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PREDICTION OF LOAN DEFAULTS USING FINANCIAL RATIOS, PAYMENT BEHAVIOUR AND MANAGER'S CHARACTERISTICS

Master's thesis

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I have written this master's thesis independently. All viewpoints of other authors, literary sources and data from elsewhere used for writing this paper have been referenced.

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Abstract

The aim of the paper is to find out what characteristics have the best loan default prediction accuracy among young small and medium-sized enterprises (SMEs). As these characteristics, SME financial ratios, payment behaviour and manager characteristics are considered. The current research gap is that these three factors have not been systematically studied together in the context of loan defaults. The analysis is conducted using logistic regression analysis. Variables were selected considering available literature. The research is based on a dataset taken from an Estonian finance company. The composed models indicate 69.8% accuracy in loan default prediction.

Keywords: default prediction, logistic regression, SMEs, financial ratios

1. Introduction

SMEs have an essential role in the economy and in many countries, SMEs account for the majority of all companies and they provide the majority of jobs and contribute to the economy (Altman & Sabato, 2007; Cultrera & Brédart, 2016; Wahyudi, 2014).

To avoid significant losses when working with financing SMEs, it is vital for a financial institution to find out what characteristics are important when evaluating credit risk and delivering credit decisions. A poorly made decision can have a very clear cost for the creditor: the cost of losing interest and repayment of principal (Abdou & Pointon, 2011). For several parties, it is essential to be aware of the early warning signals in order to avoid or reduce the number of failures (Altman & Narayanan, 1997). Ciampi et al (2018, p. 19) have summed it up: "For a lender, giving a loan to a firm that is doomed to fail is surely a costlier error than not giving a loan to a firm that is destined to survive."

In previous studies about predicting failure, mainly big companies have been investigated and the main focus has been on financial ratios (Altman & Sabato, 2007; Cultrera & Brédart, 2016; Kumar & Ravi, 2007). There are fewer studies that concentrate on SMEs. These studies are mainly focusing on financial ratios but financial statements may not be available or if they are, they may be not so trustworthy (Ciampi et al., 2018). Few studies unite SMEs financial ratios and previous payment behaviour, for example, Laitinen (2011), Altman et al (2015), Ciampi et al (2018). There are only a few studies that analyse manager's characteristics in predicting loan default: Ciampi (2015), Purves and Niblock (2018).

Before a company's bankruptcy, it is possible to observe the failure process (Dimitras et al., 1996; Ooghe & Prijcker, 2008; Laitinen & Lukason, 2014) and the most common portrait of this is a step by step decline of the company's financial situation (Lukason, 2018; Weitzel & Jonsson, 1989). Thus, the most useful way to predict loan default could be using financial ratios. Since it is also the most studied it could be the most accurate option. However, it may not be so simple with small and medium-size companies. Young SMEs have the highest risk of failure (Laitinen, 1992; Cultrera & Brédart, 2016). At the same time, their financial statements and financial ratios may not reflect any potential risks (Lukason et al., 2016).

Findings also have revealed that financial ratios do not always indicate resourceful organizational health factor (Purves & Niblock, 2018). It has also been confirmed that SMEs are undoubtedly different from large corporations from a credit point of view (Altman & Sabato, 2007).

The aim of this paper is to find out what characteristics have the best loan default prediction accuracy among young small and medium-sized enterprises (SMEs). As these characteristics, SME financial ratios, payment behaviour and manager characteristics are considered. The current research gap is that these three factors have not been systematically studied together in the context of loan defaults. The data was gathered from a small Estonian financial institution. The financial data gathered between the years 2016 and 2019 consists of 381 young Estonian SMEs.

The paper is organized as follows. The introduction is followed by the literature review, which has been split into two subsections – firstly, the definition of default; and secondly the introduction of studies using financial ratios, previous payment behaviour and manager characteristics. In the third part the data of the empirical study is described with methodology. Analysis and discussion are presented in section four. In the conclusion, the author will bring out future research directions.

2. Literature review

2.1 Failure and default

In the last 50 years business failure prediction has become one of the fundamental research domains within corporate finance (Balcaen & Ooghe, 2006). There is no definite concept of failure and it can vary depending on a specific interest (Pretorius, 2009). It is possible to present "failure" as "the inability of a firm to pay its financial obligations as they mature" (Beaver, 1966, p. 71) and liquidating bankruptcy or reorganization (Altman, 1968). Failure is a process (Balcaen & Ooghe, 2006; Laitinen, 1992; Weitzel & Jonsson, 1989), and it has been summarized as "organizations enter the state of decline when they fail to anticipate, recognize, avoid, neutralize, or adapt to external or internal pressures that threaten the organization long-term survival" (Weitzel & Jonsson, 1989, p. 94). There are several stages of decline (Weitzel & Jonsson, 1989) and all of them can be summarized as failure. One phase of failure is a default (Weitzel & Jonsson, 1989). As regards to SMEs, claims against them are not always brought to court and the company does not go through the official insolvency process. Furthermore, authors have brought out that overall there are more company discontinuances than bankruptcies (Cochran, 1981). Therefore, for SMEs it is more reasonable to use the concept of default than search for de jure failed companies. Basel Committee on Banking Supervision (2006, p. 100) has defined a default as "[t]he obligatory is past due more than 90 days on any material credit obligation to the banking group." The concept where all loss elements (unpaid principal and accrued interest) that are passed 90 days due is considered as default is also used by other authors in their studies (Back, 2005; McCann & McIndoe-Calder, 2015; Wahyudi, 2014) and this is an internationally recognized approach.

In the prediction of SME defaults, different authors point out different aspects that must be taken into consideration: legal form, number of employees (Calabrese et al. 2019), industry sector (Calabrese et al., 2019; Cultrera & Brédart, 2016), and age (Cultrera & Brédart, 2016).

2.2.1 Financial ratios

One of the first authors to reach the conclusion that financial ratios have a predictive value from research was Beaver (1966) and already in the 1960s company ratio comparisons was widely used by practitioners (Altman, 1968). The first multivariate prediction model was mostly developed by Altman (1968). Business failure prediction models are mostly based on financial ratios (Dimitras et al., 1996). There are various financial ratios and hundreds of studies that find many different financial ratios useful. However, there is no general agreement about which of these is the best in predicting failure and which of these is outstanding for predicting SMEs default. Review articles have assembled the top of most used financial ratios. In Chen and Shimerda (1981) review article, 26 studies from period 1966-1975 were summarized and 65 accounting ratios analyzed. Dimitras et al (1996), in their review article studied 158 articles on business failures from 1932-1994 and it is possible to assemble from this study the top 10 most used ratios. Gissel et al (2007) focused on the analysis of 165 bankruptcy prediction studies from 1965-2004 and made a summary of factors included in five or more studies. These review articles will also be used in the empirical part to select the financial ratios for this study. There are fewer researches that have taken into consideration SMEs financial ratios in particular: Cultrera & Brédart (2016), Ciampi (2015) and Ciampi et al (2018). Cultrera & Brédart (2016) studied Belgian SMEs and constructed a multi-dimension model with different groups of ratios (profitability, solvency, liquidity, added value, and debt structure ratios). On the other hand, Ciampi (2015, 2018) had expressed a sceptical point of view in using financial ratios for SMEs in several of his studies.

Financial ratios have been used for many different purposes: starting from testing of economic hypotheses and continuing with an evaluation of business and it's success (Barnes, 1987). Financial ratios are convenient because they simplify the comparison of different companies regardless of size and they possess the appropriate statistical properties (Barnes, 1987). An advantage of using financial ratios is that in predicting defaults there are dozens of factors that are not needed (Chen & Shimerda, 1981), for example Altman's Z-Score only uses five financial ratios (Altman, 1968). It has been confirmed that financial ratios can predict default up to five years (Beaver, 1966). Although ratio analysis provides useful information, the early studies have already concluded that not all ratios predict equally well (Beaver, 1966). There is a possibility to choose from hundreds of ratios (Chen & Shimerda, 1981) and there is no common understanding which of them are the best. Furthermore, the best result will not be reached by using too many ratios as it can cause multicollinearity (Dimitras et al., 1996).

According to reviewed articles, the most used financial ratios are current ratio, ROA and working capital divided by total assets (Table 1). As the most important ratios, despite horizon length, the authors have highlighted the liquidity/solvency category (Working Capital (that is: Current assets – Current liabilities)/Total assets, Total debt/Total assets) (Altman et al., 2015; Dimitras et al., 1996) and profitability ratios which indicates that the viability of a company depends on profit making (Dimitras et al., 1996). For successful evaluation of SMEs, the following groups of ratios were singled out: profitability, solvency, liquidity, added value and debt structure ratios (Cultrera & Brédart, 2016). In this model, the solvency ratio (cash flow/total debt) did not appear to be significant (Cultrera & Brédart, 2016). Current ratio (current assets/current liabilities) is a good predictor of the financial health of SME. The study shows that higher liquidity ratio decreases the probability of bankruptcy at one year before bankruptcy (Cultrera & Brédart, 2016).

Table 1. Summary of the analyzed articles: the most used financial ratios (compiled by the author)

Financial ratio	**Chen and Shimerda (1981)**	**Dimitras (1995)**	**Gissel (Bellovary) et al (2007)**	**Total**
Current ratio (CA/CL)	11	12	51	**74**
NI/TA	7	11	54	**72**
WC/TA	9	16	45	**70**
Retained earnings/TA		7	42	**49**
EBIT/TA	1	12	35	**48**
TD/TA	4	15	27	**46**
S/TA		7	32	**39**
Quick ratio (liquid assets/current liabilities)		9	30	**39**
CA/TA	9		26	**35**
Net income/net worth	5		23	**28**
Cash flow/ total debt		9	18	**27**
Cash flow/S		8	9	**17**
Net worth/total liabilities	12			**12**

Note: CA (Current Assets), CL (Current Liabilities), NI (Net Income), TA (Total Assets), WC (Working Capital (that is: Current Assets-Current Liabilities)), EBIT (Earnings Before Interest and Taxes), TD (Total Debt), S (Sales).

Financial ratios are a useful tool when evaluating a company. However, it is not flawless while evaluating SMEs: smaller companies have smaller values and also modest changes in the values of ratios can be fatal for a firm. In default prediction for SMEs when constructing a quantitative model using only financial ratios – the results are less accurate than in the case of larger companies (Ciampi, 2015; Altman et al., 2015). SME has less legal obligation concerning financial information and it is less reliable and accurate (Ciampi, et al., 2018; Gabbianelli, 2018). When presenting accounting information, the manager also can decide not to show all details and it may affect the truthful depiction of the company's economic situation (Gabbianelli, 2018). Moreover, it is essential to point out that some ratios are ineffective below a specific level (Ciampi et al., 2018; Ciampi & Gordini, 2013). Different authors bring out that compared with a large corporation, SME financial information is less reliable because the report is usually unaudited (Ciampi & Gordini, 2013; Karan et al., 2013; Wahyudi, 2014) and financial statements of small firms are often not as freely available as compared to listed firms (Back, 2005). At the same time, there is no warranty that the same mistakes with financial ratios would not come up with big corporations (Balcaen & Ooghe, 2006). Furthermore, the errors can occur using only one single annual account – it is ignoring the time-series of financial behaviour (Balcaen & Ooghe, 2006). Weak financial condition can be better determined from several consecutive annual accounts: the longer the financial agony has lasted the harder it is to recover from it and therefore probability for default rises (Ciampi et al., 2018). Moreover, it matches the theory about decline process, that is before final failure there are several stages: the deeper the crisis goes – the harder is to come out from this (Weitzel & Jonsson, 1989).

Studies that used financial ratios of SMEs show the following results: companies that took moderately large loans relative to total assets are highly leveraged and are more likely to default. At the same time, companies that are liquid and profitable are less likely to default (McCann & McIndoe-Calder, 2015). Some authors also got low predictive accuracy for SMEs using financial ratios compared to bigger companies (Gabbianelli, 2018).

When selecting variables, the focus is on choosing a limited number of factors, since more factors do not necessarily increase the ability to predict failure (Gissel et al., 2007). Therefore, too many financial ratios have not been selected for the current empirical work but emphasis is on the most used financial ratios and ratios indicating most predictive power as regards to SMEs: ROA (Net income to Total Assets), working capital to total assets, and total debt to total assets.

2.2.2 Previous payment behaviour

Authors of previous studies have already demonstrated that corporate default depends on several company-specific factors (Altman, 1968). More recent studies have declared that the most accurate long-range prediction results consist of financial and non-financial variables (Altman et al., 2015). In the last decades, some authors have sought for non-financial variables that would have default prediction power. Analysing previous payment behaviour in studies is a logical sequel after financial ratios. Many of studies in this field have been done in Europe and especially in the northern part. Back (2005) used 31 99 Finnish firms in his study and contained information from credit analysts about previous payment behaviour, financial position and variables related to the management's financial history. Laitinen (2011) included in his study the financial statement and non-financial information from 65 164 firms from a Finnish credit information company. Karan et al (2013) used in their study the data of 6000 Turkish retailer customers. The study by Ciampi et al (2018) used a sample of 1 200 Italian small enterprises and combined company's previous payment behaviour and financial ratios in default prediction for SMEs.

Previous payment behaviour is essential when predicting loan default – it provides important signals of company's non-viability (Karan et al., 2013; Laitinen, 2011). Moreover, other authors have summed up that the behaviour of former customers can provide a crucial historical data-set, which can be very important in predicting new applicant behaviour (Abdou & Pointon, 2011). Several authors have emphasized the importance of payment history in predicting the creditworthiness of a company (Back, 2005; Ciampi et al., 2018;

Karan et al., 2013; Laitinen, 2011). It has been pointed out that the payment history in firms may be the first indicator of future payment patterns (Back, 2005). In the study by Back (2005) it was found that previous payment disturbances affect the severe type of defaults. Laitinen (2011) in his study brought out that one the most significant variable is number of payment defaults and it is also the most crucial variable in the long run (Altman et al., 2015).

Researchers have concluded that when SME default prediction model is based on both payment behaviour-related variables and financial ratios the prediction accuracy is higher and it brings incremental information in the assessment (Ciampi et al., 2018; Laitinen, 2011). Previous payment behaviour becomes even more important with smaller companies (Ciampi et al., 2018). Authors have brought out that environmental processes can play essential role in the failing process (Ciampi et al., 2018; Ooghe & Prijcker, 2008). SMEs in particular are much more vulnerable as the financial situation may decline very fast, for instance, because essential suppliers or customers have forced the company to accept adverse conditions and this will affect company's financial health condition much more rapidly than it could be determined from financial ratios.

Back (2005) emphasizes that payment delays and other non-financial variables have even better default prediction abilities than financial ratios. The results of the study showed that previous payment patterns are very informative and there is a correlation between previous financial struggles and defaults. Results showed that from healthy companies only a few firms had delays in payment, around one or two payment defaults, but in failed companies payment delays are much more frequent and delays exceed 3 payment defaults (Back, 2005). Similar results have also been achieved by other authors wherein empirical results showed that most of statistical differences between failed and non-failed companies were found in delays in payment and payment defaults. Therefore, the total number of late payments is an important factor (Karan et al., 2013; Laitinen, 2011). Moreover, from a logical point of view, when the company is starting to have financial problems in paying everyday bills or state taxes, they will be followed by delays in loan payments which will lead to default. Previous payment behaviours are an important factor in predicting loan default, but the significance of this aspect in analysing SMEs is still undetermined.

2.2.3 Manager characteristics

In the last decade, a research trend has developed which is using non-financial variables for failure prediction (Dimitras et al., 1996). Recently, there has been more and more attempts to find other components that could predict the default of the company. As an example, using manager characteristics and analysing corporate governance mechanism (Ciampi, 2015; Purves & Niblock, 2018). However, the studies are scarce. Corporate governance concept can have a broad spectre of meaning: including boards and outside directors as well as the role of owners. The dual aspect of governance is crucial for privately-held firms: holding management accountable and enabling management to operate the enterprise (Uhlaner et al., 2007). Unhaler et al (2007) brought out in their article several important corporate governance characteristics that should be considered. Ciampi (2015) analysed the relationship between financial ratios and corporate governance characteristics. There are a few studies in which it is possible to detect precise manager characteristics that should be considered in predicting the company's loan default. The study by Back (2005), in addition to previous payment behaviour, also emphasized managers own previous payment behaviour. Purves & Niblock (2018) in their mixed method approach compared 12 successful and 12 failed companies over different sectors and from their analysis it was possible to find several manager characteristics worth considering. Süsi and Lukason (2019) explored Estonian SMEs in their study and how corporate governance is interconnected with failure risk.

Studies have confirmed that SMEs are significantly different from large corporations when speaking about prediction of loan defaults. Therefore, it would be appropriate to include corporate governance and management variables when delivering credit decisions (Ciampi, 2015; Laitinen, 2011; Wilson & Altanlar, 2014). One proposition has been to interview management before granting a credit verdict (Hasumi & Hirata, 2014), this could help ascertain management commitment and motivation (Ooghe & Prijcker, 2008). The ownership structure and manager's role are crucial not only in small enterprises but they, as an influencer, can be essential in the entire failure process of the enterprise (Crutzen & Caillie, 2008). The ownership structure is a meaningful corporate governance variable (Uhlaner et al., 2007). It has been found that compared to prediction based only on economic-financial variables versus combining economic-financial variables with corporate governance characteristics or non-financial variables, the latter has improved SME default prediction accuracy rates and therefore, different variables must be integrated (Back, 2005; Ciampi, 2015; Sun et al., 2014). Furthermore, similar results were found by authors who were not focused on SMEs (Ooghe & Prijcker, 2008; Purves & Niblock, 2018).

A peculiarity of micro and small size enterprises is an entrepreneur's persistence, flexibility, and personal responsibility managing the business and withstanding the default risk, despite the business being inefficient according to financial ratios (Uhlaner et al., 2007; Wahyudi, 2014). During company crises, a capable key manager who may solve managerial weaknesses is recruited and company will overcome financial weaknesses (Ciampi et al., 2018). The board member variables are significant predictors in the multivariate context (Altman et al., 2015; Purves & Niblock, 2018). Furthermore, it has been concluded that privately-held firms typically have owners that are active and who have a long-term relationship with the company (Süsi & Lukason, 2019; Uhlaner et al., 2007). However, the study has found that large boards with multiple directorships increase failure risks especially for younger firms (Süsi & Lukason, 2019). Gender heterogeneity variables in the board remained insignificant (Süsi & Lukason, 2019). Manager's business experience reduces failure risk (McCann & McIndoe-Calder, 2015; Purves & Niblock, 2018), but being involved simultaneously with many companies increases the risk (Süsi & Lukason, 2019). Back (2005) is confident that a good reputation is an important factor in the banking relationship. When a manager is active in several companies with a recorded payment disturbance it is an indicator for future default (Back, 2005; Laitinen, 2011). This kind of behaviour can be a systematic strategy among management and that they do not manage with the purpose of a long successful life cycle (Back, 2005). It is possible to conclude that it is appropriate to add corporate governance characteristics when delivering a credit decision, but when these characteristics stand separate from other data, they do not have predictive power.

The common understanding of what aspects of manager characteristics should be considered in predicting the company's loan default has not yet developed. Typical characteristics of credit scoring dealing with a private person are home status, income, age, Country Court judgments, marital status, time with the employer and others (Hand & Henley, 1997). Studies have confirmed that from non-financial factors the following are important: entrepreneurs/CEO/manager age (Ciampi, 2015; Purves & Niblock, 2018; Süsi & Lukason, 2019), gender (Ciampi, 2015), education (Kim & Vonortas, 2014; Purves & Niblock, 2018; Uhlaner et al., 2007), competences and skills (Ooghe & Prijcker, 2008; Crutzen & Caillie, 2008) and previous payment behaviour (Back, 2005). When evaluating manager's characteristics, it is important to have information about the manager's personal payment history because it is a premise that each person manages their own financial affairs the same way they manage a company (Back, 2005).

3. Method and data

Default prediction has evolved with many new models developed using various tools. There has been a conclusion that there is no singular tool which can be considered the best one (Alaka et al., 2018). Logistic regression has been found to be one of the top 3 in the prediction of default (Alaka et al., 2018). The main authors referred to were using the logistic regression tool in their studies: Back, 2005; Ciampi et al., 2018; Karan et al., 2013; Laitinen, 2011; Laitinen & Lukason, 2014.

The data which was necessary for this quantitative research has been received from an Estonian financial institution who issued loans to young SMEs between 2016 and 2019. The loan amount was around 2000 euros for short-term (less than one year) and the main purpose of loans was to purchase inventory, equipment or tools. Cut off point for not getting the loan was if the company or CEO had active payment defaults published by the Estonian credit information bureau. If a company or CEO had closed payment default they were included in the data set. In Estonia if a private person or company does not fulfil the obligation for at least 45 days and it is at least 30 euros and it is not disputed then it will be published by the credit information bureau (Creditinfo Eesti AS). When the debt is paid the credit information bureau displays previous payment disturbance in its register as closed, information is available for banks and credit institutions about private persons for five years and companies for seven years (Creditinfo Eesti AS). As CEO, a manager was considered as the person who had the legal right to represent the company according to the Estonian Business Register registry card at the time the loan was issued. The data set consists of default and no-default loans. As an internationally recognized approach, this financial institution considered a loan defaulted when the principal and accrued interest is unpaid for 90 days.

All together data consists of 381 young companies with their age up to five years. The majority of the companies had executed the loan obligation, constituting 285 in number and 96 were considered defaulted. Next, the data was sorted: first who did not have all the variables and second who had all the variables. In Estonia, as well as in other countries, firms must present their financial statements within six months after the end of the fiscal period. However, sometimes companies do not fulfil their obligation (Lukason, 2013). From all the data 142 firms did not submit their financial statement to Estonian Business Register by the time the loan was issued (obligation may not have fallen due). There were 239 companies altogether who had all necessary data: relevant financial information to calculate financial variables (firms who have submitted their annual report to Estonian Business Register and it was not older than two years), information about company's previous payment behaviour (information about previous payment disturbances and defaults from Estonian credit information bureau (Creditinfo Eesti AS), Country Court judgments (debt that was enforced through court), information about tax debt from Estonian Tax and Customs Board and manager characteristics. 239 companies, who had all necessary data, divides into two groups: companies who had executed the loan obligation (178) and companies who were considered defaulted (61). The dataset is provided in Table 2. The average Total Assets (TA) for the second category companies was around 36 000€. In the study only the second category was used: firms who had all the necessary data. Financial ratios were chosen from most used variables in articles and ratios which showed highest predictive power for SMEs. To evaluate previous payment behaviour three variables were used: company's previous registered payment disturbances in Estonian information bureau or in the court (in the study it was used as a binary variable: the company either had previous disturbances or not), company's tax debt one month before issuing loan regardless of its size (was used as a binary variable) and CEO's registered payment disturbances in an Estonian information bureau (was used as a binary variable). Information about manager's characteristic information was gathered from the company loan application and official registers. The data collected had been submitted before issuing the loan. All the used variables in the paper are defined in Table 3. The groups of this study (defaulted and not defaulted) are not equal in size and because of this weights are applied to remove the difference. Weights are calculated for defaulted or non-defaulted groups as 0.5 divided by the share of the individual group, which makes the group sizes precisely the same in the analysis.

Table 2. Not defaulted and defaulted companies with all necessary data (compiled by the author)

Company age	**Not defaulted**	**Defaulted**	**Total**	**Not defaulted group share**	**Defaulted group share**	**Total share**
0-1 year	22	9	**31**	70.97%	29.03%	**12.97%**
2 year	37	13	**50**	74.00%	26.00%	**20.92%**
3 years	38	14	**52**	73.08%	26.92%	**21.76%**
4 years	48	14	**62**	77.42%	22.58%	**25.94%**
5 years	33	11	**44**	75.00%	25.00%	**18.41%**
Total	**178**	**61**	**239**	**74.48%**	**25.52%**	**100.00%**

Table 3. Defining variables used in the paper (compiled by the author)

Variable code name	Type of variable	Definition
ROA	Numeric	Net income to total assets.
WC/TA	Numeric	Working capital (that is: Current assets – Current liabilities) to total assets.
TD/TA	Numeric	Total debt to total assets.
Paym1	Binary	Companies previous registered payment disturbances in Estonian credit information bureau or court. If company had payment disturbances it is coded as "1" if not then "0".
Paym2	Binary	Tax debt 1 month before issuing the loan. If company had tax debt it is coded as "1" if not then "0".
Paym3	Binary	CEO payment disturbances in Estonian credit information bureau. If CEO had any disturbances it is coded as "1" if not then "0".
CG1	Numeric	Number of company owners.
CG2	Binary	CEO involvement with other companies (as a board member or CEO). If CEO had any other involvements with other companies it is coded as "1" if not then "0".
MC1	Binary	CEO Gender. Man is coded as "3", woman "4".
MC2	Numeric	CEO Age when company received the loan.
MC3	Categorical	CEO Education where "1" Primary school, "2" Secondary school, "3" High or vocational school, "4" Higher education.
MC4	Binary	CEO Marital Status. If CEO was living with a partner or married it is coded as "1" if not then "0".
MC5	Binary	CEO Dependents. If CEO has any dependents it is coded as "1" if not then "0".
MC6	Binary	CEO Real estate ownership. If CEO has house property according to register it is coded as "1" if not then "0".

The data analysis process was as follows: first, each category of variables was tested separately to find out which variables are significant predictors in their own group, and also, the prediction accuracy of such model was highlighted. After that the variables of all categories were tested together to find out which variables are significant predictors in all groups, and the prediction accuracy of such model was brought out. In the thesis, all variables obtaining $p < 0.1$ will be considered as significant, and thus, respectively indicated and commented on. Still, it must be noted that p-values vary for variables, and thus, some of them are more significant predictors than others. For statistical analysis the author used *IBM SPSS Statistics* software.

4. Results and discussion

The number of companies that had not submitted their annual financial report was highest among companies younger than two years. It appeared that the default rate was higher among companies who were younger than two years, similar results have been found by other authors (Wilson & Altanlar, 2014). For creditor it is most challenging to evaluate newly incorporated companies because publicly available information is limited (Wilson & Altanlar, 2014). High risk of young SMEs failure has been indicated also in previous studies (Laitinen, 1992; Cultrera & Brédart, 2016). Table 4 shows the mean and median scores of financial ratios for not defaulted and defaulted companies.

Table 4. Descriptive statistics for financial ratios (compiled by the author)

		ROA	WC/TA	TD/TA
Non-defaulted	N	178	178	178
	Mean	0.20	0.15	0.65
	Median	0.17	0.28	0.44
	Std. Deviation	0.65	0.86	0.81
Defaulted	N	61	61	61
	Mean	0.20	0.13	0.68
	Median	0.17	0.35	0.50
	Std. Deviation	0.48	0.88	0.85
Total	N	239	239	239
	Mean	0.20	0.15	0.65
	Median	0.17	0.29	0.46
	Std. Deviation	0.61	0.86	0.82

Note: ROA (Net income/Total assets), WC (Working capital (that is: Current assets-Current liabilities)), TA (Total assets), TD (Total debt).

In Table 5 the results of financial ratios variable's logistic regression model are described: there is no statistically significant result. As a result, we can conclude that financial ratios variable did not have any default predictive accuracy in this study. Furthermore, previous authors have concluded that in the beginning company's financial statements and financial ratios may simply not reflect any potential risks (Lukason et al.2016) and financial information of SMEs can be less reliable and accurate (Ciampi et al., 2018; Gabbianelli, 2018).

Table 5. Financial ratios variable in the logistic regression model (1 – default, 0 – non-default) (compiled by the author)

Variable	B	S.E.	Wald	Sig.	Exp(B)
ROA	0.023	0.239	0.009	0.925	1.023
WC/TA	0.030	0.326	0.009	0.926	1.031
TD/TA	0.081	0.344	0.055	0.814	1.084
Constant	-0.060	0.306	0.038	0.845	0.942

Note 1: The accuracy of the equation was 61.20% for non-failed and 41% for defaulted. The overall accuracy for default prediction was 51.1%. ROA (Net income/Total assets), WC (Working capital (that is: Current assets-Current liabilities)), TA (Total assets), TD (Total debt).

Table 6 shows how many companies from all 239 firms had previous payment disturbances. A very small per cent of young SMEs have an official registered payment disturbance – the low number can be interpreted as delayed registration of default due to the slow progress of respective processes. Before payment default is registered in Estonian credit information bureau or debt is enforced through the court it passes through a certain process and it takes time (Creditinfo Eesti AS). Contrarily, when a tax payment date is exceeded,the information is disclosed publicly on Estonian Tax and Customs Board webpage on the next day regardless of its size. In Table 6 we see that more companies had tax debt before getting the loan compared to those who had officially registered payment disturbances.

Table 6. Descriptive statistics for previous payment behaviour (compiled by the author)

		Paym1	Paym2	Paym3
Non-defaulted	N	12	47	49
	Percent	6.74%	26.40%	27.52%
Defaulted	N	4	18	26
	Percent	6.55%	29.50%	42.62%
Total	N	16	65	75
	Percent	6.70%	27.20%	31.40%

Note: Paym1 (Companies previous registered payment disturbances in Estonian credit information bureau or court), Paym2 (Tax debt one month before issuing loan), Paym3 (CEO payment disturbances in Estonian credit information bureau).

From previous payment behaviour variables, logistic regression model includes information about CEOs personal payment disturbance as a significant variable (Table 7). This finding confirms that managers personal payment history is a likely premise. Many people manage a company as they manage their own financial affairs (Back, 2005). In the logistic regression model existing tax debt variable did not show statistical significance. However, from the descriptive statistics, we saw that there are much more companies who have tax debt before getting the loan compared to those who had officially registered payment disturbances. This payment character was used in the study as a binary variable. In this study tax debt size was not taken into account and this could have affected the result.

Table 7. Previous payment behaviour variables in the logistic regression model (1 – default, 0 – non-default) (compiled by the author)

Variable	B	S.E.	Wald	Sig.	Exp(B)
Paym1	0.278	0.541	0.264	0.607	1.320
Paym2	0.135	0.298	0.206	0.650	1.145
Paym3	0.685	0.280	5.981	0.014	1.985
Constant	-0.533	0.563	0.897	0.344	0.587

Note: The accuracy of the equation was 72.5% for non-failed and 42.6% for defaulted. The overall accuracy for default prediction was 57.5%. Paym1 (Companies previous registered payment disturbances in Estonian credit information bureau or court), Paym2 (Tax debt one month before issuing loan), Paym3 (CEO payment disturbances in Estonian credit information bureau).

From corporate governance variables, statistically most significant predictor is CEO involvement with other companies (Table 8). It is explained by previous authors that manager's business experience reduces failure risk (McCann & McIndoe-Calder, 2015; Purves & Niblock, 2018). Of the statistically significant variables, it is also important whether the CEO has children or not. Furthermore, statistically significant are gender, education, marital status and dependents. The first two also confirm previous findings in studies (Ciampi, 2015; Kim & Vonortas, 2014; Purves & Niblock, 2018; Uhlaner et al., 2007). Results about marital status and dependents is a supplement to previous studies. Being in a relationship reduces default. The reason for this can be that relationship ties increase financial stability, but in turn, children increase financial burden. Estonian statistical findings also confirmed these findings. They have pointed out that in Estonia, the household composition and number of children play an important role with regards to the risk of poverty (Statistics Estonia, 2017).

Table 8. Corporate governance and manager characteristics variables in the logistic regression model (1 – default, 0 – non-default) (compiled by the author)

Variable	B	S.E.	Wald	Sig.	Exp(B)
CG1	-0.320	0.423	0.571	0.450	0.726
CG2	-0.686	0.291	5.555	0.018	0.503
MC1	0.615	0.300	4.188	0.041	1.849
MC2	-0.015	0.017	0.796	0.372	0.985
MC3	-0.302	0.152	3.920	0.048	0.740
MC4	-0.584	0.324	3.254	0.071	0.557
MC5	0.357	0.154	5.400	0.020	1.429
MC6	-0.040	0.152	0.071	0.790	0.960
Constant	0.609	1.280	0.227	0.634	1.839

Note: The accuracy of the equation was 62.9% for non-failed and 67.2% for defaulted. The overall accuracy for default prediction was 65.1%. CG1 (number of owners in company), CG2 (CEO involvement with other companies), MC1 (CEO Gender), MC2 (CEO Age), MC3 (CEO Education), MC4 (CEO Marital Status), MC5 (CEO Dependents), MC6 (CEO Real estate ownership).

In the logistic regression model, where variables from all the groups were used, the highest statistically significant result in loan default prediction accuracy among young small and medium-sized companies was CEO involvement with other companies (Table 9). As previous authors have concluded, the corporate governance characteristics are important when evaluating a company (Uhlaner et al., 2007). Moreover, as earlier studies have found, manager's business experience is important and it reduces failure risk (McCann & McIndoe-Calder, 2015; Purves & Niblock, 2018). Close to statistical significance is information about CEO's personal payment disturbances, gender, marital status and number of dependents. Combining financial ratios, previous payment behaviour and manager characteristics improves default prediction accuracy rate: using only financial ratios prediction accuracy rate was 51.1% (Table 5), previous payment behaviour prediction accuracy rate was 57.5% (Table 7), manager characteristics prediction accuracy rate was 65.1% (Table 8) and all together it was 69.8% (Table 9). Previous authors have indicated that combining different non-financial variables improves SME default prediction accuracy rates (Back, 2005; Ciampi, 2015; Sun et al., 2014). The accuracy rate of 69.8% is moderate but for young companies it is an expected outcome and previous studies found similar results for instance Lukason & Käsper (2017).

Table 9. All variables in the logistic regression model (1 – default, 0 – non-default) (compiled by the author)

Variables	B	S.E.	Wald	Sig.	Exp(B)
ROA	0.153	0.260	0.345	0.557	1.165
WC/TA	-0.250	0.356	0.492	0.483	0.779
TD/TA	-0.083	0.379	0.048	0.827	0.920
Paym1	0.092	0.585	0.025	0.875	1.096
Paym2	0.088	0.332	0.070	0.791	1.092
Paym3	0.719	0.311	5.343	0.021	2.052
CG1	-0.380	0.444	0.733	0.392	0.684
CG2	-0.810	0.307	6.964	0.008	0.445
MC1	0.627	0.309	4.132	0.042	1.872
MC2	-0.019	0.017	1.304	0.254	0.981
MC3	-0.223	0.160	1.948	0.163	0.800
MC4	-0.669	0.343	3.809	0.051	0.512
MC5	0.363	0.163	4.976	0.026	1.438
MC6	-0.020	0.159	0.015	0.902	0.981
Constant	-0.234	1.427	0.027	0.870	0.792

Note: The accuracy of the equation was 65.7% for non-failed and 73.8% for defaulted. The overall accuracy for default prediction was 69.8%. ROA (Net income/Total assets), WC (Working capital (that is: Current assets-Current liabilities)), TA (Total assets), TD (Total debt), Paym1 (Companies previous registered payment disturbances in Estonian credit information bureau or in court), Paym2 (Tax debt one month before issuing loan), Paym3 (CEO payment disturbances in Estonian credit information bureau). CG1 (number of owners in company), CG2 (CEO involvement with other companies), MC1 (CEO Gender), MC2 (CEO Age), MC3 (CEO Education), MC4 (CEO Marital Status), MC5 (CEO Dependents), MC6 (CEO Real estate ownership).

5. Conclusion

The purpose of this study was to find out what characteristics have the best loan default prediction accuracy among young small and medium-sized enterprises (SMEs). The paper analysed 239 young Estonian companies. The financial ratios variables were chosen based on previous literature: the author selected the most used variables in articles and ratios which showed most predictive power as regards to SMEs. Information about previous payment behaviour was obtained from official registers. Information about manager's characteristics was gathered from the company loan application and official registers.

In this study, CEO involvement with other companies was shown to be statistically most significant predictor of loan default prediction among young small and medium-sized enterprises from all variables. Manager's business experience is essential and reduces failure risk (McCann & McIndoe-Calder, 2015; Purves & Niblock, 2018). Furthermore, close to statistical significance is information about CEO personal payment disturbances, gender, marital status and a number of dependents. Managers' personal payment history is a likely premise: many people manage the company as they manage their own financial affairs (Back, 2005). Results about marital status and dependents is a supplement to previous studies. Being in a relationship reduces default. The reason for this can be that ties enable stability but having children, on the contrary, increases default probability. Estonian statistics findings also confirmed these results. They have brought out that in Estonia, the household composition and number of children play an essential role in the risk of poverty (Statistics Estonia, 2017). Financial ratios variable did not have any default predictive accuracy in this study. The findings by previous authors concluding that financial information of SMEs can be less reliable and accurate, are also confirmed in this study (Ciampi et al., 2018; Gabbianelli, 2018). The overall accuracy of loan default prediction characteristics was 69.8% and it can be considered moderate, but for young companies, it is an expected result (Lukason & Käsper, 2017).

This study has filled the research gap by analysing three topics (financial ratios, payment behaviour and manager characteristics) together and provided some important findings from the literature. However, it is also exposed to several limitations. Firstly, it analysed a considerably small amount of companies and therefore, each individual company data could have a significant impact on the results. In the logistic regression model previous payment behaviour and existing tax debt variable did not show statistical significance. However, from the descriptive statistics, we saw that there were much more companies who had tax debt before getting loan compared to those who had officially registered payment disturbances. This previous payment character was used in the study as a binary variable and this could have affected the result. Therefore, tax debt structure and its formation process and its effect on SMEs default prediction accuracy should be investigated in the next studies.

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