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**PREDICTION OF YOUNG FIRM TERMINAL FAILURE USING TAX ARREARS-
BASED PAYMENT BEHAVIOUR: EVIDENCE FROM ESTONIA**

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.

Abstract

This thesis aims to examine whether firms' earlier payment behaviour predicts terminal failure among young firms in Estonia and to identify behavioural patterns of firms associated with financial distress. The analysis uses population-level data on firms liable for value added tax (VAT), established in 2011-2015 and consisting of micro, small, and medium-sized enterprises (MSMEs). Terminal failure is defined as deletion from the Estonian Business Register with outstanding unpaid debt. Independent variables are constructed from tax arrears data and are operationalised as magnitude, frequency, and persistence measures. Logistic regression and artificial neural networks are applied for predictive analysis and complemented by cluster analysis to identify behavioural patterns.

The results demonstrate that these indicators provide strong predictive power. In particular, frequency and persistence measures emerge as the most informative predictors, suggesting that repeated and persistent payment behaviour reflects the accumulation of financial strain prior to failure, while predictive accuracy increases as the failure event approaches. Non-rescheduled arrears yield slightly higher predictive performance than total arrears, and neural networks provide only moderate improvements over logistic regression. At the same time, some failures occur without prior payment behaviour signals, indicating limitations of behavioural-only models. These findings extend the literature on young-firm failure prediction, where empirical evidence remains limited and predictive accuracy has been relatively modest, by showing that payment behaviour indicators serve as effective early-warning signals in data-constrained settings. The results also have practical implications for risk assessment and early detection of financial distress among newly established firms.

Keywords: failure prediction, financial distress, young firms, MSMEs, payment behaviour, tax arrears

CERCS codes: S180, S181

Table of contents

Introduction	5
1. Literature review	7
1.1. Earlier payment behaviour as predictor of failure	7
1.2. Tax arrears as predictors of failure	11
1.3. Studies on young-firm failure prediction	14
1.4. Research gap addressed in the thesis.....	16
2. Data, variables and methods	17
2.1. Data, population and observation horizons	17
2.2. Independent variables	19
2.3. Methods	21
3. Results and discussion	23
3.1. Descriptive and explanatory analysis	23
3.2. Predictive analysis	26
3.3. Cluster analysis	32
Conclusion	35
References	38
Appendices.....	42
Appendix A	42
Appendix B	43
Appendix C	44
Appendix D	46
Appendix E.....	49
Resümee	53

Introduction

Firm failure has important implications for employment, public finances and credit markets, making the timely identification of financially distressed firms a major concern in economics and finance. Firm failure is a broad concept encompassing various outcomes, including bankruptcy, liquidation, default and other insolvency proceedings. The prediction of firm failure has been extensively studied following the foundational works of Beaver (1966) and Altman (1968), which introduced the use of accounting-based indicators for bankruptcy prediction. Subsequent research has broadened both methodological approaches and failure definitions, incorporating machine learning alongside classical statistical models and extending beyond formal bankruptcy to wider measures of financial distress (Balcaen & Ooghe, 2006; Ravi Kumar & Ravi, 2007; Sun et al., 2014). However, most studies continue to focus predominantly on mature firms, where accounting information is more reliable and failure is more closely tied to identifiable legal events. Models based primarily on accounting information are therefore well suited to mature firms but become less applicable in the context of young firms, where such information may be unavailable at the earliest stages and, once available, remains insufficient to clearly distinguish between failing and surviving firms (Laitinen, 1992; Lukason & Käsper, 2017). Accordingly, research on young-firm failure prediction remains comparatively limited and continues to rely largely on financial ratios, yet predictive performance is typically moderate due to weak separability in the early stage (Laitinen, 1992; Lukason & Käsper, 2017; Fuertes-Callén et al., 2022; Wang & Guedes, 2025). This highlights the need for complementary non-financial indicators that capture financial distress more closely.

Prior research shows that firms' earlier payment behaviour provides strong predictive signals of financial distress and failure. These variables capture not only the presence of repayment problems, but also their timing, frequency, and severity, and often improve predictive performance relative to models based on financial ratios alone (Laitinen, 1999; Back, 2005; Iwanicz-Drozowska et al., 2016; Ciampi et al., 2020). A more specific form of payment behaviour, tax arrears, has been shown to serve as an informative early-warning indicator of financial distress (Lukason & Andresson, 2019; Lukason & Valgenberg, 2021; Kohv & Lukason, 2021). Tax arrears may, however, reflect both temporary liquidity constraints and more persistent financial difficulties. In particular, the rescheduling of tax arrears may indicate short-term financial flexibility, whereas the inability to meet rescheduled obligations can signal deeper and more structural distress.

While the predictive value of payment behaviour has been well documented, its application in the context of young firm failure remains limited. This gap motivates extending the use of payment behaviour variables to young-firm failure prediction. In this regard, this thesis aims to examine whether firms' earlier payment behaviour, in particular tax arrears, predicts terminal failure among young firms in Estonia and to identify different behavioural patterns of firms associated with financial distress. The empirical analysis focuses on Estonian micro, small, and medium-sized enterprises (MSMEs), with micro-firms forming the overwhelming majority. Although prior research has examined SMEs more broadly (e.g. Back, 2005; Altman et al., 2010; Ciampi et al., 2020), evidence on micro firms remains comparatively limited despite their dominance in firm populations.

The models rely exclusively on tax arrears-based indicators as independent variables, which are operationalised along three dimensions: magnitude, frequency, and persistence, allowing the dynamics of financial distress to be examined more precisely. The study distinguishes between total and non-rescheduled tax arrears, enabling assessment of whether excluding rescheduled liabilities improves the predictive content of arrears-based indicators.

Terminal failure is defined as deletion from the Estonian Business Register with outstanding unpaid debt, including both unpaid tax debt and unpaid private debt, thereby capturing financially distressed exit beyond formal bankruptcy. This definition is particularly suitable for young firms, where exit rarely coincides with a clearly identifiable legal event and where firms approaching exit may reduce or cease financial reporting. In contrast, non-failure refers to surviving firms that remain active without outstanding unpaid debt. Within the broader framework of firm failure, this thesis conceptualises financial distress as the underlying process of financial deterioration leading to adverse outcomes, while terminal failure represents a specific observable manifestation of such outcomes, namely exit through deregistration. Accordingly, the study focuses on predicting terminal failure using indicators of financial distress derived from tax arrears-based payment behaviour. Figure 1 illustrates the conceptual distinction between financial distress as an underlying process and terminal failure as its observable outcome.

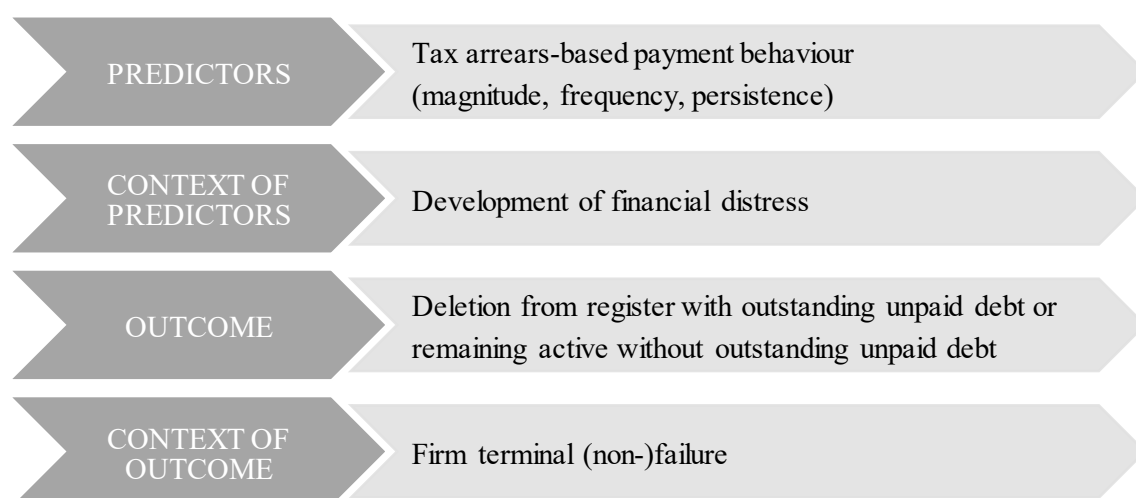


Figure 1. Conceptual framework for predicting terminal failure among young firms using tax arrears-based payment behaviour

Source: compiled by the author.

Methodologically, the study combines explanatory and predictive approaches. Average marginal effects from logistic regression are used to assess the explanatory role of payment behaviour variables, while predictive performance is evaluated using both logistic regression and artificial neural networks. Cluster analysis is further applied to identify behavioural patterns of firms and to provide further interpretation of prediction outcomes.

The thesis is structured as follows. The first section provides a review of the literature on earlier payment behaviour and tax arrears as predictors of failure, as well as on failure prediction among young firms. The second section presents the data, variable construction, and empirical methods. The third section reports and discusses the empirical results. The final section concludes the thesis.

1. Literature review

1.1. Earlier payment behaviour as predictor of failure

Earlier payment behaviour as a general category refers to firms' patterns of meeting financial obligations over time and includes payment disturbances such as delays, arrears and other repayment irregularities. The literature reviewed in this section (see Table 1 below) considers studies in which earlier payment behaviour variables are used as predictors of financial distress or firm failure. Within this broader category, tax arrears, i.e. unpaid public-law obligations, represent a specific form of payment behaviour. However, they are not the primary focus of this section and are discussed separately in Section 1.2.

Table 1

Payment behaviour variables in failure prediction studies

Author(s), country	Observation period	Payment behaviour variables
Laitinen (1999), Finland	1997	Firm-level: count of recent and older official bad debts, count of unofficially registered delays in payments, presence of bad debts (binary); Manager-level: share of responsible persons with bad debts
Back (2005), Finland	1996–1999	Firm-level: presence of recent and older official payment disturbances (binary), presence of unofficially registered payment delays (1–2 and 3+; binary); Manager-level: presence of links to distressed firms (binary), presence of managers' private payment disturbances (binary)
Altman et al. (2010), UK	2000–2007	Firm-level: count and monetary value of County Court Judgments (CCJs)
Laitinen (2011), Finland	2003–2005	Firm-level: count of payment defaults, delays and positive payment signals; Manager-level: count of board members' personal payment defaults
Karan et al. (2013), Turkey	2006	Firm-level: ratio of late paid invoices to total invoices
Wilson et al. (2014), UK	1999–2008	Firm-level: presence of CCJs and charges on assets (binary)
Iwanicz-Drozdowska et al. (2016), Finland	2003–2013	Firm-level: presence of payment delays (binary) and count, monetary value of delays scaled by total assets, positive payment observations, count of past payment defaults
Ciampi et al. (2020), Italy	2008–2015	Firm-level: presence of bank payment delays (binary), monetary value of delays scaled by EBITDA, count of cumulative unremedied delays
Altman et al. (2023), Croatia	2015–2019	Firm-level: bank account blockage duration (in days), duration category, count of blockages (per year)
Andresson & Lukason (2025), Estonia	2012–2019	Firm-level and manager-level: count, mean value and maximum value of payment defaults

Note: The table reports payment behaviour variables used in prior studies. A more detailed overview of the studies is provided in Appendix E.

Source: compiled by the author.

The types of payment behaviour variables applied in these studies vary and reflect differences in legal enforcement, reporting mechanisms, data sources, and observation levels. Prior research has employed both formally registered bad debts and unofficial creditor-reported payment delays, typically derived from credit bureau records or similar registers (Laitinen, 1999; Back, 2005). Other approaches rely on legally enforced non-payment

indicators, such as County Court Judgments in the UK, which reflect a more severe form of payment disturbance within firms' payment behaviour than routine late payments (Altman et al., 2010; Wilson et al., 2014). The literature further distinguishes between different observation levels and data sources. In addition to firm-level payment disturbances, some studies incorporate managers' or board members' payment histories, indicators derived from late-paid invoices (Karan et al., 2013), and asset-based indicators such as charges on company assets (Wilson et al., 2014). Payment problems may also be captured through banking data, including loan repayment delays and bank account blockages (Ciampi et al., 2020; Altman et al., 2023), as well as through administrative and credit registry data on unpaid obligations, including tax arrears and private debts (Andresson & Lukason, 2025).

The empirical literature demonstrates that these variables are not only informative in terms of the occurrence of payment disturbances, but also capture multiple dimensions of financial distress. First, timing distinguishes between recent and earlier payment problems, for instance by separating newly registered and older bad debts or payment disturbances (Laitinen, 1999; Back, 2005). Second, frequency reflects the repetition of payment problems, typically measured as the number of delays or payment disturbances, with evidence showing that repeated delays significantly increase the probability of financial difficulties (Back, 2005). Third, severity captures the intensity of payment problems, which may be reflected in the escalation from payment delays to formally registered non-payment events, in thresholds such as prolonged overdue payments, or in measures scaled relative to firm resources (Laitinen, 1999; Back, 2005; Iwanicz-Drozowska et al., 2016). In several studies, these dimensions are combined, allowing payment disturbances to be interpreted as indicators of an evolving distress process rather than isolated events (Back, 2005; Iwanicz-Drozowska et al., 2016; Ciampi et al., 2020).

The reviewed studies also differ substantially in research design. Geographically, they cover a range of predominantly European countries, including Finland, the UK, Italy, and Estonia, with one study based on Turkey. The datasets vary considerably in size and scope, ranging from relatively small samples of around one to several thousand firms to near-population datasets comprising millions of firms and firm-year observations, e.g. UK studies (Altman et al., 2010; Wilson et al., 2014). Methodologically, the literature spans a wide range of approaches, from traditional regression-based models, most notably logistic regression, to survival analysis and more recent machine learning techniques, including decision trees, neural networks, support vector machines, and ensemble methods such as random forests and gradient boosting.

The dependent variables also differ markedly across studies. Some focus on subjective credit risk assessments or multi-category financial health classifications (e.g. Laitinen, 1999; Back, 2005; Karan et al., 2013), which capture relatively mild or evolving forms of financial distress. In addition, several studies consider early-stage default events, such as the emergence of unresolved debt or bank account blockages (e.g. Altman et al., 2023; Andresson & Lukason, 2025), which reflect the onset of payment difficulties prior to formal insolvency. In contrast, other studies examine terminal failure events, such as bankruptcy, insolvency proceedings, or firm exit (e.g. Altman et al., 2010; Wilson et al., 2014; Iwanicz-Drozowska et al., 2016; Ciampi et al., 2020). This variation reflects differences in how financial distress and failure are operationalised in both credit risk assessment and firm failure prediction contexts.

In most studies, payment behaviour variables are not used in isolation but are combined with financial ratios and other firm-level characteristics. These typically include firm size, age, industry, and various control variables, as well as broader contextual factors such as macroeconomic conditions. Several studies further extend the analysis by incorporating managerial or governance-related variables, including payment behaviour of board members or links to previously distressed firms, thereby capturing additional dimensions of firm default risk beyond firm-level payment behaviour.

Despite these differences, a consistent finding across the literature is that payment behaviour variables provide substantial predictive information for financial distress and failure. Prior payment delays and disturbances are shown to be strong predictors, often improving the performance of models based on financial ratios (Laitinen, 1999; Back, 2005; Altman et al., 2010), particularly in settings where annual financial data are limited or less timely (Wilson et al., 2014; Ciampi et al., 2020). Models that combine financial and non-financial variables, including payment behaviour, generally achieve higher predictive accuracy than those relying on financial ratios alone (Iwanicz-Drozowska et al., 2016; Ciampi et al., 2020). These findings support the interpretation of firms' earlier payment behaviour indicators as informative predictors of both current and developing financial distress. Building on this general framework, the next section focuses specifically on tax arrears as a distinct form of payment behaviour and examines their role in the empirical literature.

1.2. Tax arrears as predictors of failure

Tax arrears represent unpaid public-law obligations and constitute a specific form of payment behaviour. They are intuitively associated with firms' liquidity constraints and broader financial pressures, entail potential enforcement and compliance consequences, and thus provide informative signals of financial distress. The literature reviewed in this section can be divided into two groups (see Table 2 below), namely studies using tax arrears as predictors of firm failure and studies predicting future tax arrears based on prior arrears behaviour. The dependent variables in these studies cover a range of adverse firm outcomes, including legally formalised failure events such as bankruptcy, other distress-related outcomes such as administrative deletion and loan default, and tax arrears themselves, which are modelled either as a continuous process or in terms of their onset.

The reviewed studies are heavily concentrated in Estonia, with one study based on China. Sample sizes range from a few thousand firms to large-scale datasets covering tens or hundreds of thousands of firms. Methodologically, the literature combines traditional statistical approaches, most notably logistic regression, with a wide range of machine learning techniques, including neural networks, decision trees, random forests, and other models.

Table 2

Studies applying tax arrears in failure research

Panel A – Tax arrears as predictors of firm failure

Author(s), country	Dependent variable	Tax arrears variables
Lukason & Andresson (2019), Estonia	Bankruptcy (binary status)	Firm-level: count and longest consecutive sequence of month-ends with tax arrears, maximum and median value of tax arrears
Lukason & Valgenberg (2021), Estonia	Firm failure (binary status)	Firm-level: count of month-ends with tax arrears, maximum and median value of tax arrears, asset-scaled maximum and median value
Kohv & Lukason (2021), Estonia	Bank loan default (binary status)	Firm-level: count of month-ends with tax arrears, maximum and median value of tax arrears
Andresson & Lukason (2024), Estonia	Onset of permanent payment default (binary status)	Manager-level: count of month-ends with disturbances (tax and private debt), maximum and mean value of disturbances across managed firms

Panel B – Tax arrears as predictors of subsequent tax arrears

Author(s), country	Dependent variable	Tax arrears variables
Siimon & Lukason (2021), Estonia	Tax arrears occurrence in the next month (binary status)	Firm-level: monetary value of monthly tax arrears (no aggregation), monetary value of aggregated tax arrears, count of consecutive months with and without tax arrears, median value and standard deviation of monthly tax arrears
Zheng & Li (2023), China	Tax arrears occurrence in year t+1 (binary status)	Firm-level: count of tax arrears and trust-breaking events; Related firm-level: average count of tax arrears and trust-breaking events of related enterprises
Jahhu & Pihelgas (2025), Estonia	Tax arrears onset by duration (binary status)	Firm-level: count of month-ends with tax arrears, maximum value, mean value and median value of tax arrears

Note: The table summarizes tax arrears variables used in prior studies. A more detailed overview of the studies is provided in Appendix E.

Source: compiled by the author.

Tax arrears are measured through a range of variables capturing different aspects of payment behaviour. The most commonly used measures reflect the severity of arrears, such as maximum, mean, or median arrears values, sometimes additionally standardized relative to firm size. A second group of variables captures the frequency of payment problems, typically measured as the number of month-ends with arrears over a given observation window. A third dimension relates to the persistence of payment problems, including measures such as the longest consecutive sequence of arrears (Lukason & Andresson, 2019) and indicators of consecutive arrears and non-arrears periods, capturing both distress spells and recovery phases (Siimon & Lukason, 2021). In addition, several studies make use of the availability of monthly tax arrears data by constructing lagged or aggregated time-series measures, thereby capturing the dynamics of arrears rather than relying on single-period observations (Siimon & Lukason, 2021; Jahhu & Pihelgas, 2025).

The timing dimension is reflected both in the distinction between recent and more distant arrears and in the temporal structure of the empirical designs. Some studies adopt dynamic approaches based on rolling or moving windows of monthly data, allowing the analysis of how predictive power varies with distance to the failure event (Lukason & Andresson, 2019; Siimon & Lukason, 2021). Others rely on fixed one-period-ahead frameworks using lagged annual or yearly information, where predictors are aligned to a specific forecast horizon (Jahhu & Pihelgas, 2025; Zheng & Li, 2023).

In most studies, tax arrears variables are combined with additional predictors capturing firm characteristics and broader contextual factors. These typically include financial ratios measuring profitability, liquidity, solvency, and efficiency, as well as firm size, age, and reporting behaviour (Kohv & Lukason, 2021). Some studies incorporate governance-related variables, such as managers' prior payment disturbances across firms, thereby extending the analysis beyond firm-level behaviour (Andresson & Lukason, 2024). Others introduce macroeconomic indicators, business characteristics, or relational variables capturing connections between firms, such as shared ownership or contact information, reflecting potential transmission of financial distress within networks (Zheng & Li, 2023).

Empirical findings across these studies are highly consistent. Tax arrears variables exhibit strong predictive power across a wide range of outcomes and are frequently found to outperform traditional financial ratios, particularly when financial information is outdated or unavailable (Lukason & Andresson, 2019; Lukason & Valgenberg, 2021; Kohv & Lukason, 2021). Their predictive strength is especially pronounced in shorter time horizons, where recent arrears provide highly informative signals of forthcoming failure or continuing non-compliance (Lukason & Andresson, 2019; Siimon & Lukason, 2021). Measures capturing recurrence and persistence further improve predictive performance, indicating that repeated or continuous payment problems are strongly associated with a higher risk of default (Lukason & Andresson, 2019; Kohv & Lukason, 2021; Siimon & Lukason, 2021). In studies where tax arrears are modelled as the dependent variable, prior arrears emerge as the dominant predictors of subsequent arrears, confirming the importance of behavioural persistence and short-term dynamics (Siimon & Lukason, 2021; Jahhu & Pihelgas, 2025). Overall, models combining tax arrears with financial and other non-financial variables tend to achieve the highest predictive accuracy (Lukason & Andresson, 2019; Kohv & Lukason, 2021).

These findings highlight the role of tax arrears as a strong early-warning indicator of financial distress. At the same time, the existing literature focuses predominantly on established firms with limited attention to the role of tax arrears in the early stages of firm life. This creates scope for further research on how tax arrears can be used to capture emerging distress in young firms, where traditional financial indicators may be less informative.

1.3. Studies on young-firm failure prediction

The early-life failure literature, as well as the broader literature on young firms, does not rely on a single standard definition of firm “newness”. Instead, firm age is typically operationalised as an empirical grouping variable determined by data availability and research design rather than a unified theoretical category. This is evident in empirical studies, where dataset-driven age thresholds are applied, such as up to three years since first hire for young employers (Davis et al., 2007), six years or younger for young firms (Evans, 1987) or distinctions between firms younger than ten years and mature firms (Haltiwanger et al., 2010). This lack of standardisation is also reflected in policy-oriented research. For example, the OECD defines in their paper young firms as those aged five years or less, while explicitly noting that this threshold is not theoretically grounded but rather a convention in the literature, typically within a range of three to five years (Calvino et al., 2025). Similarly, definitions of start-ups vary across jurisdictions (European Startup Nations Alliance, 2025) and often combine age criteria with additional characteristics of innovation and growth orientation. In European practice, start-ups are frequently defined as firms younger than ten years (European Startup Network, 2020; Startup Estonia, 2020).

In early-life failure prediction studies examined in more detail below, the operational definitions of young firms vary across empirical settings and are reflected in the observation windows applied. For example, Laitinen (1992) examines newly founded firms during their first three to four years after foundation. Lukason and Käsper (2017) treat the first five years of operation as the key early-life stage, while Fuertes-Callén et al. (2022) analyse start-ups over an eight-year post-entry observation period. Overall, these patterns indicate that “young firm” is not a fixed theoretical construct but an empirically contingent category reflecting early stages of firm development.

Compared with the extensive bankruptcy prediction literature on mature firms, research on early-life failure and the development of relevant prediction models remains relatively limited. This imbalance has been noted both in early work on newly founded firms and in more recent studies on start-ups (Laitinen, 1992; Lukason & Käsper, 2017; Fuertes-Callén et al., 2022). Table 3 shows that most studies rely predominantly on accounting-based financial variables, most commonly liquidity, profitability, leverage or capital structure, cash-flow measures, and firm size, sometimes extended to include additional efficiency or labour-related indicators. Despite differences in context and methodology, the underlying explanatory logic is consistent across studies.

Table 3

Studies on young-firm failure prediction

Author(s), country	Dependent variable	Predictor variables
Laitinen (1992), Finland	Firm failure (binary status)	Financial variables: profitability, liquidity, solvency; Firm-related variables: firm size, sales growth rate, velocity of capital
Wilson & Altanlar (2014), UK	Insolvency (binary status)	Behavioural variables: presence of County Court Judgments and charges on assets (binary); Non-financial variables: timeliness of reporting, board characteristics, macroeconomic and regional factors
Lukason & Käsper (2017), Estonia	Bankruptcy (binary status)	Financial variables: liquidity, profitability, capital structure (solvency), productivity
Fuertes-Callén et al. (2022), Spain	Bankruptcy (binary status and survival time)	Financial variables: liquidity, profitability, leverage; Non-financial variables: firm size, employee-related indicators (productivity, salary)
Wang & Guedes (2025), Portugal	Firm failure (binary status)	Financial variables: liquidity and solvency, profitability, leverage, activity and efficiency; Non-financial variables: firm size, firm age

Source: compiled by the author.

A recurring finding is that young-firm failure is closely associated with weak internal financing capacity and fragile financial structure. Laitinen (1992) identifies cash flow-based and indebtedness-related ratios as the most informative predictors, while Lukason and Käsper (2017) similarly indicate that liquidity and capital structure variables emerge as strong predictors in early-stage prediction models. Fuertes-Callén et al. (2022) reinforce this general pattern by showing that bankruptcy risk is higher among start-ups that are unprofitable and more indebted. More recent evidence confirms that profitability, leverage, and liquidity remain central predictors for SMEs and new ventures (Wang & Guedes, 2025).

At the same time, the literature indicates that accounting financial variables alone provide only limited discriminatory power in early-life settings. Although failed and surviving firms differ on average already in the first years, survivors being more profitable, more liquid, less indebted, and larger (Fuertes-Callén et al., 2022), predictive performance remains moderate, with classification accuracies typically around 67–70% across studies (Lukason & Käsper, 2017; Fuertes-Callén et al., 2022; Wang & Guedes, 2025). Consistent with this pattern, Laitinen (1992) documents substantial classification errors in the early years and shows that predictive accuracy improves as the failure event approaches. As a result, these findings indicate that early financial statements contain useful but insufficient information for identifying subsequent failure of young firms.

One reason is that the early phase of firm life is inherently unstable. Many young firms pass through a period of vulnerable performance, so temporary weakness is not restricted to firms that eventually fail. As a result, both failing and surviving firms may exhibit similarly weak financial profiles in the post-entry “valley of death”, making it difficult to distinguish failure and survival trajectories on the standard financial ratios alone (Lukason & Käsper, 2017). This difficulty is also consistent with Laitinen’s (1992) finding that some firms that later failed were not clearly distinguishable in the earliest stage and became easier to identify only when deterioration intensified over time.

Overall, the young-firm failure literature suggests that early-life failure prediction is constrained by three related features: the limited number of empirical studies, reliance on accounting-based indicators, and weak separability between failing and surviving firms in early stages. Recent evidence further indicates that failure prediction models for new ventures perform worse than those for more established SMEs, pointing to the need for additional non-financial metrics in early-stage contexts (Wang & Guedes, 2025). Wilson and Altanlar (2014) demonstrate that early-stage failure in newly incorporated firms can be predicted even in the absence of accounting data, using non-financial and behavioural event-based indicators such as court judgments for unpaid debts and creditor charges on assets, together with governance-related variables, with model performance reaching an AUC of approximately 0.75. These findings suggest that firms’ earlier payment behaviour may provide additional early-warning value by capturing observable repayment problems during the early-life trajectory.

1.4. Research gap addressed in the thesis

The reviewed literature therefore indicates three related but only partly overlapping research streams. First, studies on payment behaviour show that repayment irregularities provide substantial predictive information on financial distress and failure, often improving models based on accounting data. Second, the tax arrears literature demonstrates that unpaid tax debt is a particularly informative high-frequency form of payment behaviour. Third, studies on young-firm failure prediction show that early-life prediction remains difficult because accounting indicators are often unavailable, delayed, or insufficiently discriminating in the first years of operation.

While each stream provides important insights, their intersection remains insufficiently examined. Existing payment behaviour and tax arrears studies mainly analyse mature firms or combine behavioural and financial variables, whereas young-firm prediction studies continue to rely predominantly on accounting information. Consequently, there is

little empirical evidence on the standalone predictive value of payment behaviour indicators in young-firm failure prediction. Hence, this thesis addresses this gap by applying tax arrears-based behavioural indicators to young-firm failure prediction, distinguishing between total and non-rescheduled arrears, comparing cumulative and year-specific information, and outlining firms' behavioural patterns.

2. Data, variables and methods

2.1. Data, population and observation horizons

The empirical analysis is based on population-level data of Estonian limited liability young firms liable for value added tax (VAT), established between 2011 and 2015. VAT liability implies a minimum level of economic activity¹ and therefore excludes firms with negligible or purely formal operations. The population consists of micro, small, and medium-sized enterprises (MSMEs), with micro-firms forming the overwhelming majority. The data combine two sources: the Estonian Tax and Customs Board and the private credit information bureau Krediidiregister. Independent variables are constructed from monthly tax arrears data provided by the Estonian Tax and Customs Board. Two definitions of tax arrears are applied throughout the analysis: total tax arrears and non-rescheduled tax arrears. The latter exclude arrears that have been formally rescheduled with the tax authority. Non-rescheduled arrears may arise either because firms have not applied for rescheduling or because rescheduling has been denied by the Estonian Tax and Customs Board. Therefore, such arrears may indicate more severe payment behaviour problems than total tax arrears.

The dependent variable reflects firm terminal (non-)failure and is defined as a binary indicator taking the value 1 for failed firms and 0 for non-failed firms. Terminal failure corresponds to deletion from the Estonian Business Register during 2017–2019 with outstanding unpaid debt at the time of deletion². This includes both unpaid tax debt and/or unpaid debt to private creditors (e.g., supplier-, banking-, or mobile-related debts), although the majority relate to tax arrears. This broader debt-based definition captures financially distressed exit more comprehensively than a purely tax-based one. A broader definition is preferred because the presence of tax arrears at the time of deletion may depend on the nature of a firm's business activity. For example, exporting firms may not owe value added tax,

¹ Mandatory VAT registration threshold for firms was 16,000 EUR in taxable turnover per calendar year in 2011 - 2015.

² A small number of firms may also have undergone official insolvency proceedings, but this is not reported separately.

while owner-managed firms without employees may have limited labour-tax obligations. Including private debts therefore reduces the risk of overlooking financially distressed firms without substantial tax liabilities and ensures that the dependent variable reflects broader underlying financial distress. Non-failed firms are defined as firms that remained active as of 31 December 2019 (the cut-off date) and had no unpaid debt at that date. This does not preclude the possibility that such firms experienced debts during earlier stages of their life cycle. Some firms may have had temporary payment disturbances and subsequently recovered. Firms that had unpaid debts at the cut-off date but were not deleted from register are excluded from the sample, as their final status at the cut-off date is not observable and their inclusion would introduce a potential bias.

The initial population consists of 13,993 firms, of which 2,308 are classified as failed firms and 11,685 as non-failed firms at the end of 2019. The observation period is limited to 31 December 2019 in order to exclude the effects of extraordinary policy interventions associated with the COVID-19 pandemic, such as temporary tax interest suspensions and altered tax arrears enforcement. The period is also bounded at the earlier end to avoid distortions related to the 2008–2009 global financial crisis. The resulting time frame therefore reflects a relatively stable macroeconomic and regulatory environment.

For each firm, earlier payment behaviour is observed as monthly trajectories of tax arrears from the time of establishment, indexed from T1 and extending up to T60, corresponding to the first 60 months of operations. This forward-looking alignment ensures comparability across firms founded in different calendar years by placing them at equivalent early-life stages. Compared to backward alignment commonly used in bankruptcy studies on mature firms, this approach is particularly suitable for young firms. In such settings, the timing of failure is not precisely observable, as deletion from the business register may occur with administrative delay and failing firms often cease reporting prior to deregistration.

Three horizon-specific datasets are constructed for the analysis: D36, D48, and D60, covering the first 36, 48, and 60 months of operations, respectively. These datasets allow the role of tax arrears-based payment disturbance histories to be examined over progressively longer observation horizons.

A key methodological issue is the treatment of incomplete payment disturbance trajectories. If a firm is deleted from the register before reaching the end of a given observation horizon, the remaining months are structurally unobserved. Treating these unobserved post-deletion months as zero arrears would bias the data by making earlier-deleted firms appear artificially stable. To avoid this bias, failed firms are required to have

reached the end of the respective observation horizon while still being listed in the Estonian Business Register. Accordingly, firms with lifetimes shorter than three, four, and five years are excluded from D36, D48, and D60, respectively. Among non-failed firms, no additional filtering is required for D36 and D48, whereas in D60 non-failed firms with their ongoing lifetime shorter than five years are excluded to ensure complete 60-month trajectories. Table 4 summarizes the resulting sample structure and exclusion rules.

Table 4

Sample structure and filtering criteria

Observation horizon	D36	D48	D60
Total number of firms	13,972	13,684	10,407
Non-failed firms (0)	11,685	11,685	9,183
Failed firms (1)	2,287	1,999	1,224
Share of failed firms	16.4%	14.6%	11.8%
Mean lifetime (years)	6.3	6.4	6.9
Mean lifetime (non-failed)	6.5	6.5	7.0
Mean lifetime (failed)	5.4	5.6	6.3
Minimum lifetime requirement	Lifetime ≥ 3 years	Lifetime ≥ 4 years	Lifetime ≥ 5 years

Source: compiled by the author.

Overall, the applied filtering ensures that all firms included in each dataset have complete payment behaviour trajectories over the respective observation horizon, thereby improving comparability across firms and avoiding resulting bias. The same sample construction procedure is applied under both definitions of tax arrears, namely total arrears and non-rescheduled arrears.

2.2. Independent variables

Independent variables are constructed from firm-level monthly tax arrears trajectories (T1-T60), capturing firms' earlier payment behaviour through observed payment disturbances. Two alternative variable constructions are applied. Cumulative variables summarize arrears over the full observation horizon, namely the first 36, 48, or 60 months of firm life. Year-specific variables decompose the same arrears history into consecutive 12-month periods, allowing the timing of arrears-based payment disturbances to be examined more explicitly. Accordingly, the 36-month horizon contains year-specific variables for years 1-3; the 48-month horizon for years 1-4; and the 60-month horizon for years 1-5. This design makes it possible to examine whether failure is better explained by the cumulative burden of arrears or by arrears concentrated in particular stages of the firm's life cycle. Following the conceptual framework of Lukason and Andresson (2019), the variables capture three

dimensions of arrears behaviour: monetary magnitude, frequency, and persistence. A summary of independent variables is provided in Table 5.

Table 5

Description of independent variables

Variable	Description	Dimension
MAXPD	Natural logarithm of the highest observed monthly tax arrears within the observation horizon or yearly sub-period	Magnitude
MEANPD	Natural logarithm of the arithmetic mean of monthly tax arrears over the observation horizon or yearly sub-period	Magnitude
MEDPD	Natural logarithm of the median monthly tax arrears within the observation horizon or yearly sub-period	Magnitude
COUNT	Number of months with tax arrears exceeding 10 EUR	Frequency
SEQMAX	Longest consecutive sequence of months with tax arrears exceeding 10 EUR	Persistence

Note: All tax arrears variables are based on month-end observations, corresponding to the last day of each month.

Source: compiled by the author.

The monetary magnitude of arrears is measured using three indicators calculated over the relevant observation horizon or yearly sub-period: the natural logarithm of maximum arrears, mean arrears, and median arrears. These measures capture, respectively, extreme distress episodes, average arrears intensity, and the central tendency of arrears over the period. Since arrears amounts are strongly right-skewed, all monetary magnitude variables are ln-transformed to stabilize variance and reduce the influence of extreme observations. Values below 1 EUR are set to zero prior to transformation to avoid undefined or economically negligible logarithmic values.

The frequency and persistence of arrears are captured through two additional variables. Frequency is measured as the number of months during which arrears exceeded 10 EUR. This threshold excludes negligible balances that are unlikely to reflect substantive financial distress. Persistence is measured as the longest consecutive sequence of months with arrears above the same threshold. This variable distinguishes temporary liquidity difficulties from prolonged uninterrupted arrears periods, the latter being more strongly associated with structural financial weakness. For example, six months with tax arrears may occur either as six isolated monthly episodes or as one uninterrupted six-month sequence. Although both cases contain the same number of months with arrears, they reflect different underlying behavioural patterns.

The selection of these variables is supported by prior empirical evidence showing that larger, more frequent and more persistent payment disturbances increase the probability of firm failure (Laitinen, 1999; Back, 2005; Lukason & Valgenberg, 2021). Accordingly, all tax arrears variables are expected to be positively associated with failure probability.

2.3. Methods

The empirical analysis combines explanatory and predictive approaches and is complemented by cluster analysis. The analysis is conducted across three observation horizons (36, 48, and 60 months) and under two tax arrears definitions: total arrears and non-rescheduled arrears. Tax arrears-based payment behaviour variables enter the analysis in two forms: cumulative indicators summarizing the full observation horizon and year-specific indicators capturing consecutive 12-month periods. Table 6 summarizes the model setup.

Table 6

Overview of model setup

Model type	Specification	Variables used	Model setup
Logistic regression	Univariate (cumulative)	MAXPD, MEANPD, MEDPD, COUNT, SEQMAX	5 models per horizon
	Univariate (year-specific)	Year-specific variables (Y1–Yk) for MAXPD, MEANPD, MEDPD, COUNT, SEQMAX	15 / 20 / 25 models per horizon
Logistic regression / Artificial neural network	Multivariate (cumulative)	MAXPD, MEANPD, MEDPD, COUNT, SEQMAX	1 model per horizon
	Multivariate (year-specific)	All year-specific variables (Y1–Yk × 5 variables)	1 model per horizon
K-means clustering	Cumulative	MAXPD, MEANPD, MEDPD, COUNT, SEQMAX	K = 4

Note: Horizons D36, D48, D60 are each estimated for total tax arrears and for non-rescheduled tax arrears. Year-specific models include three years Y1–Y3 for D36, four years Y1–Y4 for D48, and five years Y1–Y5 for D60.

Source: compiled by the author.

First, explanatory analysis is conducted using descriptive statistics, Welch's ANOVA, and univariate logistic regressions. The results are reported as average marginal effects, computed in R, which indicate how a one-unit increase in a variable is associated with a change in predicted failure probability. Average marginal effects are preferred over marginal effects at the mean, as the estimates of these two approaches may differ substantially, as demonstrated by Wilson and Altanlar (2014). Univariate logistic regressions are used to avoid multicollinearity and to isolate the marginal effect of individual variables (see Appendix A).

This approach follows prior studies employing marginal effects in failure prediction research (e.g. Andresson & Lukason, 2024; Andresson & Lukason, 2025).

Second, predictive analysis is performed using classification models based on logistic regression (LR) and artificial neural networks (ANN) (e.g. Fuertes-Callén et al., 2022; Lukason & Valgenberg, 2021; Andresson & Lukason, 2025). Logistic regression serves as a benchmark method widely used in failure prediction, whereas neural networks are capable of capturing nonlinear relationships. The artificial neural network for this analysis is specified as a multilayer perceptron with two hidden layers, estimated in IBM SPSS Statistics using a 50/50 training – testing split. As ANN results may vary across runs, the best-performing result of three runs is retained. Additional settings are reported in Appendix B. To ensure comparability, balanced datasets are constructed for prediction by applying synthetic minority oversampling technique (SMOTE) until the number of failed and non-failed observations is equal.

Both univariate and multivariate model specifications are estimated. Multivariate cumulative models include MAXPD, MEANPD, MEDPD, COUNT, and SEQMAX. Multivariate year-specific models include all available yearly variables for the respective horizon (Y1–Y3 for 36 months, Y1–Y4 for 48 months, and Y1–Y5 for 60 months). Model performance is evaluated using classification accuracy and the area under the receiver operating characteristic curve (AUC). For the best-performing artificial neural network model in each horizon, Type I and Type II classification errors are additionally reported. In this study, Type I error refers to missed failures, that is, failed firms incorrectly classified as non-failed, whereas Type II error refers to false alarms, that is, non-failed firms incorrectly classified as failed.

In the final stage of the analysis, k-means cluster analysis is applied to identify behavioural types based on firms' payment behaviour patterns derived from tax arrears and to provide additional interpretation of classification outcomes and prediction errors. Clustering is performed using five cumulative variables, which capture the magnitude, frequency, and persistence of arrears over the entire observation horizon. The analysis is conducted separately for each observation horizon and tax arrears definition. Balanced datasets are used to avoid class-driven clustering bias. Several clustering solutions ($K = 3-5$) were evaluated, and a four-cluster solution was selected for further interpretation, as it provided the clearest and most economically interpretable behavioural hierarchy, while the elbow criterion indicated diminishing improvements in cluster separation beyond four clusters.

3. Results and discussion

3.1. Descriptive and explanatory analysis

Descriptive statistics are reported for the 36-month observation horizon under both total tax arrears and non-rescheduled tax arrears definitions, allowing direct comparison of the distributions of tax arrears-based indicators. The 36-month horizon includes the largest number of firms and provides a representative overview of firms' payment behaviour as reflected in tax arrears.

The descriptive statistics and Welch's robust ANOVA tests (see Table 7 below) confirm statistically significant differences across all tax arrears-based indicators ($p < 0.001$) between failed and non-failed firms. Failed firms exhibit markedly higher monetary magnitude, greater frequency, and longer persistence of tax arrears. Furthermore, these differences are evident not only in mean values but also in medians: while the typical non-failed firm exhibits zero arrears across variables, the median failed firm displays sustained and frequent payment disturbances. This pattern indicates that the observed differences are not driven solely by extreme observations but reflect systematic behavioural divergence between the groups.

Table 7

Descriptive statistics for cumulative tax arrears indicators (36-month horizon)

		MAXPD		MEANPD		MEDPD		COUNT		SEQMAX	
Firm status		Total	NR	Total	NR	Total	NR	Total	NR	Total	NR
Non-failed N=11,685	Mean	1.52	1.44	0.82	0.74	0.07	0.05	1.07	0.89	0.70	0.53
	SD	2.85	2.76	1.81	1.68	0.68	0.56	3.35	2.89	2.34	1.81
	Median	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Failed N=2,287	Mean	6.35	6.32	5.11	5.04	3.19	3.07	15.00	14.61	13.06	12.43
	SD	3.28	3.28	3.16	3.15	3.74	3.70	11.78	11.70	11.45	11.26
	Median	7.33	7.29	5.80	5.67	0.00	0.00	15.00	14.00	11.00	10.00
All firms N=13,972	Mean	2.31	2.24	1.52	1.45	0.58	0.54	3.35	3.13	2.72	2.48
	SD	3.43	3.38	2.62	2.55	2.00	1.94	7.66	7.43	6.85	6.55
	Median	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Welch ANOVA statistic and p-value		4330; <0.001	4444; <0.001	3952; <0.001	4023; <0.001	1584; <0.001	1514; <0.001	3146; <0.001	3110; <0.001	2643; <0.001	2541; <0.001

Note: NR denotes non-rescheduled tax arrears. Monetary magnitude variables are natural logarithms of arrears amounts.

Source: compiled by the author.

Across definitions, non-rescheduled tax arrears display slightly lower levels than total arrears, suggesting that part of the observed arrears dynamics relates to formally rescheduled tax arrears that firms have acknowledged and agreed to settle. Welch ANOVA statistics indicate modest variation in discriminatory strength across variables, with magnitude measures (MAXPD, MEANPD) exhibiting relatively stronger between-group separation than frequency and persistence measures. Importantly, the overall distributional patterns and statistical significance remain consistent across both definitions, indicating robust discriminatory capacity.

The average marginal effects (see Table 8 below) confirm a positive and statistically significant relationship between tax arrears-based indicators and firm terminal failure across all observation horizons and under both total and non-rescheduled arrears definitions. All variables are significant ($p < 0.001$), indicating that increases in arrears magnitude, frequency, and persistence are associated with higher failure probabilities. For cumulative variables, marginal effects decline as the observation horizon extends from 36 to 60 months. This decline is relatively moderate for monetary magnitude indicators, but more pronounced for frequency and persistence measures, where effects become substantially smaller as the observation horizon lengthens.

Table 8

Average marginal effects for tax arrears-based variables across observation horizons

Variable	D36		D48		D60	
	Total	NR	Total	NR	Total	NR
MAXPD	0.0387	0.0392	0.0380	0.0388	0.0351	0.0361
MEANPD	0.0469	0.0482	0.0439	0.0449	0.0392	0.0401
MEDPD	0.0600	0.0660	0.0508	0.0574	0.0426	0.0472
COUNT	0.0161	0.0173	0.0102	0.0108	0.0072	0.0075
SEQMAX	0.0212	0.0255	0.0136	0.0165	0.0096	0.0113

Note: NR denotes non-rescheduled tax arrears. Values represent average marginal effects from univariate logistic regressions, expressed in probability units. All effects are statistically significant at the 0.1% level ($p < 0.001$). Monetary magnitude variables are natural logarithms of arrears amounts.

Source: compiled by the author.

However, this pattern should be interpreted with caution. The observed decline in marginal effects does not imply that payment disturbances become less economically relevant over time. Rather, it reflects the inclusion of earlier periods within longer observation horizons, during which many firms, both surviving and failing, exhibit little or no payment disturbances. As these periods contribute little to distinguishing between failed and non-failed

firms, their inclusion mechanically reduces the estimated marginal effects. Across variables, monetary magnitude indicators (MAXPD, MEANPD, MEDPD) consistently exhibit larger marginal effects than frequency and persistence measures (COUNT, SEQMAX), while non-rescheduled arrears generally produce slightly stronger effects than total arrears, indicating that unresolved payment obligations provide clearer signals of financial distress.

Year-specific variables provide a more informative view of the timing of payment disturbances and their relationship to firm terminal failure, enabling comparison of equivalent stages of firm development across different horizons (see Table 9 below).

Table 9

Average marginal effects for year-specific tax arrears-based variables across horizons

Variable	D36		D48		D60	
	Total	NR	Total	NR	Total	NR
Y1_MAXPD	0.0384	0.0390	0.0345	0.0350	0.0258	0.0262
Y2_MAXPD	0.0380	0.0387	0.0349	0.0356	0.0285	0.0290
Y3_MAXPD	0.0374	0.0380	0.0346	0.0353	0.0293	0.0298
Y4_MAXPD	—	—	0.0349	0.0355	0.0298	0.0305
Y5_MAXPD	—	—	—	—	0.0307	0.0312
Y1_MEANPD	0.0504	0.0518	0.0455	0.0468	0.0344	0.0354
Y2_MEANPD	0.0450	0.0465	0.0417	0.0432	0.0349	0.0361
Y3_MEANPD	0.0421	0.0433	0.0392	0.0405	0.0341	0.0353
Y4_MEANPD	—	—	0.0379	0.0386	0.0330	0.0339
Y5_MEANPD	—	—	—	—	0.0327	0.0331
Y1_MEDPD	0.0644	0.0698	0.0570	0.0618	0.0397	0.0423
Y2_MEDPD	0.0515	0.0568	0.0471	0.0521	0.0385	0.0420
Y3_MEDPD	0.0443	0.0488	0.0411	0.0452	0.0359	0.0395
Y4_MEDPD	—	—	0.0366	0.0389	0.0322	0.0345
Y5_MEDPD	—	—	—	—	0.0292	0.0298
Y1_COUNT	0.0601	0.0639	0.0534	0.0568	0.0398	0.0419
Y2_COUNT	0.0371	0.0405	0.0347	0.0380	0.0305	0.0333
Y3_COUNT	0.0297	0.0316	0.0281	0.0300	0.0265	0.0285
Y4_COUNT	—	—	0.0243	0.0246	0.0228	0.0236
Y5_COUNT	—	—	—	—	0.0197	0.0191
Y1_SEQMAX	0.0700	0.0777	0.0619	0.0686	0.0457	0.0497
Y2_SEQMAX	0.0422	0.0495	0.0393	0.0462	0.0347	0.0401
Y3_SEQMAX	0.0318	0.0369	0.0302	0.0352	0.0291	0.0342
Y4_SEQMAX	—	—	0.0248	0.0268	0.0235	0.0259
Y5_SEQMAX	—	—	—	—	0.0192	0.0199

Note: NR denotes non-rescheduled tax arrears. Values represent average marginal effects from univariate logistic regressions. All effects are statistically significant at the 0.1% level ($p < 0.001$). Monetary magnitude variables are natural logarithms of arrears amounts.

Source: compiled by the author.

In particular, aligning the final observed year across horizons allows a consistent comparison of marginal effects before failure, corresponding to the third, fourth, and fifth years for the 36-, 48-, and 60-month horizons, respectively. These aligned comparisons show that marginal effects remain substantial across all horizons but gradually decline as the observation horizon increases. For example, the marginal effect of MAXPD decreases from 0.0374 in the final year of the 36-month horizon to 0.0349 in the 48-month horizon and 0.0307 in the 60-month horizon. A similar pattern is observed for COUNT (0.0297, 0.0243, and 0.0197, respectively). This indicates that arrears-based indicators are more strongly associated with failure among firms observed over shorter lifetimes, whereas for firms with longer lifetimes, distress signals emerge more gradually and are less pronounced in marginal effect terms.

The results are consistent with prior evidence that firms' earlier payment behaviour constitutes an informative early-warning signal of firm failure, particularly in SME contexts where non-financial information may complement or even outperform accounting-based indicators, as shown by Back (2005) for payment delays and Kohv and Lukason (2021) for tax arrears. In line with this literature, the present results confirm that both the magnitude and occurrence of arrears are systematically associated with failure risk.

The analysis of average marginal effects further shows that monetary magnitude indicators exhibit stronger effects than frequency- and persistence-based measures, aligning with findings by Wilson and Altanlar (2014), who show that more severe and realised payment problems exhibit larger marginal effects on failure probability than earlier or precautionary signals. At the same time, this contrasts with studies such as Andresson and Lukason (2025), where frequency-based indicators emerge as the most consistent predictors for MSMEs of different ages, suggesting that the relative importance of arrears-based dimensions may depend on measurement design and firm context.

Across horizons, marginal effects decline as the horizon length increases. This pattern reflects a mechanical dilution arising from the inclusion of earlier, relatively stable periods that contribute little to discrimination. While prior research has documented a similar horizon-related decline in predictive performance (Iwanicz-Drozdzowska et al., 2016), the present results show how this effect also appears in marginal-effect estimates for young firms.

3.2. Predictive analysis

The univariate logistic regression results indicate that all tax arrears-based variables have substantial predictive power across all observation horizons and arrears definitions.

Using cumulative variables (see Table 10 below), predictive accuracy ranges from approximately 72% to 87%, demonstrating that even single behavioural variables capture meaningful information about failure risk among young firms. Frequency and persistence measures (COUNT and SEQMAX) consistently achieve the highest predictive accuracy, reaching up to 87.6% in longer horizons. This suggests that repeated and prolonged payment disturbances provide stronger discrimination between failed and non-failed firms than the magnitude of individual arrears episodes. In contrast, monetary magnitude indicators (MAXPD, MEANPD, MEDPD) remain informative but exhibit less predictive performance. For cumulative variables, predictive accuracy increases with the length of the observation horizon, reflecting the accumulation of arrears information over time. This improvement is particularly noticeable for frequency- and persistence-related measures.

Table 10

Prediction accuracy of univariate logistic regressions, cumulative variables

Variable	D36		D48		D60	
	Total	NR	Total	NR	Total	NR
MAXPD	79.6%	79.9%	80.4%	81.0%	80.7%	81.3%
MEANPD	80.0%	80.6%	82.0%	82.7%	83.9%	84.4%
MEDPD	72.3%	71.8%	75.7%	75.2%	74.4%	74.0%
COUNT	81.3%	81.5%	84.1%	85.0%	86.3%	86.6%
SEQMAX	81.1%	82.0%	84.3%	85.7%	86.6%	87.6%

Note: NR denotes non-rescheduled tax arrears.

Source: compiled by the author.

Finally, differences between total and non-rescheduled arrears are relatively modest but systematic, with non-rescheduled arrears generally yielding slightly higher predictive accuracy, suggesting that unresolved payment obligations provide clearer signals of financial distress.

The analysis based on year-specific variables provides additional insight into the temporal structure of predictive performance. Within each observation horizon, predictive accuracy increases markedly as variables move closer to the failure event (see Table 11 below). For example, in the 60-month horizon, accuracy rises from approximately 55–64% in the first year (Y1) to 84–88% in the final observed year (Y5), depending on the variable. A similar progression is observed for other horizons, indicating that payment disturbances become substantially more informative as firms approach failure.

Table 11

Prediction accuracy of univariate logistic regressions, year-specific variables

Variable	D36		D48		D60	
	Total	NR	Total	NR	Total	NR
Y1_MAXPD	69.4%	69.4%	68.1%	68.1%	63.8%	63.8%
Y2_MAXPD	77.5%	77.6%	76.6%	76.7%	72.9%	72.9%
Y3_MAXPD	80.0%	80.5%	79.7%	80.1%	77.3%	77.7%
Y4_MAXPD	—	—	82.5%	83.2%	80.6%	81.3%
Y5_MAXPD	—	—	—	—	84.1%	85.0%
Y1_MEANPD	69.3%	69.3%	68.0%	68.0%	63.6%	63.6%
Y2_MEANPD	77.3%	77.6%	76.5%	76.6%	72.5%	72.7%
Y3_MEANPD	80.2%	80.8%	79.8%	80.3%	77.2%	77.6%
Y4_MEANPD	—	—	83.2%	84.1%	81.2%	81.8%
Y5_MEANPD	—	—	—	—	84.8%	85.6%
Y1_MEDPD	59.1%	58.8%	58.1%	57.8%	54.7%	54.6%
Y2_MEDPD	72.2%	72.0%	70.5%	70.3%	64.7%	64.5%
Y3_MEDPD	79.8%	79.9%	78.8%	78.8%	73.7%	73.4%
Y4_MEDPD	—	—	84.1%	84.5%	80.6%	80.7%
Y5_MEDPD	—	—	—	—	86.9%	87.1%
Y1_COUNT	69.3%	69.3%	68.0%	68.0%	63.6%	63.7%
Y2_COUNT	76.9%	76.9%	75.7%	75.7%	71.5%	71.3%
Y3_COUNT	81.4%	81.6%	80.7%	81.0%	76.7%	77.6%
Y4_COUNT	—	—	85.1%	85.9%	82.4%	82.6%
Y5_COUNT	—	—	—	—	87.6%	88.1%
Y1_SEQMAX	69.3%	69.3%	68.0%	68.0%	63.6%	63.7%
Y2_SEQMAX	76.3%	76.3%	75.1%	75.1%	70.3%	72.9%
Y3_SEQMAX	80.7%	81.8%	79.9%	81.1%	77.3%	77.3%
Y4_SEQMAX	—	—	85.6%	86.0%	82.3%	82.4%
Y5_SEQMAX	—	—	—	—	87.7%	88.3%

Note: NR denotes non-rescheduled tax arrears.

Source: compiled by the author.

When comparable final observed years before failure are aligned across horizons, specifically the third, fourth, and fifth years for the 36-, 48-, and 60-month horizons, predictive accuracy remains consistently high and even increases slightly with longer horizons. This confirms that payment disturbances immediately preceding failure are particularly strong predictors of failure. At the same time, a different pattern emerges when the same year of firm life is compared across horizons. For example, the predictive accuracy of the first year (Y1) variables declines from 36-month to 60-month horizon, indicating that early arrears are less informative in datasets containing firms with longer observable histories. This suggests that firms in longer horizons often exhibit extended early periods of

stable behaviour before distress emerges. Consequently, the predictive content of arrears-based indicators depends primarily on their timing. Variables measured closer to failure contain concentrated distress signals, whereas earlier yearly variables provide weaker discrimination, especially in longer-horizon datasets. This interpretation is further supported by comparing cumulative and year-specific variables. Cumulative measures include behaviour over the entire observation period and therefore dilute the distress signal by incorporating early stable phases, whereas year-specific variables, particularly those measured immediately before failure, capture the most informative stage of financial deterioration.

The multivariate models demonstrate strong and consistent predictive performance across all observation horizons, model specifications, and arrears definitions (see Table 12 below). Both logistic regression (LR) and artificial neural network (ANN) models achieve high levels of accuracy, with values ranging from approximately 82% to nearly 90%, indicating that arrears-based measures jointly provide substantial information for identifying failure risk among young firms.

Table 12

Predictive performance of multivariate models across observation horizons

Horizon /Model	LR				ANN			
	Total		NR		Total		NR	
	AUC	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC	Accuracy
D36								
Cumulative	0.873	82.2%	0.876	82.4%	0.874	82.2%	0.878	82.7%
Year-specific	0.874	81.6%	0.874	81.8%	0.877	82.5%	0.879	83.0%
D48								
Cumulative	0.909	84.8%	0.914	86.0%	0.911	86.1%	0.917	86.8%
Year-specific	0.874	85.4%	0.916	86.0%	0.908	86.2%	0.916	87.0%
D60								
Cumulative	0.924	87.0%	0.928	87.7%	0.925	88.1%	0.931	88.4%
Year-specific	0.874	88.0%	0.874	88.6%	0.928	88.6%	0.931	89.6%

Note: NR denotes non-rescheduled tax arrears. Cumulative model includes MAXPD, MEANPD, MEDPD, COUNT, and SEQMAX. Year-specific model includes all yearly variables (Y1–Yk) for the corresponding horizon. ANN results report the best of three runs. Source: compiled by the author.

Comparing model types, ANN models consistently outperform logistic regression, although the differences are moderate. The performance advantage of ANN becomes more pronounced in longer horizons and in year-specific specifications, suggesting that nonlinear relationships among variables contribute additional predictive value when year-specific

temporal information is available. Differences between cumulative and year-specific specifications are relatively small in shorter horizons but become more informative in longer horizons. In the 60-month horizon, the year-specific ANN model achieves the highest predictive performance (accuracy 89.6%, AUC 0.931), slightly outperforming the cumulative specification. This indicates that disaggregated temporal information provides additional predictive value when longer payment histories are available. Across all specifications, models based on non-rescheduled arrears consistently achieve slightly higher predictive performance than those based on total arrears, reinforcing earlier findings that unresolved payment obligations provide clearer signals of financial distress.

The classification performance of the best-performing ANN models for each horizon is reported in Table 13. Overall accuracy increases from 83% in the 36-month horizon to 89.6% in the 60-month horizon, accompanied by a substantial reduction in both Type I and Type II errors. In particular, the rate of missed failures (Type I error) declines from 27.1% to 15.9%, while false alarms (Type II error) decrease from 7.1% to 4.9%. This indicates that longer observation horizons and year-specific variable sets improve the model's ability not only to classify firms correctly overall but also to reduce economically costly misclassification of failure events. Finally, the variable importance analysis for best-performing ANN models (Appendix C) reveals a clear and consistent pattern across all horizons. Variables corresponding to later periods dominate the predictive structure, with frequency and persistence (COUNT and SEQMAX) emerging as the most influential predictors.

Table 13

Classification performance of best ANN models

Horizon / Model	Accuracy	Type I error	Type II error
D36 NR / Year-specific (Y1–Y3)	83.0%	27.1%	7.1%
D48 NR / Year-specific (Y1–Y4)	87.0%	19.8%	6.0%
D60 NR / Year-specific (Y1–Y5)	89.6%	15.9%	4.9%

Note: NR denotes non-rescheduled tax arrears. Type I error denotes the proportion of failed firms incorrectly classified as non-failed (missed failures). Type II error denotes the proportion of non-failed firms incorrectly classified as failed (false alarms).

Source: compiled by the author.

The results confirm that the magnitude, frequency, and persistence of tax arrears exhibit strong predictive power even in univariate settings, indicating that tax arrears-based payment behaviour indicators alone provide meaningful discrimination in young-firm failure prediction. A key finding is that their predictive content increases as firms approach failure,

which is consistent with Back (2005), who show that recent payment disturbances are more informative than earlier ones. Extending this evidence, arrears indicators measured closer to failure are more informative, and aligned final periods remain highly predictive across horizons. While prior research documents that payment-related variables retain predictive value over longer horizons (Iwanicz-Drozdowska et al., 2016), the present results clarify how this effect manifests in a systematic distance-to-failure pattern.

The prediction accuracy achieved in this study (89.6%) is comparable to results reported in prior research using payment-related variables in different settings. Similar levels of performance have been documented for models incorporating payment behaviour within non-financial variables (Back, 2005), for tax-arrears-based bankruptcy prediction up to 24 months prior to failure (Lukason & Andresson, 2019), and for bank loan default prediction using tax arrears (Kohv & Lukason, 2021), with reported accuracies of 86.36%, 89.9% and 83.5%, respectively. At the same time, the relative importance of arrears-based dimensions differs from prior evidence. While earlier studies show that maximum tax arrears are among the strongest univariate predictors (Kohv & Lukason, 2021; Lukason & Andresson, 2019), the present results indicate that frequency and persistence measures outperform magnitude-based indicators both in univariate classification accuracy and in multivariate variable importance. The latter is consistent with Kohv and Lukason (2021), who also find that frequency dominates in multivariate models.

The results show that artificial neural networks outperform logistic regression across all specifications, particularly when year-specific temporal information is incorporated. This is consistent with prior evidence demonstrating the superior performance of machine learning methods in failure prediction, for example in Fuertes-Callén et al. (2022) for young firms and Andresson and Lukason (2025). However, the improvement remains moderate, indicating that the predictive structure of arrears-based indicators is largely captured by linear relationships and that nonlinear gains are minor.

Finally, models based on non-rescheduled arrears consistently outperform those based on total arrears, indicating that unresolved payment obligations provide clearer signals of financial distress. This finding is consistent with recent evidence on the role of arrears composition in Jahhu and Pihelgas (2025). While that study focuses on the onset of tax arrears and the present study on firm terminal failure, both approaches highlight the importance of the institutional status of tax debt by distinguishing between total and non-rescheduled definitions.

3.3. Cluster analysis

The cluster analysis identifies four distinct behavioural types of firms. The cluster structure is highly consistent across all prediction horizons and arrears definitions, indicating stable patterns of earlier payment behaviour among young firms, reflected in tax arrears dynamics. Importantly, the clusters follow a clear progression from firms with almost no arrears to firms experiencing severe and persistent payment disturbances and almost certain failure. At the same time, the clustering results help explain prediction errors observed in the empirical models. Certain firms exhibit ambiguous earlier payment behaviour patterns, while others fail without observable prior payment behaviour signals, limiting the ability of statistical and machine learning models to perfectly separate failing firms from surviving ones. Table 14 presents the clustering results for the 36-month horizon, while the results for other horizons and arrears definitions are reported in Appendix D.

Table 14

Cluster profiles of firms (36-month observation horizon, $K = 4$)

Panel A – Cluster interpretation					
Firm type	Interpretation				
No-Arrears	Firms with almost no tax arrears and lowest share of failed firms.				
Minor Irregular Arrears	Firms with occasional small arrears episodes, resulting in elevated but less certain failure risk.				
Recurring Arrears	Firms with larger arrears that occur repeatedly over time and with a high share of failed firms.				
Severe Persistent Arrears	Firms with severe and prolonged arrears and very high failure risk.				
Panel B – Cluster means of arrears variables					
Firm type	COUNT	SEQMAX	MAXPD	MEANPD	MEDPD
No-Arrears	0.15	0.13	0.54	0.12	0.00
Minor Irregular Arrears	5.80	3.80	7.26	4.65	0.02
Recurring Arrears	19.70	15.55	8.05	6.83	4.24
Severe Persistent Arrears	29.99	28.92	8.05	7.54	7.65
Panel C – Cluster distribution					
Firm type	N (%)	Non-failed (0)	Failed (1)	Share of failed firms	
No-Arrears	12,333 (52.8%)	9,769	2,564	20.8%	
Minor Irregular Arrears	4,554 (19.5%)	1,711	2,843	62.4%	
Recurring Arrears	3,504 (15.0%)	180	3,324	94.9%	
Severe Persistent Arrears	2,979 (12.7%)	25	2,954	99.2%	

Note: Monetary magnitude variables are natural logarithms of tax arrears amounts. N (%) denotes the number and percentage of firms in each cluster.

Source: compiled by the author.

The largest group of firms belongs to the No-Arrears cluster, representing approximately 53–60% of firms across the horizons. Firms in this cluster exhibit almost no payment disturbances throughout the observation period. The values of frequency and persistence indicators, as well as magnitude variables, remain extremely low (COUNT and SEQMAX close to zero). The share of failed firms within this group remains relatively low, ranging from approximately 17% to 21% depending on the observation horizon. This cluster therefore represents financially stable firms that generally meet their payment obligations and rarely accumulate arrears.

The second cluster contains firms with Minor Irregular Arrears, which experience occasional but non-persistent payment disturbances. In the 36-month horizon, firms in this group accumulate arrears approximately 16% of horizon length (COUNT 5.8 months on average), with relatively short sequences (SEQMAX 3.8 months). Although the maximum and mean arrears magnitudes are relatively high, the median arrears value remains close to zero, indicating that arrears episodes occur in short bursts rather than continuously. The share of failed firms in this cluster is considerably higher than in the financially stable group, reaching approximately 62% for the 36-month horizon and increasing to around 80% in the longer horizons. This pattern suggests that these firms experience episodic financial difficulties rather than persistent distress.

The third cluster, Recurring Arrears firms, is characterized by substantially higher levels of arrears frequency and persistence. Firms in this cluster accumulate payment disturbances during a larger portion of the observation period, with average values of COUNT and SEQMAX indicating that arrears occur repeatedly across time. For example, in the 36-month horizon firms in this group experience arrears in approximately 20 months on average, with the longest uninterrupted sequence of arrears exceeding 15 months. Although arrears do not occur continuously, they appear repeatedly throughout the observation horizon. The share of failed firms within this cluster is very high, typically ranging between 95% and 98% across horizons, indicating that repeated payment disturbances strongly increase the probability of terminal firm failure.

The fourth cluster represents Severe Persistent Arrears firms, which constitute the most distressed group in the sample. Firms in this cluster accumulate arrears during the majority of the observation period, with extremely long uninterrupted sequences. For example, for the 36-month horizon the average longest arrears sequence approaches 29 months, indicating nearly continuous payment disturbances. The magnitude of arrears is also highest in this cluster, as reflected in the maximum, mean, and median arrears variables. The

share of failed firms in this group exceeds 99% across all datasets, demonstrating that persistent and severe payment disturbances are almost always associated with eventual terminal firm failure. Such firms appear to struggle for survival already from the earliest stages of their existence, which is consistent with the “born dead” chronic failure process identified by Lukason et al. (2016) among young manufacturing micro firms.

More generally, the clustering results indicate that firms differ primarily in the frequency and persistence of arrears within their payment behaviour. The clusters follow a clear progression from rare arrears to persistent payment disturbances. This finding is consistent with the earlier predictive analysis, where the frequency variable (COUNT) and the persistence variable (SEQMAX) emerged as the strongest predictors of firm failure. In contrast, variables capturing the magnitude of individual arrears episodes exhibit a less systematic relationship with failure risk, suggesting that repeated payment delays provide a stronger signal of financial distress than isolated large arrears events.

The clustering results provide further insight into the origins of prediction errors observed in the empirical models. While most surviving firms belong to the No-Arrears cluster, a notable proportion of failed firms (17% – 20%) also appear in this group. These firms do not exhibit observable payment behaviour signals prior to failure and can therefore be interpreted as sudden failure cases. Since no behavioural signals are present, such firms are inherently difficult to identify using models that rely on payment disturbance variables. Consequently, the No-Arrears cluster represents a direct and unavoidable source of Type I error (missed failures). At the same time, the Minor Irregular Arrears cluster represents the most ambiguous behavioural group. Firms in this cluster appear both among surviving and failing firms. Their earlier payment behaviour patterns resemble early stages of financial distress, however, such behaviour may correspond either to temporary financial difficulties or to the initial phase of more persistent distress. As a result, this cluster forms a zone of overlapping behaviour between surviving and failing firms, making it difficult for predictive models to clearly distinguish between the two groups. This ambiguity leads to both Type I errors (missed failures) and Type II errors (false alarms).

This study contributes to the literature on young firm failure prediction by identifying distinct behavioural types of firms based on their earlier payment behaviour patterns. To the best of the author’s knowledge, this represents the first systematic application of tax arrears-based clustering to young firms, thereby extending prior research that has predominantly relied on financial indicators or has examined payment behaviour primarily in more mature firms. These findings are consistent with the short-range firm failure process (SFFP)

identified by Lukason and Laitinen (2019) for the SME segment. Based on financial ratios, they show that a substantial proportion of firms (73%) does not exhibit prolonged observable decline prior to bankruptcy, indicating that deterioration becomes visible only shortly before failure. In this sense, the absence of arrears among failing young firms can be interpreted as analogous sudden failure cases, where deterioration emerges too late to generate detectable behavioural signals.

More broadly, the identification of two distinct sources of classification error, signal absence and signal ambiguity, also aligns with prior literature. Lukason and Käsper (2017) demonstrate that in the case of government-funded start-ups, no failure-specific financial pattern can be identified in early stages, and firms with different outcomes often exhibit highly similar characteristics. Similarly, the taxonomy of (non-)defaulted firms in the MSME segment proposed by Andresson and Lukason (2025) shows that defaulted firms may emerge from multiple distinct risk configurations, while some failing firms exhibit no pronounced risk signals and remain indistinguishable from non-failing firms. Their analysis incorporates a broader set of behavioural indicators, including managerial characteristics, payment history, and firm-level behavioural variables, but does not explicitly distinguish behavioural patterns among young firms.

Conclusion

This thesis examined whether firms' earlier payment behaviour, measured using tax arrears-based indicators, predicts terminal failure among young firms and identified distinct behavioural patterns associated with financial distress. The analysis was based on population-level data of Estonian young firms liable for value added tax (VAT), established between 2011 and 2015, with micro-firms forming the overwhelming majority. Terminal (non-)failure referred to firms either deleted from the Estonian Business Register with outstanding unpaid debt, including both unpaid tax debt and unpaid private debt, or to surviving firms that remained active without outstanding unpaid debt as of the end of 2019. Tax arrears-based indicators were operationalised as measures of magnitude, frequency, and persistence under both total and non-rescheduled tax arrears definitions and were examined using cumulative and year-specific specifications across multiple observation horizons. The empirical analysis combined descriptive, explanatory, predictive, and clustering approaches. Logistic regression and artificial neural networks were applied to evaluate the predictive performance of tax arrears-based payment behaviour indicators, while cluster analysis was used to identify behavioural patterns of firms and to interpret prediction errors. Together, these approaches

enabled a more comprehensive analysis of the relationship between firms' earlier payment behaviour and young-firm terminal failure.

The results demonstrated that tax arrears-based payment behaviour indicators provide strong predictive power for young-firm failure, even in the absence of traditional accounting-based information. Measures capturing the frequency and persistence of tax arrears, in particular the number of months with arrears and the longest consecutive arrears sequence, consistently outperform magnitude-based indicators in classification performance. Predictive accuracy increases as the observation horizon extends and as variables approach the failure event, indicating that more recent payment behaviour contains the most informative signals of financial distress. Models based on non-rescheduled tax arrears yield slightly higher predictive performance than those based on total arrears, suggesting that unresolved payment obligations provide clearer signals of distress. Artificial neural networks outperform logistic regression, although the improvement remains moderate, indicating that the predictive structure is largely captured by linear relationships. The best-performing artificial neural network model, based on the longest observation horizon and year-specific variables, achieved an accuracy of 89.6%, with a Type I error rate of 15.9% and a Type II error rate of 4.9%. At the same time, a subset of firms fails without observable prior payment behaviour signals, while others exhibit ambiguous patterns characterised by irregular but non-persistent arrears. Such cases highlight the limitations of behavioural-only prediction models and the inability of statistical and machine learning approaches to fully separate failing and surviving firms.

The findings contribute to the literature in several ways. First, they extend the application of tax arrears-based payment behaviour indicators to the context of young-firm failure, where accounting information is often limited or unavailable. Second, they distinguish between total and non-rescheduled tax arrears, showing that unresolved tax liabilities provide clearer signals of financial distress. Third, they analyse the timing of payment behaviour across different observation horizons, highlighting the importance of temporal proximity in distress prediction. Finally, by incorporating cluster analysis, the study provides additional insight into distinct payment behavioural types of firms and their association with failure risk.

The results also have practical implications. Payment behaviour indicators can serve as effective early-warning signals for financial institutions, tax authorities, and other stakeholders involved in risk assessment. Their usefulness is especially pronounced in data-

constrained environments, where financial statements are unavailable, delayed, or of limited informational value.

Several limitations should be acknowledged. First, the analysis is confined to the Estonian institutional context and may not be directly generalisable to countries with different legal and reporting environments. Second, the models rely exclusively on tax arrears-based behavioural indicators and do not incorporate other variables, which may provide additional explanatory power. Third, the analysis is conducted within a stable macroeconomic period, and results may differ under conditions of economic shocks or crises. Future research could address these limitations by integrating additional firm-level, network-based or relational data characteristics, applying the framework in other institutional settings, and examining the role of macroeconomic conditions and external shocks in shaping payment behaviour and firm failure dynamics, especially in early-stage firm development.

Overall, the findings demonstrate that firms' earlier payment behaviour constitutes a valuable source of information for predicting terminal failure among young firms and offers a robust empirical basis for its use as an early-warning signal in both academic research and practical applications.

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Appendices

Appendix A

Correlation matrix for arrears indicators (60-month horizon), total arrears

	MAXPD	MEANPD	MEDPD	COUNT	SEQMAX
MAXPD	1	.959***	.410***	.953***	.952***
MEANPD	.959***	1	.476***	.957***	.952***
MEDPD	.410***	.476***	1	.495***	.490***
COUNT	.953***	.957***	.495***	1	.995***
SEQMAX	.952***	.952***	.490***	.995***	1

Note: Spearman correlations. *** indicates statistical significance at the 0.1% level ($p < 0.001$).

Correlation matrix for arrears indicators (60-month horizon), non-rescheduled arrears

	MAXPD	MEANPD	MEDPD	COUNT	SEQMAX
MAXPD	1	.956***	.404***	.953***	.950***
MEANPD	.956***	1	.470***	.954***	.947***
MEDPD	.404***	.470***	1	.483***	.480***
COUNT	.953***	.954***	.483***	1	.995***
SEQMAX	.950***	.947***	.480***	.995***	1

Note: Spearman correlations. *** indicates statistical significance at the 0.1% level ($p < 0.001$).

Appendix B**Variable Model Architecture Description of ANN models**

Parameter	Value
Model type	Multilayer Perceptron
Rescaling of covariates	Standardized
Hidden layers	2
Activation function	Sigmoid
Optimization	Scaled conjugate gradient
Training method	Batch
Partition	50% training, 50% testing
Error function	Sum of squares

Note: For other settings the default options of IBM SPSS Statistical package are applied.

Appendix C**Variable importance of ANN models, non-rescheduled arrears****Panel A – 36-month horizon**

Variable	Importance	Normalized importance
Y3_MEDPD	0.116	100.0%
Y2_MEDPD	0.106	92.0%
Y3_SEQMAX	0.099	85.5%
Y1_COUNT	0.088	76.0%
Y1_SEQMAX	0.085	73.2%
Y3_COUNT	0.077	66.9%
Y1_MAXPD	0.076	65.4%
Y2_COUNT	0.074	63.6%
Y2_MAXPD	0.071	61.8%
Y1_MEDPD	0.049	42.7%
Y1_MEANPD	0.039	33.8%
Y3_MAXPD	0.038	32.8%
Y2_SEQMAX	0.029	25.3%
Y2_MEANPD	0.028	24.0%
Y3_MEANPD	0.025	21.4%

Panel B – 48-month horizon

Variable	Importance	Normalized importance
Y4_SEQMAX	0.125	100.0%
Y4_COUNT	0.105	84.2%
Y4_MEDPD	0.105	84.2%
Y1_COUNT	0.096	76.4%
Y1_SEQMAX	0.094	74.8%
Y2_SEQMAX	0.067	53.7%
Y1_MAXPD	0.050	39.6%
Y2_COUNT	0.048	38.0%
Y2_MAXPD	0.045	35.9%
Y3_SEQMAX	0.040	31.8%
Y1_MEDPD	0.039	30.7%
Y2_MEDPD	0.036	28.7%
Y1_MEANPD	0.031	25.1%
Y3_MEDPD	0.027	21.6%
Y2_MEANPD	0.023	18.3%
Y3_MEANPD	0.020	16.2%
Y4_MAXPD	0.017	13.9%
Y3_MAXPD	0.011	8.7%
Y4_MEANPD	0.011	8.4%
Y3_COUNT	0.010	7.9%

Panel C – 60-month horizon

Variable	Importance	Normalized importance
Y5_SEQMAX	0.116	100.0%
Y5_MEDPD	0.115	99.1%
Y5_COUNT	0.106	91.5%
Y2_COUNT	0.098	84.5%
Y3_COUNT	0.092	79.1%
Y1_COUNT	0.077	66.6%
Y3_MEDPD	0.065	56.0%
Y5_MEANPD	0.064	55.3%
Y4_MEDPD	0.037	32.4%
Y3_MAXPD	0.034	29.1%
Y3_SEQMAX	0.030	26.2%
Y1_MEDPD	0.022	18.7%
Y1_MEANPD	0.019	16.6%
Y1_SEQMAX	0.018	15.1%
Y4_MEANPD	0.017	14.5%
Y3_MEANPD	0.015	13.2%
Y5_MAXPD	0.014	11.7%
Y2_MEDPD	0.013	11.5%
Y1_MAXPD	0.012	10.5%
Y2_SEQMAX	0.009	8.1%
Y4_MAXPD	0.007	6.2%
Y2_MAXPD	0.007	5.9%
Y2_MEANPD	0.006	5.2%
Y4_SEQMAX	0.005	4.0%
Y4_COUNT	0.004	3.4%

Note: Importance values are derived from artificial neural network models and normalized such that the most important variable within each horizon equals 100%.

Appendix D**Cluster analysis results of firms based on cumulative arrears**

Table D1. Cluster profiles of firms (36-month horizon, K=4)

Panel A – Cluster means of arrears variables

Firm type	COUNT		SEQMAX		MAXPD		MEANPD		MEDPD	
	Total	NR	Total	NR	Total	NR	Total	NR	Total	NR
No-Arrears	0.2	0.1	0.1	0.1	0.5	0.4	0.1	0.1	0.0	0.0
Minor Irregular Arrears	5.8	5.2	3.8	3.3	7.3	7.1	4.7	4.4	0.0	0.0
Recurring Arrears	19.7	19.5	15.6	14.9	8.1	8.0	6.8	6.8	4.2	4.1
Severe Persistent Arrears	30.0	29.8	28.9	28.5	8.1	8.0	7.5	7.5	7.7	7.6

Panel B – Cluster distribution

Firm type	N (%)		Non-failed (0)		Failed (1)		Share of failed firms	
	Total	NR	Total	NR	Total	NR	Total	NR
No-Arrears	12,333 (52.8%)	12,176 (52.1%)	9,769	9,727	2,564	2,449	20.8%	20.1%
Minor Irregular Arrears	4,554 (19.5%)	4,857 (20.8%)	1,711	1,815	2,843	3,042	62.4%	62.6%
Recurring Arrears	3,504 (15.0%)	3,479 (14.9%)	180	126	3,324	3,353	94.9%	96.4%
Severe Persistent Arrears	2,979 (12.7%)	2,858 (12.2%)	25	17	2,954	2,841	99.2%	99.4%

Note: NR denotes non-rescheduled tax arrears. Monetary magnitude variables are natural logarithms of tax arrears amounts.

N (%) denotes the number and percentage of firms in each cluster.

Table D2. Cluster profiles of firms (48-month horizon, K=4)

Panel A – Cluster means of arrears variables

Firm type	COUNT		SEQMAX		MAXPD		MEANPD		MEDPD	
	Total	NR	Total	NR	Total	NR	Total	NR	Total	NR
No-Arrears	0.9	0.8	0.6	0.5	1.9	1.9	0.9	0.9	0.0	0.0
Minor Irregular Arrears	15.4	15.0	10.7	9.9	8.0	7.9	6.1	6.0	0.3	0.2
Recurring Arrears	30.6	30.3	25.5	24.6	8.3	8.2	7.3	7.2	6.6	6.4
Severe Persistent Arrears	41.5	41.2	40.2	39.7	8.0	8.0	7.6	7.6	7.7	7.7

Panel B – Cluster distribution

Firm type	N (%)		Non-failed (0)		Failed (1)		Share of failed firms	
	Total	NR	Total	NR	Total	NR	Total	NR
No-Arrears	13,765 (58.9%)	14,011 (60.0%)	10,887	11,085	2,878	2,926	20.9%	20.9%
Minor Irregular Arrears	3,490 (14.9%)	3,360 (14.4%)	697	534	2,793	2,826	80.0%	84.1%
Recurring Arrears	3,318 (14.2%)	3,269 (14.0%)	84	56	3,234	3,213	97.5%	98.3%
Severe Persistent Arrears	2,797 (12.0%)	2,730 (11.7%)	17	10	2,780	2,720	99.4%	99.6%

Note: NR denotes non-rescheduled tax arrears. Monetary magnitude variables are natural logarithms of tax arrears amounts.

N (%) denotes the number and percentage of firms in each cluster.

Table D3. Cluster profiles of firms (60-month horizon, K=4)

Panel A – Cluster means of arrears variables

	COUNT		SEQMAX		MAXPD		MEANPD		MEDPD	
Firm type	Total	NR	Total	NR	Total	NR	Total	NR	Total	NR
No-Arrears	1.1	1.0	0.7	0.6	2.1	2.2	0.9	0.9	0.0	0.0
Minor Irregular Arrears	17.1	16.7	11.6	10.7	8.0	8.0	6.0	5.9	0.1	0.0
Recurring Arrears	34.5	33.9	27.4	26.0	8.3	8.3	7.1	7.1	4.9	4.6
Severe Persistent Arrears	48.7	47.7	45.5	44.1	8.7	8.6	8.0	7.9	8.1	8.0

Panel B – Cluster distribution

	N (%)		Non-failed (0)		Failed (1)		Share of failed firms	
Firm type	Total	NR	Total	NR	Total	NR	Total	NR
No-Arrears	10,234 (55.7%)	10,517 (57.3%)	8,476	8,653	1,758	1,864	17.2%	17.7%
Minor Irregular Arrears	2,866 (15.6%)	2,672 (14.5%)	593	455	2,273	2,217	79.3%	83.0%
Recurring Arrears	2,899 (15.8%)	2,770 (15.1%)	94	66	2,805	2,704	96.8%	97.6%
Severe Persistent Arrears	2,367 (12.9%)	2,407 (13.1%)	20	9	2,347	2,398	99.2%	99.6%

Note: NR denotes non-rescheduled tax arrears. Monetary magnitude variables are natural logarithms of tax arrears amounts.

N (%) denotes the number and percentage of firms in each cluster.

Appendix E

Empirical studies used in the literature review

Panel A – Payment defaults studies

Author(s), country	Sample	Method	Dependent variable	Payment behaviour variables	Other predictor variables
Laitinen (1999), Finland	3,200	LR, OLS	Analyst-assessed credit risk status (continuous 0–100 and binary risky vs non-risky status)	Firm-level: count of recent and older official bad debts, count of unofficially registered delays in payments, presence of bad debts (binary); Manager-level: share of responsible persons with bad debts	Financial variables: profitability, capital structure/ leverage, firm size, group-level solvency; Non-financial variables: industry risk, responsible-person characteristics and bankruptcy links, legal form
Back (2005), Finland	3,199	MLRP	Firm financial distress status (5-category)	Firm-level: presence of recent and older official payment disturbances (binary), presence of unofficially registered payment delays (1–2 and 3+; binary); Manager-level: presence of links to distressed firms (binary), presence of managers' private payment disturbances (binary)	Financial variables: profitability/efficiency, leverage; Non-financial variables: firm age, firm size, group membership
Altman et al. (2010), UK	5.8M firm-year obs.	LR	Insolvency (binary status)	Firm-level: count and monetary value of County Court Judgments (CCJs)	Financial variables: liquidity, profitability, leverage, working capital, cash-flow coverage; Non-financial variables: firm size, firm age, industry risk, group membership/subsidiary status, reporting and compliance
Laitinen (2011), Finland	62,327	LR	Firm viability status in bankruptcy or reorganization proceedings (binary)	Firm-level: count of payment defaults, delays and positive payment signals; Manager-level: count of board members' personal payment defaults	Financial variables: profitability, liquidity, solvency/leverage, cash flow, firm size; Non-financial variables: industry risk, firm age, board characteristics, legal form, audit modifications, reporting timeliness
Karan et al. (2013), Turkey	6,304 retail customers	LR, UTADIS (MCDA)	Retail customer creditworthiness (binary status)	Firm-level: ratio of late paid invoices to total invoices	Non-financial variables: retailer type, geographic location; Payment history and behavioural variables: purchase volume, payment timing, purchasing regularity, transaction variability, leverage ratio

Wilson et al. (2014), UK	1.4M	Discrete-time SA	Insolvency (binary status)	Firm-level: presence of CCJs and charges on assets (binary)	Financial variables: liquidity, leverage, profitability, working capital, net worth change; Non-financial variables: macroeconomic conditions, firm age, firm size, industry sector; Managerial variables: founder/ director and board characteristics
Iwanicz-Drozdowska et al. (2016), Finland	59,099	LR	Bankruptcy (binary status)	Firm-level: presence of payment delays (binary) and count, monetary value of delays scaled by total assets, positive payment observations, count of past payment defaults	Financial variables: profitability, liquidity, solvency, cash flow, firm size, growth, changes in ratios; Non-financial variables: firm type, industry, firm age, environmental risk, audit, board-member characteristics
Ciampi et al. (2020), Italy	1,200	SOM, LR, hazard analysis	Firm default status based on initiation of bankruptcy or liquidation proceedings (binary)	Firm-level: presence of bank payment delays (binary), monetary value of delays scaled by EBITDA, count of cumulative unremedied delays	Financial variables: profitability, leverage, liquidity, debt-servicing capacity; Non-financial variables: firm size, firm age, business sector, geographic location, corporate governance
Altman et al. (2023), Croatia	2,040	LASSO logit, MDA, RF, GB (XGBoost)	Firm payment default status based on bank account blockage for over 30 or 60 days (binary)	Firm-level: bank account blockage duration (in days), duration category, count of blockages (per year)	Financial variables: liquidity, leverage, profitability, interest-rate risk exposure; Non-financial variables: management- and employee-related variables, exports, R&D, political connections, firm age, sector, region, year
Andresson & Lukason (2025), Estonia	43,936	LR, DT, ANN, cluster	Firm default status based on unresolved debt leading to firm dissolution (binary)	Firm-level and manager-level: count, mean value and maximum value of payment defaults	Managerial variables: accounting disclosure violations, earlier wealth; Payment history and behavioural variables: financial performance, governance, accounting disclosure, firm context

Panel B – Tax arrears studies

Author(s), country	Sample	Method	Dependent variable	Payment behaviour variables	Other predictor variables
Lukason & Andresson (2019), Estonia	4,515	LR, ANN (MP)	Bankruptcy (binary status)	Firm-level: count and longest consecutive sequence of month-ends with tax arrears, maximum and median value of tax arrears	Financial variables: profitability, liquidity, leverage/solidity, productivity, interest burden, cash flow
Lukason & Valgenberg (2021), Estonia	45,399	LR, ANN, DT	Firm failure (binary status)	Firm-level: count of month-ends with tax arrears, maximum and median value of tax arrears, asset-scaled maximum and median value	Financial variables: profitability, solvency, liquidity, efficiency
Kohv & Lukason (2021), Estonia	12,901 obs.	LR, ANN (MP)	Bank loan default (binary status)	Firm-level: count of month-ends with tax arrears, maximum and median value of tax arrears	Financial variables: liquidity, profitability, solvency, efficiency; Payment history and behavioural variables: annual report delays
Andresson & Lukason (2024), Estonia	44,183	LR, ANN, DT	Onset of permanent payment default (binary status)	Manager-level: count of month-ends with disturbances (tax and private debt), maximum and mean value of disturbances across managed firms	Financial variables: profitability, productivity, solvency and capital structure, liquidity
Siimon & Lukason (2021), Estonia	49,156	DT, RF, KNN, ANN (MLP)	Tax arrears occurrence in the next month (binary status)	Firm-level: monetary value of monthly tax arrears (no aggregation), monetary value of aggregated tax arrears, count of consecutive months with and without tax arrears, median value and standard deviation of monthly tax arrears	
Zheng & Li, (2023), China	986,471	GB (LightGBM)	Tax arrears occurrence in year t+1 (binary status)	Firm-level: count of tax arrears and trust-breaking events; Related firm-level: average count of tax arrears and trust-breaking events of related enterprises	Macroeconomic variables: city tax revenue index, city GDP growth, industry GDP share, industry GDP growth; Firm characteristics: registered capital, industry, location, type
Jahhu & Pihelgas (2025), Estonia	33,052	LR, ANN	Tax arrears onset by duration (binary status)	Firm-level: count of month-ends with tax arrears, maximum value, mean value and median value of tax arrears	Financial variables: liquidity, solvency, profitability, productivity, risk score; Firm characteristics: assets, sales, age, export status

Panel C – Young-firm studies

Author(s), country	Sample	Method	Dependent variable	Payment behaviour variables	Other predictor variables
Laitinen (1992), Finland	40	Univariate analysis, LDA	Firm failure (binary status)		Financial variables: profitability, liquidity, solvency; Firm-related variables: firm size, sales growth rate, velocity of capital
Wilson & Altanlar (2014), UK	4.4M firm-year obs.	DHM	Insolvency (binary status)	Behavioural variables: presence of County Court Judgments and charges on assets (binary)	Non-financial variables: timeliness of reporting, board characteristics, macroeconomic and regional factors
Lukason & Käsper (2017), Estonia	417	LR, factor, cluster	Bankruptcy (binary status)		Financial variables: liquidity, profitability, capital structure (solvency), productivity
Fuertes-Callén et al. (2022), Spain	6,167	SA, LR, ANN, DT	Bankruptcy (binary status and survival time)		Financial variables: liquidity, profitability, leverage; Non-financial variables: firm size, employee-related indicators (productivity, salary)
Wang & Guedes (2025), Portugal	331,500	LR	Firm failure (binary status)		Financial variables: liquidity and solvency, profitability, leverage, activity and efficiency; Non-financial variables: firm size, firm age

Note: ANN – artificial neural networks; DT – decision tree; DHM – discrete-time hazard model; ET – extremely randomized trees; GB – gradient boosting; KNN – k-nearest neighbours; LDA – linear discriminant analysis; LR – logistic regression; MDA – multivariate discriminant analysis; MCDA – multiple criteria decision analysis; MLP / MP – multilayer perceptron; MLRP – multinomial logistic regression; OLS – ordinary least squares; RF – random forest; SA – survival analysis; SOM – self-organizing map; SVM – support vector machine; UTADIS – utilities additives discriminantes.

Resüme**NOORTE ETTEVÕTETE EBAÕNNESTUMISE ENNUSTAMINE MAKSUVÕLGADEL
PÕHINEVA MAKSEKÄITUMISE ABIL EESTI ETTEVÕTETE NÄITEL**

Jekaterina Holm

Käesoleva magistritöö eesmärk on analüüsida, kas ettevõtete varasem maksekäitumine, mõõdetuna maksuvõlgadel põhinevate näitajate abil, võimaldab prognoosida noorte ettevõtete ebaõnnestumist ning tuvastada finantsraskustega seotud erinevaid käitumismustreid. Varasemad uuringud on näidanud, et maksekäitumise näitajad võimaldavad finantsraskusi varakult tuvastada, kuid nende rakendamine noorte ettevõtete kontekstis, sealhulgas mikroettevõtete puhul, mis moodustavad suure osa ettevõtluspopulatsioonist, on seni olnud suhteliselt piiratud.

Analüüs põhineb Eesti käibemaksukohustuslastest ettevõtete populatsiooniandmetel ning hõlmab aastatel 2011–2015 asutatud ettevõtteid, millest valdava osa moodustavad mikro-, väikese ja keskmise suurusega ettevõtted (MSME-d). Ettevõtte ebaõnnestumine on defineeritud kui ettevõtte kustutamine Äriregistrist tasumata võlgnevustega perioodil 2017–2019. Võlgnevused hõlmavad nii maksuvõlgu kui ka erasektori võlgu. Sõltumatud muutujad põhinevad maksuvõlgade andmetel ning kajastavad ettevõtete maksekäitumist kolme dimensiooni kaudu, eristades maksevõlgade ulatust, esinemissagedust ja püsivust. Analüüsis eristatakse kahte maksuvõlgade definitsiooni: kogu maksuvõlad ja ajatamata maksuvõlad. Lisaks kasutatakse nii kumulatiivseid kui ka aastapõhiseid näitajaid erinevate vaatlusperioodide lõikes.

Metoodiliselt kombineeritakse seletav, prognoosiv ja klasteranalüütiline lähenemine. Seletavas analüüsis kasutatakse kirjeldavat statistikat ja ühe muutujaga logistilisi regressioone, mille abil hinnatakse üksikmuutujate mõju ning mille tulemused esitatakse keskmiste marginaalefektidena. Prognoosianalüüsis rakendatakse logistilist regressiooni ja tehiskorrelatsioonid, et hinnata maksuvõlgadel põhinevate maksekäitumise näitajate prognoosivõimet. Täiendavalt kasutatakse klasteranalüüsi, et tuvastada erinevad maksekäitumise profiilid ning tõlgendada prognoosivõimet.

Tulemused näitavad, et maksuvõlgadel põhinevad maksekäitumise näitajad on noorte ettevõtete ebaõnnestumise prognoosimisel informatiivsed ning võimaldavad saavutada kõrge prognoositäpsuse ka traditsiooniliste finantsnäitajate puudumisel. Kõige olulisemateks ennustajateks osutuvad maksevõlgade sagedust ja püsivust kirjeldavad näitajad. Prognoositäpsus suureneb vaatlusperioodi pikenemisel ning lähenedes ebaõnnestumise

sündmusele, mis rõhutab maksekäitumise ajastuse olulisust. Ajatamata maksuvõlgadel põhinevad mudelid saavutavad mõnevõrra kõrgema prognoositäpsuse kui kogu maksuvõlgadel põhinevad mudelid. Tehisnärvivõrgud ületavad logistilist regressiooni prognoositäpsuses, kuid erinevus jääb mõõdukaks, viidates sellele, et peamised seosed on valdavalt lineaarsed. Samal ajal esineb ettevõtteid, mille puhul ebaõnnestumisele ei eelne selgeid maksekäitumise signaale, ning ettevõtteid, mille maksekäitumine on ebaregulaarsuse tõttu raskesti tõlgendatav. See piirab üksnes käitumisandmetel põhinevate mudelite täpsust.

Uuringu tulemused täiendavad teaduskirjandust, laiendades maksuvõlgadel põhinevate maksekäitumise näitajate kasutamist noorte ettevõtete ebaõnnestumise prognoosimisel, eristades kogu- ja ajatamata maksuvõlgasid ning tuues esile erinevad maksekäitumise profiilid. Tulemustel on ka praktiline väärtus, kuna vastavaid mudeleid on võimalik rakendada finantsasutustes, maksuametites ja teistes riskihindamisega seotud organisatsioonides.

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