SL	1	ANOVA	0.000*	0.000*
		ISMT	0.024⁺	0.023⁺
	2	ANOVA	0.000*	0.000*
		ISMT	0.000⁺	0.000⁺
Turn_TA	1	ANOVA	0.359	0.499
		ISMT	0.615	0.594
	2	ANOVA	0.076	0.124
		ISMT	0.451	0.594
Eq_TA	1	ANOVA	0.873	0.837
		ISMT	0.000⁺	0.000⁺
	2	ANOVA	0.758	0.694
		ISMT	0.000⁺	0.000⁺
NI_TA	1	ANOVA	0.785	0.842
		ISMT	0.044⁺	0.044⁺
	2	ANOVA	0.487	0.308
		ISMT	0.615	0.458
NI_Turn	1	ANOVA	0.140	0.140
		ISMT	0.012⁺	0.011⁺
	2	ANOVA	0.001*	0.001*
		ISMT	0.209	0.132

Notes: * indicates that ANOVA p-value =< 0.05. ⁺ indicates that Independent Samples Median Test p-value =< 0.05. Group 1 consists of 403 survived and 75 permanently insolvent companies. Group 2 consists of 342 survived and 75 permanently insolvent companies.

LR Model for All Survived and Permanently Insolvent Firms

As described in table 6, the results of the first LR analysis show, that during the first financial year after receiving the governmental start-up grant, the liquidity ratio Cash Stock to Short-term Liabilities is the only financial variable from this research, which could predict permanent insolvency. Decrease in the value of this ratio will increase the probability of permanent insolvency.

Table 6. Variables in the equation from LR analysis 1.

Variables	B	S.E.	Wald	df	Sig.	Exp(B)
Cash_SL	0.432	0.108	16.126	1	0.000	1.541
Constant	-0.271	0.108	6.251	1	0.012	0.763

Table 7 shows the overall predictive performance of the first LR model is 59.7%. The group of permanently insolvent firms obtained 84.0% classification accuracy, while the group of survived firms obtained only 35.5% classification accuracy. Applying Altman's Z´´-score to the same sample resulted overall classification accuracy of 44.6% (84% on survived firms and only 5.3% on permanently insolvent firms). Stahlman's model showed a little better results based on the first test's sample. Although, it resulted 90.1% classification accuracy on survived companies, it failed with the result of 12% on permanently insolvent companies, all of which makes 51.1% overall predictive performance. Z´´-score LR-model failed to identify any permanently insolvent firms and classified all the firms in the sample as survived.

Table 7. Prediction accuracy of the LR analysis 1.

Observed	Predicted		
	Y = 0	**Y= 1**	**% Correct**
Y = 0	201	38	84.0
Y = 1	154	85	35.5
Overall %			59.7

Table 8 shows the results of the second LR analysis, which indicates that financial ratios significant in the LR model for the second year differed from those significant in the model for the first year. The predictors which could be included to the model are the profitability ratio Net Income to Turnover and liquidity ratio Current Assets to Short-term Liabilities. Decrease in the value of those ratios will increase the probability of permanent insolvency. It is worth mentioning, that the second year's LR analysis only included five variables of the six, because two profitability variables showed multicollinearity and only the variable with the highest classification accuracy was included.

Table 8. Variables in the equation from LR analysis 2.

Variables	B	S.E.	Wald	df	Sig.	Exp(B)
NI_Turn	1.675	0.752	4.955	1	0.026	5.338
CA_SL	0.716	0.119	35.985	1	0.000	2.046
Constant	-1.063	0.175	36.929	1	0.000	0.346

Table 9 shows that the overall predictive performance of the second LR model is 65.6%. The group of permanently insolvent firms obtained 81.3% classification accuracy, while the group of survived firms obtained 49.9%. Altman's Z´´-score showed overall classification accuracy of 44.1% (85.5% on survived firms and only 2.7% on permanently insolvent firms). Stahlman's model showed better results based on the second test's sample. It resulted 91.6% classification accuracy on survived companies, but it failed with the result of 18.7% on permanently insolvent companies, resulting 55.1% in overall predictive performance. Altman's LR-model failed to identify any permanently insolvent firms and classified all the firms in the sample as survived.

Table 9. Prediction accuracy of the LR analysis 2.

Observed	**Predicted**		
	Y = 0	**Y= 1**	**% Correct**
Y = 0	194	45	81.3
Y = 1	120	119	49.9
Overall %			65.6

LR Model for Survived Without Defaults and Permanently Insolvent Firms

Table 10 shows the results of the third LR analysis, which indicates that during the first financial year after receiving the governmental start-up grant, the liquidity ratio, Cash Stock to Short-term Liabilities, is the only financial variable from this test, which could predict permanent insolvency. Decrease in the value of this ratio will increase the probability of permanent insolvency.

Table 10. Variables in the equation from LR analysis 3.

Variables	B	S.E.	Wald	df	Sig.	Exp(B)
Cash_SL	0.451	0.115	15.385	1	0.000	1.570
Constant	-0.292	0.116	6.293	1	0.012	0.747

Table 11 shows, that the overall predictive performance of the third LR model is 59.8%. The group of permanently insolvent firms obtained 84.0% classification accuracy, while the group of survived firms obtained only 35.7% classification accuracy. Altman's Z´´-score had 45.3% overall predictive performance (84.9% classification accuracy on survived firms and 5.3% on permanently insolvent firms). Stahlman's model showed 91.3% classification accuracy on survived companies and 12% on permanently insolvent companies, which resulted 51.6% overall. Altman's LR-model failed to identify any permanently insolvent firms and classified all the firms in the sample as survived.

Table 11. Prediction accuracy of the LR analysis 3.

Observed	Predicted		
	Y = 0	**Y= 1**	**% Correct**
Y = 0	175	33	84.0
Y = 1	134	74	35.7
Overall %			59.8

As described in table 12, the results of the fourth LR analysis show, that during the second financial year after receiving the governmental start-up grant, the significant financial ratios differed from the first year's results. Significant variables in the model are the profitability ratio Net Income to Turnover and liquidity ratio Current Assets to Short-term Liabilities. Decrease in the value of those ratios will increase the probability of permanent insolvency. The fourth test, like the second test, also included only five variables for the same reasons.

Table 12. Variables in the equation from LR analysis 4.

Variables	B	S.E.	Wald	df	Sig.	Exp(B)
NI_Turn	1.855	0.812	5.215	1	0.022	6.389
CA_SL	0.736	0.128	32.818	1	0.000	2.088
Constant	-1.125	0.190	35.123	1	0.000	0.325

Table 13 shows that the overall predictive performance of the fourth LR model is 67.9%. The group of permanently insolvent firms obtained 84.0% classification accuracy, while the group of survived firms got 51.8%. Applying Altman's Z´´-score to the same sample resulted 44.2% classification accuracy (85.7% on survived firms and 2.7% on permanently insolvent firms). Stahlman's model showed 55.4% overall predictive performance (92.1% classification accuracy on survived companies and 18.7% on permanently insolvent companies). LR-model failed to identify any permanently insolvent firms and classified all the firms in the sample as survived.

Table 13. Prediction accuracy of the LR analysis 4.

Observed	Predicted		
	Y = 0	**Y= 1**	**% Correct**
Y = 0	175	33	84.0
Y = 1	101	108	51.8
Overall %			67.9

Conclusion

The prediction of failure of newly founded firms has received scant attention in the literature, but there are no studies specifically focusing on government supported start-ups. Still, this is an important knowledge for business owners, clients, creditors and possible buyers to assess the risks of a potential insolvency. The purpose of this study was to create a reliable prediction model that could predict a possible permanent insolvency of a newly founded firm, which has been granted a governmental start-up grant.

Six financial ratios from different categories, from one and two years after firm foundation, were applied in logistic regression analysis to find out the best determinants of start-up firm failure. According to the logit model, only the Cash to Short-term liabilities ratio enables to predict firm failure one year after foundation, whereas profitability ratio Net Income to Turnover and liquidity ratio Current Assets to Short-term Liabilities enables to predict it two years after foundation.

The sample that was used to create the model was later tested with three different universal bankruptcy prediction models. Applying these models on the sample proved, that universal bankruptcy prediction models are inefficient in predicting the failure of Estonian start-up firms supported by government, as their prediction accuracies remain in most cases below 50%. Thus, besides the scientific essence of finding out the best post-foundation predictors for such firms, the results of the study are applicable in practice by different stakeholders when making financing decisions. For example, Enterprise Estonia can use this model to evaluate whether to hand out a growth support to a firm that already has received a start-up grant.

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