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FORECASTING CORPORATE PERMANENT INSOLVENCY WITH FINANCIAL RATIOS AND TAX ARREARS

Master's thesis

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I have composed this master's thesis independently. All materials, viewpoints from literature and other sources used to write this thesis have been referenced.

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Abstract

The aim of this paper is to find out whether and in which circumstances information about tax arrears enables to predict permanent insolvency with higher accuracy than financial ratios. Data consisted of 1093 and 2586 non-failed Estonian SMEs from the period of 2015 to 2017 and logistic regression was used as the predictive method. In total, five models were composed – one for financial ratios and others based on tax arrears from different periods with a length of 12 months. The results confirm that using tax arrears as explanatory variables substantially improves prediction accuracy. Usage of tax arrears in failure prediction resolves the issue of information asymmetry, *i.e.* when poorly performing firms fail to submit annual report(s). The novelty of this paper lies in the fact that when other forms of payment disturbances have been previously analyzed, tax arrears have not been previously used in forecasting studies.

Keywords: failure prediction, tax arrears, payment behavior, permanent insolvency, logistic regression

CERCS: S181, S190, S192

1. Introduction

Failure prediction is an important field for evaluating risk in business decision-making. Failure prediction is especially important and widely used in banking and the financial sector for credit risk analysis. In addition, forecasting corporate failure holds value for investors, trade partners and tax authorities. First studies in failure prediction date back to the 1960s – Beaver (1966) and Altman (1968) used linear statistical tools to determine the state of a firm. In the 1980s, Ohlson (1980) introduced a non-linear model of logistic regression to bankruptcy prediction. Since the 1990s, artificial intelligence and machine learning tools have been more popular in failure prediction than statistical techniques, though they are often outperformed by latter in accuracy (Ravi & Kumar, 2006; Alaka *et al.*, 2018; Sun *et al.*, 2014; Altman *et al.*, 2017). So far, no single best tool has been developed that would always outperform others – each has its strengths and weaknesses. Ensemble and hybrid models are the newest techniques in failure prediction that yield better results than single-models (Sun *et al.*, 2014). New techniques in failure prediction fall under machine learning (*e.g.* pattern recognition models), but their usage in practice is often limited by legal constraints due to low transparency (Jayasekera, 2018).

In prior studies, failure has been mainly defined (Ciampi *et al.*, 2020; Karan *et al.*, 2013; Laitinen, 2011; Back, 2005) as a (court declared) permanent insolvency[1], also known as bankruptcy[2], which does not incorporate *de facto* permanent insolvency. In this study, permanent insolvency is used as a term to describe firms that cannot and do not repay their debts. Knowing firm's state of permanent insolvency as early as possible is often crucial to avoid losses; hence, forecasting the *de facto* permanent insolvency (*i.e.* out of court insolvency) is more practical than using *de jure* permanent insolvency. While *de jure*

1 Often defined by "start of insolvency proceedings" or "payment defaults (overdue 90 days)", mostly dependent on a specific countries Commercial Code.

2 Bankruptcy is a form of failure which means *de jure* permanent insolvency, *i.e.* firms who go through formal process of insolvency proceeding. In this paper, *de facto* permanent insolvency is the subject under research, *i.e.* firms with tax arrears, who do not go through process of insolvency proceedings.

permanent insolvency as a dependent variable is factual, it takes careful consideration of an extra set of rules and thresholds to correctly classify firms *de facto* permanent insolvency.

The Estonian practice in commercial register allows to delay the submission of annual report(s) up to six months, after which a warning is issued. It is common practice for firms to legally delay the filing of an annual report up to six months without penalties. Consequently, the newest data available about the going concern firms can be up to 1.5 years old. Moreover, many firms in risk of insolvency deliberately do not publish financial statements (Lukason, 2013). According to the Estonian Commercial Code[3], after the first warning, firms have another six months to file a missing annual report; if they fail to comply with the injunction, court will initiate a compulsory liquidation (*i.e.* forced termination) that will end with deletion of firm from the commercial register.

With regard to permanently insolvent firms, newest available data can be at least three years old, but often due to the legal processing time of a firm's compulsory liquidation, data availability extends up to four years. When it comes to SMEs, their last financial data does not often indicate any distress in the firm (Lukason, 2016). Therefore, variables based on financial data have shortcomings mainly due to financial data being expired – they do not represent the up-to-date state of firms' financial position. For that reason, it has been suggested that secondary variables combined with financial data be used, which could yield higher prediction accuracies for failed firms or determine early warning signs (Laitinen & Lukason, 2019).

Up to now, financial ratios have been and are still the most used variables to forecast failure. Aside from financial ratios, the importance of non-financial variables have also been emphasized – macroeconomic; corporate governance; industry, sector and firm specific; previous payment dynamics (Altman *et al.*, 2015; Dimitras *et al.*, 1996). While

3 Process of compulsory liquidation, due to failure to submit annual report set in the Estonian Accounting Act, that ends with court ruling on deletion of a company from the commercial register is laid out in Commercial Code §60.

payment behavior related variables have been used in just a few studies as independent variables (Ciampi *et al.*, 2020; Back, 2005; Karan *et al.*, 2013; Laitinen, 2011), tax arrears[4] have never been used in previous studies. Data on tax arrears is available throughout the year for each month and therefore could offer solid ground to improve models based solely on financial variables. Moreover, their importance increases when financial data is not available, which is common for firms facing a risk of insolvency. With availability of tax arrears, shortcomings related to expired financial data are evened out.

The aim of this paper is to find out whether and in which circumstances information about tax arrears enables to predict permanent insolvency with higher accuracy than financial ratios. Tax arrears are used to compose different variables for four periods and are compared with financial ratios calculated from the last available annual report. As permanent insolvency, a specific group of firms, namely forcefully liquidated because of not submitting annual report(s), are used. Permanently insolvent firms have been chosen because it is common in Estonian practice that many firms who get terminated from the e-Business Register, have tax arrears and never go through the formal process of bankruptcy or liquidation. This study uses the Estonian permanently insolvent firms population data from 2011 to 2017. The structure of the following article is: literature overview covering the theoretical background on variable(s) and method selection; data and methods explaining the empirical work that was carried out; results and discussion followed by concluding remarks.

2. Literature overview

2.1. Variables used in failure prediction studies

Choosing explanatory variables is one of the first tasks in research design for forecasting firms' failure. Financial ratios have been and still are the most popular variables used in forecasting studies. Choice of the dimension of variables is mostly subjective and limited to

4 *i.e.* unpaid tax debt due

availability of data or sample specific, while selection is done based on previous academic literature or by statistical techniques. Financial variables are mostly chosen from three categories: solvency, liquidity and profitability, as these are best indicators of firms' financial health. Artificial intelligence tools have become more popular in the past two decades and due to the fact that these tools mostly do not require prior selection of variables (all-inclusive is the default practice), not many reviews on selection of variables have been written lately. Majority of reviews concentrate on comparisons of different methods and models accuracies.

There are comprehensive reviews written on variables used in previous corporate failure prediction studies (Ravi & Kumar, 2006; Dimitrias *et al.*, 1996; Bellovary *et al.*, 2007; Altman & Narayanan, 1996). These reviews incorporate failure prediction studies from the 1930s up to 2007. The most extensive comparison (165 studies) was carried out by Bellovary *et al*. (2007), while other reviews compare around 40 to 60 studies. Reviews by Bellovary *et al.* (2007) and by Ravi & Kumar (2006) have been chosen for comparison of financial ratios used in previous studies, which can be seen in Table 1. These reviews cover studies from a broad period and include financial and non-financial firms across different sectors and are not subject to a specific country or region. Bellovary *et al.* (2007) put stronger emphasis on older studies based on univariate and multivariate discriminant analysis tools, while Ravi & Kumar (2006) used more newer studies after the 1980s that include various statistical and intelligent techniques.

The variety of financial ratios used is large, but most studies stick to specific variables that describe profitability, short-term and long-term financial health of firms. Comparison of reviews reveal that profitability ratio in the form of EBIT to total assets or net income to total assets is most popular in previous studies. In addition, it draws out that liquidity category variables are most frequent in forecasting studies, but used in different forms. The popularity of liquidity ratios can be accounted to the fact that a forecast horizon of one year is dominant in forecasting studies. Liquidity ratios are followed by financial structure whereby their importance should increase with a longer forecast horizon. From turnover ratios, only sales to total assets has been used moderately in previous studies. From Table 1 it concludes that Bellovary *et al.* (2007) and Ravi & Kumar (2006) have reached similar results with popular financial variables used in previous studies.

Table 1. Comparison of reviews on financial ratios used in failure forecasting studies (composed by author)

		Bellovary, Giacomino, Akers (2007)		Kumar & Ravi (2007)	
	Years	1930-2007		1968-2005	
	number of studies	165		62	
	Domain	Rank	No. of studies	Rank	No. of studies
EBIT/total assets & net income/total assets	Profitability	1	89	1	39
total equity/total assets & total debt/total assets	Financial structure	2	62	3	25
current assets/current liabilities	Liquidity	3	51	2	30
working capital/total assets	Liquidity	4	45	4	23
sales/total assets	Turnover	5	32	5	18
quick assets/current liabilities	Liquidity	6	30	6	16
quick assets/total assets	Liquidity	7	29	8	10
current assets/total assets	Liquidity	8	26	7	11
current liabilities/total assets	Financial structure	9	13	10	6
cash flow/total debt	Solvency	10	12	9	8

Note: Category of domain is based on du Jardin's (2017) classification. Marginal variations among financial ratio calculations exist.

Aside from financial data, non-financial variables have gained increasing popularity. Drawbacks in default predictions based solely on financial ratios, especially among SMEs, due to the lack of accounting data availability, can be overcome with non-financial variables, which leads to significant improvement in default prediction accuracy (Ciampi, 2015; Lukason & Laitinen, 2019). Under non-financial data are classified corporate governance, sector and firm specific, macroeconomic, relational data and previous payment behavior related data. Previous payment behavior related variables have been used only in

Table 2. Comparison of related studies with payment behavior variables (composed by author)

	Ciampi *et al.* (2020)	Back (2005)	Karan *et al.* (2013)	Laitinen (2011)
Research question	The study aims to verify the potential of combining corporate prior payment behavior and Kohonen maps for small enterprise default prediction.	The purpose of this study is to investigate if non-financial variables affect the probability of financial difficulties in small and medium sized firms.	The main objective of this study is to develop credit risk prediction models using massive payment history data and non-financial factors of the retailer companies.	The purpose of this study is to develop a model for viability based on financial variables but also on non-financial variables.
Country	Italy	Finland	Turkey	Finland
Sector	Manufacturing	Randomized	Retailers	Randomized
Data(set) years	2005-2015	1997	2006	2004
Sample size and method	Training sample of 1200 SME-s. Test sample of 800 firms (stratified random sampling by turnover, location and business sector)	Estimation sample of 1600 firms and holdout sample 1599 firms (randomly selected from 5 categories of firms)	Training sample of 1260 and testing sample of 5404 companies (randomly categorized from pool of 6304)	Estimation sample of 43732 firms and testing sample of 15853 firms (randomly categorized from sample chosen by viability and bankruptcy measures)
Methods	Logistic regression (LR), discrete-time hazard analysis (DT), self organizing map-based trajectories (TBM)	Multinomial logistic regression	Logistic regression, multiple criteria decision analysis	Logistic regression
Variables	Financial ratios (FR), prior payment behavior (PB)	Financial ratios, non-financial variables	Payment history data, firm-specific non-financial information	Financial ratios, non-financial variables
Selected financial ratios	Bank loans/turnover Net financial position/turnover EBIT/turnover Interest expense/EBITDA	Total debt/total assets Return on investment		Return on investment Quick ratio Equity ratio Cash flow to sales
Selected payment behavior related variables	Past due and/or overdrawn exposures for more than 60 days (binary) Past due and/or overdrawn exposures for more than 60 days/EBITDA Number of cumulative non-remedied payment delays exceeding 60 days	Payment disturbance < 1 year (binary) payment disturbance > 1 year (binary) 1-2 payment delays (binary) 3+ payment delays (binary)	Number of late paid invoices/total number of invoices Sum of early paid days before payment date Standard deviation of time between invoices Total debt/total purchase	Log number of active delays in payment Log number of payment defaults during last 12 months Log number of active positive payment signals
Models	2 categories of models for each method, based on financial ratios and financial ratios combined with payment behavior-related variables	3 models based on financial ratios, not-financial variables and both combined	1 model based on firm specific factors and payment history	2 models based on financial variables and financial variables with non-financial variables
Forecasting period	1- ,2- ,3-year	1-year	6-months	1-year
Forecasting accuracy (test and control)	For 1-year: LR/FR 80.87%, DT/FR 80.97%, TBM/FR 82.64%, 1-year LR/FR+PB 81.99%, DT/FR+PB 81.98%, TBM/FR+PB 85.73%	Financial ratio model 72.32%, Non-financial model 86.02%, Combined model 85.08%	Model based on multiple criteria 90%, Model based on logistic regression 98.89%	Financial variable model 63%, combined model 89.2%
Research results	Trajectory based models are more effective than logistic and hazard models. Payment behavior related variables significantly increase default prediction, when added to financial ratios.	Payment disturbances occurring before the analyzed period significantly increase the probability of financial difficulties. Model based on non-financial variables had higher classifying percent than model based on financial variables.	Models based on previous payment history offer equal prediction ability compared with previous results from 1965 to 2007.	Non-financial variables bring incremental information for viability assessment over financial ratios. Non-financial variables include more updated information. They also refer to background and payment behavior of firm neglected by financial variables

some studies (Ciampi *et al.*, 2020; Back, 2005; Karan *et al.*, 2013; Laitinen, 2011), but specifically tax arrears as independent variables have never been used. Höglund (2017) has used genetic algorithm to predict tax defaults as a dependent variable. Full comparison of relevant studies using previous payment behavior related explanatory variables is visible in Table 2.

2.2. Payment behavior variables

While many non-financial variables about SMEs may not be available, different types of payment defaults in some form (unpaid loans, wages, services, goods; filing history; tax arrears) are mostly accessible. Studies in comparison have not used tax arrears as explanatory variables, but private late payments, invoices and unpaid loans have been used instead of tax payment disturbances. These studies (Table 2) confirm that payment behavior related variables are statistically significant and increase default prediction accuracy when combined with financial information. In Back's (2005) study, model based on non-financial variables outperformed financial ratio model and combined model achieving 86% accuracy. Laitinen (2011) compared the financial ratio model with the combined model resulting in 89.2% accuracy against 63%. Karan *et al.* (2013) used payment history data and non-financial information to forecast a 6-month horizon reaching 98.9% accuracy. Only Ciampi *et al.* (2020) found small marginal improvement in prediction power with payment behavior related variables.

Payment behavior related variables selected in the model were often in binary form, *i.e.* if payment disturbance exceeded a certain time limit or the number of disturbances (or late payments) exceeded a threshold. Ciampi *et al.* (2020) used 60 days as a threshold, while Laitinen (2011) and Back (2005) used a one year time frame. All studies in the comparison have included logistic regression as one of the methods to analyze data with a forecasting period varying from six months to three years. In conclusion, Back (2005) has found that models incorporating non-financial variables offer higher classifying accuracy than models only based on financial data. Laitinen (2011) has reached a similar conclusion, adding that non-financial variables hold more up-to-date information about firms. The most general and important conclusion is that payment behavior related variables and previous payment history data significantly increases forecasting accuracy.

In Estonia, poorly performing firms (low liquidity and profitability) systematically delay the submission of annual report(s), which leads to information asymmetry (Lukason & Camacho-Miňano, 2019) and therefore using secondary variables combined with or instead of financial variables is required for up-to-date information about the firm. Tax arrears are preferred over other forms of payment disturbances because they are available in the full extent, while defaults to private creditors and payment disturbances are mostly accessible in a limited amount. Hence, tax arrears should yield higher prediction power.

2.3. Technique selection

After selecting variable class(es), choosing a classification tool is the next step in research design. Tools used in failure prediction are categorized as statistical or artificial intelligence tools. Among the most popular statistical tools are logistic regression (LR) and multivariate discriminant analysis (MDA) (Alaka *et al.*, 2018; Ravi & Kumar, 2006). Among artificial intelligent tools, most popular are support vector machines (SVM), artificial neural network (ANN), rough sets (RS), case based reasoning (CBR), decision tree (DT) and genetic algorithm (GA) (Alaka *et al.*, 2018, Ravi & Kumar, 2006). Though MDA has been the most used tool up to now, its popularity comes from earlier times. The variety of tools to choose from is higher than ever, yet in recent decades ANN and LR stand out as the most used techniques to forecast corporate failure (Alaka *et al.*, 2018; Balcaen, S., Ooghe, H. 2006; Ravi & Kumar, 2006). Ensemble and hybrid models with visual techniques have been new innovations in failure prediction.

Alaka *et al.* (2018) found that the choice of tool is often based on popularity and is not based on criteria they should satisfy nor limitations imposed by data and sample. With the increase of the forecasting horizon, the accuracy of the models declines; the effect of time on information value and thereby on the accuracy of the models has been analyzed by du Jardin (2017). When machine learning tools and ensemble models outperform traditional tools in short-term prediction, they do not in past a 3-year horizon (du Jardin, 2017). Considering the fact that in decision-making, intelligent tools' results are not interpretable and they may lead to different solutions in repeated runs, traditional tools are still held in high regard in practice (du Jardin, 2017; Alaka *et al.*, 2018). For this study, logistic regression has been chosen as the statistical tool to analyze data. Logistic regression has been selected for the transparency of its results, high generalizability and reasonable accuracy compared to other methods (Alaka *et al.*, 2018). Furthermore LR's fully deterministic binary output provides coefficients and significances to variables, which enables direct comparison of different models.

3. Data & Method

Data on permanent insolvency cases of Estonian SMEs has been gathered from 2015 to 2017. A population of 1093 permanently insolvent firms has been deleted from commercial register with tax arrears during this period due to failure to submit annual report(s). Years 2018 and 2019 have not been included due to heterogeneity with the data of previous years. Since 2018, value added tax liability[5] has been increased from 16 000 € to 40 000 €, but availability of time-series data for 2018-2019 during the time of empirical work was not complete nor sufficient for separate analysis. Latest available annual reports for the deleted firms are from the period of 2011-2013. Hence a random sample of 2586[6] non-failing firms have been chosen from the same period to match annual reports for comparison.

All chosen firms for both groups were liable to pay value added tax during the period, namely turnover above 16 000 €. Smaller firms have been excluded to keep the population homogeneous due to possible large anomalies in financial ratios and lack of sufficient

5 Value-Added Tax Act § 19. Obligation to register as a taxable person.

6 Selected non-failed group sample was tested against a random sample of equal size and no significant. difference between variance and means were detected.

economic significance. Besides, firms with below 16 000 € turnover can't have value added tax debt. In addition, firms were constrained with having assets less than 2 000 000 € and turnover less than 2 000 000 €. Table 3 shows the structure of primary data for failed and non-failed firms, comparison between assets and turnover size in groups. Firms' annual reports and tax arrears data has been used to calculate independent variables. Tax arrears data is in an accumulated form, majority of arrears are either social tax, income tax or value added tax; in a lesser form it includes customs and excise duties.[7] It is not reasonable to differentiate between possible objects of tax as monetary obligations are performed in the order they were created.[8] Accumulated form of tax arrears at the end of each month assures that behavior of tax arrears is not random or incidental.

Table 3. Structure of data (composed by author)

	Failed	Non-failed
Annual Reports		
Year 2011	458	814
Year 2012	341	873
Year 2013	294	899
Total	1093	2586
Turnover by size		
< 25 000 €	124 (11.3%)	330 (12.8%)
25 000 € – 50 000 €	219 (20.0%)	616 (23.8%)
50 000 € – 100 000 €	227 (20.8%)	623 (24.1%)
100 000 € – 200 000 €	211 (19.3%)	481 (18.6%)
> 200 000 €	312 (28.5%)	536 (20.7%)
Assets by size		
< 25 000 €	374 (34.3%)	682 (26.4%)
25 000 € – 50 000 €	231 (21.2%)	517 (20.0%)
50 000 € – 100 000 €	189 (17.3%)	503 (19.5%)
100 000 € – 200 000 €	158 (14.5%)	395 (15.2%)
> 200 000 €	138 (12.7%)	491 (19.0%)

As outlined in Section 2, only a scant amount of studies, which use different types of payment defaults as independent variables, are available. In this study, two groups of independent variables have been used – financial ratios and payment disturbances in the

7 Complete list of possible corporate taxes are listed in Taxation Act § 3. Tax system.
8 Taxation Act § 105. Payment and set-off.

form of tax arrears. Dependent variables take a value of 0 for a failed firm (deleted with tax arrears) and a value of 1 for non-failed. A selection of independent variables based on financial ratios has been carried out in two stages. First, a group of the most used financial ratios have been chosen (Table 1) based on reviews of failure prediction studies. Secondly, due to the shortened version of annual reports for SMEs, the choice of financial ratios has come down to fewer options. Finally, financial ratios were selected to represent different categories: profitability – return on assets, financial structure – equity ratio, liquidity – working capital to total assets, turnover – asset turnover ratio.

Tax arrears' variables have been chosen for four different periods. One period represents the time of last available information from the annual report and the following periods time after the last available annual report submission up to the forced termination of the firm from the commercial register. The length of a period is 12 months and three tax arrears' variables are calculated for each period – maximum, median and duration (number of months with tax arrears). Variables are calculated using month-end data on tax arrears for each 12-month period. Month-end data on tax arrears is used because social and income tax due date is around the 10th of each month and value added tax due date is usually 10 days before the end of the month, therefore changes in tax arrears are registered for the present month.

Recurring occurrences of unpaid taxes on month-end basis should indicate financial problems in firm and not be random in that instance. Period of t (months 1-12 before) for tax arrears' variables represents a year of annual report information and hence is calculated one year back from the annual report submission date to match the time of annual report information. Periods of t+1 (months 1-12 after), t+2 (months 13-24 after) and t+3 (months 25-36 after) represent years on from the annual report submission date closer to the time of deletion of failed firms. Table 4 lists all selected variables with definitions, characteristics and formulas. The correlation matrix of selected variables is visible in Appendix A.

Table 4. Independent variables (composed by author)

Variables	Characteristics	Description	Formula
Financial ratios			
ROA_T	Profitability ratio	Return on assets	$ROA_T = \frac{Net\ \ income_T}{Total\ \ assets_T}$
ER_T	Financial structure	Equity Ratio	$ER_T = \frac{Total\ \ equity_T}{Total\ \ assets_T}$
$WCTA_T$	Liquidity ratio	Working capital over total assets	$WCTA_T = \frac{Current\ \ assets_T - Current\ \ liabilities_T}{Total\ \ assets_T}$
ATR_T	Turnover	Assets turnover ratio	$ATR_T = \frac{Turnover_T}{Total\ \ assets_T}$
Tax arrears			
MAX_T	Payment behavior	Maximum value of month end tax arrears (for 12 months)	$MAX_T = max(x_{1,\mathrm{T}} \ldots x_{12,\mathrm{T}})$
MED_T	Payment behavior	Median value of month end tax arrears (for 12 months)	$MED_T = median(x_{1,\mathrm{T}} \ldots x_{12,\mathrm{T}})$
DUR_T	Payment behavior	Number of month ends with tax arrears	$DUR_T = \sum_{i=1}^{12} I_{\mathrm{i,T}}\ \ with\ \ I_{\mathrm{i,T}} = \{1\ \ if\ \ x_{\mathrm{i,T}} > 100\ \ else\ \ 0\}$

Note: T can take values t, t+1, t+2 or t+3. For tax arrears there are 4 different periods of variables from t to t+3. t represents the period of 12 months prior to the annual report submission date; t+1 12 months after the submission, t+2 months 13-24 and t+3 months 25-36 after the submission. MAX, MED and DUR variables are calculated on month-end data for each period. $x_{\mathrm{i,T}}$ indicates month end tax arrears for period T.

Due to the fact that logistic regression is sensitive to outliers, which are present especially among failed firms, data transformation has been used to normalize groups. Financial ratios were winsorized at 5% and 95% and natural logarithm of tax arrears' variables were used to get more robust results with higher predictive power. Since conditional probabilities of logistic regressions are not even for unbalanced data – larger class is overestimated (Menardi & Torelli, 2010), Synthetic Minority Oversampling Technique (SMOTE) has been used to reach balanced data. Five logistic regression permanent insolvency prediction models were analyzed – one for each set of variables. The model based on financial ratios and one model of tax arrears' variables (period t) represent the same time period, while the other three periods represent the time between the last available annual report and the deletion of the firm, offering additional information about the firm while annual report(s) are not submitted.

4. Results & Discussion

The descriptive statistics of independent variables for the 3679 firms is presented in Table 5 in three groups: all, failed and non-failed. Financial ratios of failed firms in relation to non-failed firms show lower mean and median values, also a higher standard deviation, but it is not clear whether the difference is significant for the model. Asset turnover ratio is an exception[9], as it shows higher mean and median values for failed firms mainly due to many high values that are present even after winsorization. With regard to tax arrears' variables, a difference between the failed and non-failed group is visible throughout all four periods. The mean value of maximum month-end tax arrears for the failed group starts at 1809 € for the period of last available annual report and increases up to 4283 € for the period of t+1; 10 380 € for the period of t+2 and 12 927 € for the period of t+3. In comparison, the mean value of maximum month-end tax arrears of the non-failed group is between 30 € and 60 €. The median value of month-end tax arrears behaves n similar fashion – the failed group's value is more than 50 times larger and the difference increases with the passing of time from the last available annual report.

The number of months (duration in months) with tax arrears larger than 100 € reveal, that on average, failed firms have tax debts of seven to eight months for earlier periods and closer to deletion it increases up to 9-10 months, while non-failed firms show almost no month-ends with tax arrears. From descriptive statistics it concludes, that for the first two periods (12 months prior and after the submission of the last annual report), more than half

9 According to financial theory (Altman, 1968; Wilcox, 1971), under normal conditions higher asset turnover ratio should decrease firms probability for failure, but the values for assets of failing firms decrease towards zero, which can yield to high ATR value if they are still operating and making sales.

Table 5. Descriptive statistics of independent variables (composed by author)

	All					Failed					Non-Failed				
	Mean	SD	Median	Min	Max	Mean	SD	Median	Min	Max	Mean	SD	Median	Min	Max
ATR_t	2.7	3.0	1.8	0.2	19.3	4.1	4.6	2.5	0.4	19.3	2.1	1.8	1.6	0.2	6.8
ER_t	0.5	0.4	0.6	-0.9	1.0	0.4	0.5	0.4	-0.9	1.0	0.6	0.3	0.6	0.1	1.0
ROA_t	0.1	0.3	0.1	-1.2	0.8	0.1	0.5	0.1	-1.2	0.8	0.1	0.2	0.1	-0.3	0.6
$WCTA_t$	0.3	0.4	0.3	-1.1	1.0	0.2	0.5	0.2	-1.1	1.0	0.3	0.4	0.4	-0.4	0.9
MAX_t	569.2	4914.9	0.0	0.0	137207.4	1809.2	8748.9	0.0	0.0	137207.4	45.1	1054.0	0.0	0.0	47845.4
MAX_{t+1}	1296.3	7880.4	0.0	0.0	269253.1	4283.2	13988.1	0.0	0.0	269253.1	33.8	579.5	0.0	0.0	16528.2
MAX_{t+2}	3109.6	26307.4	0.0	0.0	965668.9	10380.3	47487.3	1626.2	0.0	965668.9	36.6	539.4	0.0	0.0	16528.2
MAX_{t+3}	3880.0	58042.8	0.0	0.0	3272173.7	12927.8	105967.3	909.8	0.0	3272173.7	55.9	787.4	0.0	0.0	26356.3
MED_t	425.3	3884.3	0.0	0.0	88579.4	1382.7	6994.1	0.0	0.0	88579.4	20.7	501.7	0.0	0.0	23333.9
MED_{t+1}	1106.5	7292.4	0.0	0.0	268569.0	3671.0	13012.2	0.0	0.0	268569.0	22.6	427.4	0.0	0.0	14361.4
MED_{t+2}	2738.5	19077.1	0.0	0.0	754864.6	9163.6	34156.6	1502.3	0.0	754864.6	22.8	372.4	0.0	0.0	12900.1
MED_{t+3}	3376.0	36424.5	0.0	0.0	1810747.1	11275.8	66174.1	903.5	0.0	1810747.1	37.0	571.0	0.0	0.0	20215.8
DUR_t	2.6	4.3	0.0	0.0	12.0	7.5	4.6	9.0	0.0	12.0	0.6	1.9	0.0	0.0	12.0
DUR_{t+1}	2.6	4.3	0.0	0.0	12.0	7.5	4.6	9.0	0.0	12.0	0.5	1.8	0.0	0.0	12.0
DUR_{t+2}	3.2	5.0	0.0	0.0	12.0	9.4	4.5	12.0	0.0	12.0	0.5	1.9	0.0	0.0	12.0
DUR_{t+3}	3.2	5.0	0.0	0.0	12.0	9.5	4.4	12.0	0.0	12.0	0.6	1.9	0.0	0.0	12.0

of failed firms had no tax arrears, but for the last two periods and therefore closer to the deletion date, there is an increase in the number of firms with tax arrears. Non-failed firms' tax arrears' variables are relatively stable throughout the time periods under surveillance, compared to the failed group values. An increase in the values of the failed group's tax arrears' variables with an increase in periods can be accounted on the fact that disturbances in tax payment increase and gain volume up to the point of deletion.

The proposed five models' variables individual results as single-predictors are visible in Table 6 – each variable was used disjointly as a single-predictor to test accordance with the theory and report individual prediction power for comparison. Behavior of financial ratios were drawn from Altman (1968) and Wilcox (1971) and payment behavior of tax arrears from Table 2. Model set 1 consists only of financial variables, model set 2 includes tax arrears' variables 12 months prior to the submission of the last available annual report and hence indicate the same period as the annual report. Model sets 3 to 5 represent periods after the last available annual report, moving closer to the date of deletion from the commercial register. The variable coefficient sign indicates the way in which, all else being equal, the variable value classifies observations. According to financial theory (Altman, 1968, Wilcox 1971), increase of these financial ratios should increase probability of a firm to be classified non-failed, yet this is not true for asset turnover ratio, explained previously.

Comparison of the individual accuracy of variables reveals that tax arrears' variables on average offer significantly higher classification accuracy than financial ratios. Periods closer to deletion yield higher accuracy for tax arrears' variables compared to earlier periods. While the classification accuracy for duration variables remains stable at around 85% throughout the periods, the accuracy of maximum and median variables significantly improves for periods closer to the deletion date. For the first two periods, prediction power of duration variable is stronger than median or maximum tax arrears, but for the second and third periods it is exceeded by latter two by a margin of 5%. This can be explained with time effect, where periods of t and t+1 represent on average the 4th and 3rd year prior to deletion, when many failed firms do not yet indicate any problems – lower median and maximum tax arrears compared to later periods. Firms who already have longstanding tax arrears (duration variable) for earlier periods (t and t+1) indicate strong increase in tax arrears for median and maximum value up to deletion.

Table 6. Logistic regression models and results for individual variables (composed by author)

Model	Variable	Accuracy	Sign	P-value	Theory
M1 (FR)	ATR_t	58.03%	-	0.000	No
	ER_t	61.62%	+	0.000	Yes
	ROA_t	50.53%	+	0.000	Yes
	$WCTA_t$	55.08%	+	0.000	Yes
M2 (12P)	MAX_t	58.76%	-	0.000	Yes
	MED_t	58.76%	-	0.000	Yes
	DUR_t	85.77%	-	0.000	Yes
M3 (12F)	MAX_{t+1}	70.91%	-	0.000	Yes
	MED_{t+1}	70.88%	-	0.000	Yes
	DUR_{t+1}	86.46%	-	0.000	Yes
M4 (24F)	MAX_{t+2}	91.41%	-	0.000	Yes
	MED_{t+2}	91.45%	-	0.000	Yes
	DUR_{t+2}	86.83%	-	0.000	Yes
M5 (36F)	MAX_{t+3}	89.55%	-	0.000	Yes
	MED_{t+3}	89.55%	-	0.000	Yes
	DUR_{t+3}	85.96%	-	0.000	Yes

Note: Accordance with theory for financial ratio analysis is derived from Altman (1968) and Wilcox (1971) and for tax arrears is derived from payment behavior literature (Table 2).

Having higher individual accuracy value for median and maximum value of tax arrears for periods of t+2 and t+3, shows that when time of deletion draws closer outstanding tax arrears drastically increase, while duration variable is limited to maximum value of 12 months and remains relatively same throughout the period for many failing firms. These results recommend having a stronger emphasis on the duration of monthly tax arrears three or four years prior to failure and a maximum or median value two or one year prior to failure. Although single variable models are not as efficient as more complicated models consisting of a diversity of variables (Jackson & Wood, 2013), using tax arrears' variables result in a relatively high classification accuracy on their own, which mainly accounts to the fact that systematic occurrence of tax arrears is often a direct reference to high risk of insolvency.

Five logistic regression models, which are visible in Table 7, have been analyzed and compared – each model consists of a set of variables presented in Table 6. The results confirm that models based on tax arrears offer higher predictive power compared to the financial ratio model. Model 1 and 2 represent data from the same period, yet the model based on tax arrears offers around 20% higher accuracy than the model consisting of financial variables. The financial ratio model predicted with an accuracy of 64.6% based on 4 years old data, while the accuracy of results with a 1-year horizon based on financial ratios from articles in comparison (Table 2) varied from 63% up to 80.9% for logistic regression. Ciampi *et al.* (2020) reported up to three years prior to failure and reached 71.5% classification accuracy with logistic regression. With each 12-month period after the submission of the last annual report models' overall accuracy increases (M3 87.28%, M4 92.82%, M5 93.89%). Classification accuracy for a year prior to failure in related literature (either payment behavior variables or combined model, see Table 2) – 82% Ciampi *et al.* (2020), 86% Back (2005) and 89.2% Laitinen (2011), while tax arrears variables resulted in an accuracy of 93.9% for a year prior to deletion.

Table 7. Analyzed logistic regression models (composed by author)

Model	Accuracy	TP	TN	FP	FN	FNR	FPR	AUC
M1 (FR)	64.62%	1353	1472	714	833	38.11%	32.66%	0.719
M2 (12P)	85.75%	1891	1858	328	295	13.49%	15.00%	0.902
M3 (12F)	87.28%	1929	1887	299	257	11.76%	13.68%	0.915
M4 (24F)	92.82%	1974	2084	102	212	9.70%	4.67%	0.968
M5 (36F)	93.89%	2076	2029	157	110	5.03%	7.18%	0.974

Note: TP – true positive; TN – true negative; FP – false positive; FN – false negative; FNR (Type I error) – false negative ratio (FN/(TP+FN)); FPR (Type II error) – false positive ratio (FP/(TN+FP)); AUC – area under curve.

Conflicting results can be seen between models 4 and 5. Even if model 5 offers higher overall accuracy, its individual variables are outperformed by model 4. This difference becomes especially important in comparison of type II error, which increases from 4.67% for model 4 to 7.18% for model 5. This conflict can be accounted to the fact that model 5 (period of t+3) already includes some deletion dates of failed firms and hence their tax arrears are deleted from the data-set and take value of 0, so they are classified as non-failed[10]. This effect is also somewhat amplified by oversampling of the minority group.

Models' performance was also tested with an artificial neural network resulting in marginally better accuracy, but the difference from logistic regression was not significant. Du Jardin (2017) has compared the accuracy of models with a forecasting horizon of four and five years and found that the range of decline in correctly classified firms from a one year to four or five year horizon is in total 15.5% (85% to 69.5%). The decline of accuracy from model five to two (4-years) in this study is merely 8.14% for tax arrears' variables. These results suggest that information from tax arrears loses its value more slowly than other variable classes.

Table 8 shows the results of grouped logistic regression models with accuracy values, where variable groups have been aggregated one-by-one. The predictive power of grouped models exceeds individual models by a small margin leading to a conclusion that tax arrears from earlier periods carry over to later periods and up to the deletion of a firm. In addition, these results confirm that the financial failure of firms is a long process and starts years prior to forced termination. In these results for individual models, model 2 represents four years prior to failure for most firms and model 5 one year prior to failure. In terms of predictive power, tax arrears four years prior to deletion have a classification accuracy of 85% which increases up to 93% for a year prior to deletion, while financial variables offer an overall accuracy of 65% for 4 years prior to deletion. In addition to the higher predictive

10 This effect can be reduced by changing cut-off percentage for observed logistic regression model by margin of deleted firms count during the period to total failed firms.

power of tax arrears for the period of financial ratios, data on unpaid taxes is available up to the end of the failure process and decreases type I and type II error rates year-by-year. Variables based on tax arrears outperform the financial ratio model and offer information about firms facing permanent insolvency while they do not submit annual reports.

Table 8. Results of logistic regression grouped models (composed by author)

Model	Accuracy
M1	64.62%
M6 (M1+M2)	87.24%
M7 (M1+M2+M3)	89.75%
M8 (M1+M2+M3+M4)	92.98%
M9 (M1+M2+M3+M4+M5)	95.75%

In this study, tax arrears' variables were formed based on month-ends accumulated data for four different periods, each with a length of 12 months. Variables were calculated as maximum, median and duration of months with tax arrears. Yet there exist many alternatives and variations to be tested in future research – different mathematical averages, thresholds based on a country's insolvency proceedings and volatility measurements. In addition, different lengths of periods for month-end data could be considered. Longer periods place more emphasis on duration variables, while the predictive power of median and maximum variables could increase from using shorter periods. Depending on the choice of the forecasting horizon, overlapping periods can be used to increase the duration variable's range of months with tax arrears; in this study duration variables in most cases either took a value of 0 or 12, hence longer periods could show other trends. With availability of defaults to private creditors, it could be combined with tax arrears.

5. Conclusion

The aim of this paper was to find out, whether and in which circumstances information about tax arrears enables to predict permanent insolvency with higher accuracy than financial ratios. Firms in risk of insolvency often do not publish annual report(s), which makes forecasting their future status based on financial ratios imprecise and especially increases the false positive ratio in prediction power. For that purpose, tax arrears were used to determine permanently insolvent firms during the period of 2015 to 2017 and variables based on tax arrears were formed to compare results with financial ratios from the latest available annual report(s). Due to the nature of the compulsory liquidation process in the Estonian commercial register, the latest available annual reports of the majority of failed firms from the years 2015 to 2017, are from the period of 2011 to 2013. Hence, a random sample of solvent firms were selected from the period of 2011 to 2013.

Financial variables were initially ranked based on popularity of usage in failure prediction studies and later a group of four based on popularity and availability were used in the model. For tax arrears' variables, four different periods were formed, where first period of 12-months represents the time of the last annual report information and the following three periods a time between the submission of the last annual report and deletion from commercial register. For four different periods, three different tax arrears' variables were calculated: maximum, median and duration on month-ends data. Logistic regression was used to analyze the proposed five different models for each set of variables including individual accuracy of single-variables and combined models.

The results of this study confirm that tax arrears' variables have a higher classification accuracy for the same period than that of the last available annual report. The financial ratio model reported an overall accuracy of 64.6%, while the tax arrears model reported 85.8%. In addition, tax arrears' data offers information for the period between the last available annual report and compulsory liquidation, of which the models reported increasing accuracy year-by-year, reaching over 90% classification accuracy for a year prior to deletion. Regarding tax arrears' variables, the duration of monthly tax arrears offered a similarly high accuracy throughout the selected four periods, while the maximum and median prediction power of monthly tax arrears increased significantly for years closer to deletion.

Financial ratios are the most used variables to forecast firms’ financial failure. Yet it is rather common for failing firms to delay or even withhold the submitting of annual report(s), which hinders the use of financial ratios as primary variables. Data from the annual report(s) is already around six months old, which in Estonia can be delayed up to one year over the legal deadline. Hence, the use of tax arrears to predict failing firms who face permanent insolvency holds high value in practice, offering up-to-date monthly data. The study can be extended by looking into other forms of payment disturbances to private creditors (listed in section 2) and combining them with tax arrears. Regarding to tax arrears’ variables, future studies could also experiment with different time periods, instead of 12 months using 6- or 18-month periods, and using different mathematical approaches for the calculation of variables. Since 2018, the increase in value added tax threshold suggests differentiating tax arrears into groups for future research; this would facilitate inclusion of a larger set of firms that are outside of value added tax liability.

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Appendix A. Correlation matrix of independent variables

	ATR_t	ER_t	ROA_t	$WCTA_t$	MAX_t	MED_t	DUR_t	MAX_{t+1}	MED_{t+1}	DUR_{t+1}	MAX_{t+2}	MED_{t+2}	DUR_{t+2}	MAX_{t+3}	MED_{t+3}	DUR_{t+3}
ATR_t	1	-0.212	-0.161	-0.075	0.027	0.037	0.185	0.054	0.040	0.189	0.059	0.081	0.228	0.045	0.067	0.230
ER_t	-0.212	1	0.522	0.746	-0.157	-0.154	-0.305	-0.182	-0.180	-0.303	-0.083	-0.108	-0.292	-0.051	-0.063	-0.295
ROA_t	-0.161	0.522	1	0.481	-0.097	-0.098	-0.126	-0.095	-0.098	-0.120	-0.041	-0.038	-0.103	-0.023	-0.030	-0.101
$WCTA_t$	-0.075	0.746	0.481	1	-0.118	-0.112	-0.184	-0.100	-0.091	-0.181	-0.027	-0.044	-0.160	-0.012	-0.017	-0.159
MAX_t	0.027	-0.157	-0.097	-0.118	1	0.943	0.247	0.516	0.533	0.242	0.143	0.198	0.188	0.057	0.084	0.178
MED_t	0.037	-0.154	-0.098	-0.112	0.943	1	0.234	0.556	0.587	0.232	0.157	0.218	0.184	0.063	0.094	0.174
DUR_t	0.185	-0.305	-0.126	-0.184	0.247	0.234	1	0.353	0.327	0.968	0.148	0.210	0.854	0.051	0.079	0.794
MAX_{t+1}	0.054	-0.182	-0.095	-0.100	0.516	0.556	0.353	1	0.960	0.357	0.285	0.394	0.287	0.075	0.113	0.267
MED_{t+1}	0.040	-0.180	-0.098	-0.091	0.533	0.587	0.327	0.960	1	0.329	0.279	0.386	0.266	0.069	0.103	0.245
DUR_{t+1}	0.189	-0.303	-0.120	-0.181	0.242	0.232	0.968	0.357	0.329	1	0.150	0.212	0.875	0.052	0.080	0.808
MAX_{t+2}	0.059	-0.083	-0.041	-0.027	0.143	0.157	0.148	0.285	0.279	0.150	1	0.812	0.187	0.825	0.906	0.196
MED_{t+2}	0.081	-0.108	-0.038	-0.044	0.198	0.218	0.210	0.394	0.386	0.212	0.812	1	0.252	0.761	0.779	0.237
DUR_{t+2}	0.228	-0.292	-0.103	-0.160	0.188	0.184	0.854	0.287	0.266	0.875	0.187	0.252	1	0.103	0.140	0.937
MAX_{t+3}	0.045	-0.051	-0.023	-0.012	0.057	0.063	0.051	0.075	0.069	0.052	0.825	0.761	0.103	1	0.971	0.118
MED_{t+3}	0.067	-0.063	-0.030	-0.017	0.084	0.094	0.079	0.113	0.103	0.080	0.906	0.779	0.140	0.971	1	0.163
DUR_{t+3}	0.230	-0.295	-0.101	-0.159	0.178	0.174	0.794	0.267	0.245	0.808	0.196	0.237	0.937	0.118	0.163	1

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