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Can Failure Process Information Improve Bankruptcy Prediction? Evidence from Finland

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Abstract

Bankruptcies result in significant financial and social losses for all stakeholders of companies each year. For this reason, researchers have been working for decades to develop effective methods for predicting bankruptcy. Most prediction models are based on financial ratios extracted from the last financial statements before bankruptcy. However, researchers have given less attention to the process that led the company to bankruptcy. The purpose of this study is to investigate whether information about the process can improve bankruptcy prediction. The benchmark model was based on three financial ratios measuring profitability, liquidity, and solvency. The process model was constructed using these ratios and their processes leading up to bankruptcy. The process of each ratio was measured by two dimensions: the form and the level of the process. The importance of process information was assessed using data from Finnish limited companies. The data included 147 bankrupt companies and 23,386 active companies. The results of the logistic regression analysis showed that process information helps improve prediction accuracy, but the effect is not strong.

Keywords

Bankruptcy, Prediction of Bankruptcy, Failure Process, Process Measures, Finnish Firms

1. Introduction

The objective of this study is to contribute to the research on failure prediction by introducing a novel, failure process-based approach to predicting bankruptcy. Bankruptcies result in significant financial and social losses for all stakeholders of companies each year. For this reason, researchers have spent decades developing the most effective methods for predicting bankruptcy (Ravi Kumar & Ravi, 2007;

Sun, Li, Huang, & He, 2014). With an effective method, the symptoms of bankruptcy can be reliably identified, and potential bankruptcy can still be avoided through management actions. Reliable warning signals also provide time for financiers to secure and restructure their receivables. In fact, efficient warning signals can assist all stakeholders (Giannopoulos & Sigbjørnsen, 2019: p. 1127). Bankruptcy prediction has become one of the most important and interesting research topics in finance due to its central importance to stakeholders. Thus, researchers have applied various advanced statistical methods and innovative variables to bankruptcy prediction to increase its accuracy (Balcaen & Ooghe, 2006; Bellovary, Giacomino, & Akers, 2007; Shi & Li, 2019).

Most of the developed bankruptcy prediction models are static and rely solely on key financial ratios from the last financial statements of the company (before bankruptcy) to assess bankruptcy risk in the short term (one-year period). In the longer term, the reliability of these prediction models typically declines significantly (du Jardin & Severin, 2011, 2012; du Jardin, 2015, 2017, 2021). Prior studies have shown that bankruptcy risk is particularly based on three key financial factors: profitability, liquidity, and solvency. In many countries, legal bankruptcy is more a matter of profitability and solvency than liquidity, which emphasizes the minor role of liquidity in predictions. The triggering factor for the failure process is almost always reduced, weak profitability leading to losses and, ultimately, poor solvency (Lukason & Laitinen, 2019; Laitinen, 2021). Numerous financial ratios measuring these three key factors have been used in studies (Bellovary, Giacomino, & Akers, 2007). However, financial ratios are close substitutes for each other, meaning that there are no significant differences in efficiency between different ratios referring to the same factor. This suggests that adding new key ratios to the models does not significantly improve their performance.

If the bankruptcy prediction model is based on key financial ratios calculated from the last financial statements before bankruptcy and the prediction span is one year, the accuracy of the model is typically good. In this case, the proportion of correct binary classifications (between bankrupt and active firms) can reach 80% - 90% or even higher (du Jardin, 2015, **Table 1**). Such results can be achieved with models based on many different key ratios, as these ratios are significantly correlated and can serve as substitutes for each other (Laitinen, 2021). Therefore, when bankruptcy is approaching, all correlated key figures typically weaken significantly, pointing to an immediate bankruptcy risk. In this distressed situation, a statistical prediction model based on almost any relevant indicator tends to perform well.

In short-term prediction models, it is difficult to improve an already high classification accuracy. This is because the key ratios from the last financial statements included in the models largely capture the information that indicates bankruptcy risk. As a result, adding or changing key ratios does not always enhance prediction accuracy. In many cases, even incorporating changes or trends in key figures into the model does not improve short-term prediction accuracy (Laitinen, 1993).

Therefore, efforts have been made to improve accuracy by adding cash-flow or non-financial indicators (such as the firm's age, managerial characteristics, and payment defaults) to the model alongside traditional accrual-based indicators (Aziz, Emanuel, & Lawson, 1988; Keasey & Watson, 1987). However, improvements in model accuracy have often been marginal or negligible, and significant improvements are quite rare (Altman, Sabato, & Wilson, 2010).

One of the most promising approaches to predicting bankruptcy is to consider the bankruptcy process in failure prediction (du Jardin & Severin, 2011, 2012; du Jardin, 2015, 2017, 2021). Several studies have identified different processes to expand the understanding of the various stages of bankruptcy (Ooghe & de Prijcker, 2008; Flores-Jimeno & Jimeno-Garcia, 2017; Jimeno-Garcia, Rodriguez-Merayo, & Vidal-Blasco, 2017; Lukason & Laitinen, 2019). The additional importance of process information lies in considering financial data from previous years, in addition to the most recent year. This can be achieved in several ways. In its simplest form, it can be done by measuring the variation in financial indicators over time (Altman, Haldeman, & Narayanan, 1977; Dambolena & Khoury, 1980).

This study also belongs to the class of process research, as it introduces a new approach emphasizing the importance of the process. The bankruptcy or failure process refers to how the key financial figures of companies approaching bankruptcy behave before the event occurs. According to prior research, the most typical bankruptcy process involves a strong decline in key ratios in the last 1 - 2 years. Another common process is when key figures are already weak several years before bankruptcy and continue to decline systematically as the bankruptcy approaches. In almost all cases, the initial trigger in the bankruptcy process is a decline in profitability (Lukason & Laitinen, 2019).

Taking the process into account when predicting bankruptcy has been relatively under-researched compared to its potential and significance. The results from this approach have often been encouraging and promising when compared with those of traditional methods (du Jardin & Severin, 2011, 2012; du Jardin, 2015, 2017, 2021). However, these process-based approaches are typically complex and rely on advanced statistical techniques. For this reason, new and innovative research should focus on simplifying and systematizing the approach that incorporates the failure process. The objective of this study is to present a new and general approach that can be used to assess the significance of the process in bankruptcy prediction. To demonstrate this, the method is applied to empirical data based on the last financial statements of bankrupt companies and the financial statements of active companies from the corresponding years. This is a short-term forecasting model, in which the key figures from the last accounting period are used to predict bankruptcy within a one-year horizon.

The contribution of this study to previous failure prediction research lies in systematically incorporating process variables, describing the progression of key ratios in a simple way, into the traditional financial ratio model. The basic financial model is based on three key ratios calculated for failing firms from their last financial statements before bankruptcy. The process variables included in the model are used to highlight the importance of the process in improving immediate bankruptcy prediction accuracy. This new approach is illustrated with empirical data based on the financial statements of Finnish companies from the research period 2018-2023. The research data includes the financial statements of a total of 23,533 companies, of which 147 are bankrupt and 23,386 are active (non-bankrupt). The research design is intentionally kept simple to encourage further exploration of process analysis. Therefore, interesting topics like cash-flow analysis and earnings management are excluded from the research. Although this pioneering study is limited to Finnish firms, the approach can be applied to companies in other countries as well. Future studies focusing on international applications are encouraged.

This research report is divided into four sections. The first section briefly describes the background and objectives of the study. The second section presents the study's framework. First, it provides a brief overview of relevant previous studies focusing on the failure process. Second, the idea and basic concepts of the new approach are discussed in detail. The third section presents the empirical data and statistical methods used in the study. For simplicity, binary logistic regression analysis is used to generate the statistical results. The section then presents the empirical results from the new approach and compares them with the results from the traditional approach. The final section of the study summarizes the findings and discusses ways in which the simplified approach can be developed in future research.

2. Framework of the Study

2.1. Previous Research on Bankruptcy Process

In this brief review, the focus is on studies that consider the bankruptcy or failure process from a perspective relevant to this study. One of the earliest researchers on bankruptcy processes is Argenti (1976), who recognized that company key figures do not behave in the same way when bankruptcy is approaching, as commonly assumed by traditional statistical prediction methods. These common methods include, for example, Beaver's (1966) univariate analysis of key financial ratios and Altman's (1968) multivariate analysis (discriminant analysis) based on a Z-score derived from several financial ratios. Argenti shared the view that predicting a collapse is more reliable if the stages of failure are understood and identified. Based on case study evidence, Argenti (1976: p. 150) argued that there are three typical bankruptcy processes (trajectories), the identification of which is useful in anticipating bankruptcy.

The first trajectory describes a newly founded (small) company that, in many cases, never generates profit throughout its existence, with its key financial figures remaining consistently weak. The second trajectory is quite different from the first, as the financial performance of this company can quickly rise to an excellent level (the stage of "fantastic development") before it suddenly collapses into insolvency and bankruptcy. The third trajectory identified by Argenti describes a company that has been operating in the market for a long time. Initially, the company's financial performance is very strong, but it then declines rapidly before stabilizing at a lower level (the plateau). Eventually, the company experiences another decline, this time leading to insolvency.

The typology created by Argenti is useful for understanding how companies collapse in practice. If an analyst can identify, with the help of accounting and other background information, which trajectory the company's development follows, this information can be used to predict potential bankruptcy. In fact, Argenti (1983) later developed the so-called A-score, a tool for understanding the causes and processes of managerial crises within a company, which may, in turn, lead to bankruptcy. In his A-score model, the variables and logic of the model chronologically follow the failure process. Argenti reported that the model was tested by 1000 analysts in seven countries over a five-year period. They found that the misclassification rate was about 5%. Later, Keasey and Watson (1987) successfully tested the contributions of Argenti (1983) in failure prediction.

Laitinen (1991) used financial statement data collected through the matching method from Finnish companies to identify different bankruptcy processes. The research started with the assumption that if a company can be identified as following a certain process with the help of comprehensive information, the financial development leading to bankruptcy can be better understood and predicted. Laitinen used factor analysis to identify bankruptcy processes. Six theoretically motivated (identical investments model) financial variables (five financial ratios and one growth variable) from the time-series of variables were selected for the factor analysis. Laitinen identified three different types of bankruptcy processes. The first type was the chronic failure firm, whose financial performance was weak for years before bankruptcy. Predicting its bankruptcy is not difficult, as almost all indicators are weak. The second type was the revenue-financing failure firm, where the most obvious feature of the process was a sudden deterioration in revenue financing two years before bankruptcy. The third type was the acute failure firm, whose bankruptcy is difficult to predict until a year before the event, when the key indicators weaken significantly. Thus, Laitinen's research provided significant empirical insights into how the most important financial ratios behave before bankruptcy in different types of processes.

D'Aveni (1989) identified three distinct failure processes that are remarkably similar to those identified by Laitinen. D'Aveni used a specifically designed D-score to portray failure processes over a five-year period prior to bankruptcy declaration. These D-scores were calculated based on the equity-to-debt ratio and managerial prestige. D'Aveni (1989) theoretically proposed three types of failure processes: suddenly failing firms, gradually failing firms, and lingeringly failing firms. Suddenly failing firms became non-viable within a year before bankruptcy, with the collapse happening very quickly. Gradually failing firms, on the other hand, began experiencing financial difficulties two to three years prior to bankruptcy, with a more noticeable decline. Finally, firms classified as lingering failures were non-viable for a long period before bankruptcy declaration. Thus, the suddenly failing firm shares characteristics with the acute failure firm, while the lingeringly failing firms resemble the chronic failure firm. Additionally, gradually failing firms exhibit characteristics similar to those of revenue-financing failure firms. Empirical evidence supporting these theoretical considerations was obtained by clustering the D-scores to test the failure process types. D'Aveni focused more on the strategic and managerial aspects of the processes than on the financial aspects, though he also paid attention to the indebtedness of the failing firms. Later, D'Aveni presented failure processes as downward spirals (Hambrick & D'Aveni, 1988).

Du Jardin & Severin (2011, 2012) employed advanced statistical methods to incorporate failure process information into failure prediction. They used financial variables to design trajectories, which were then used to forecast potential failure. Initially, Du Jardin & Severin used a self-organizing map and later a Kohonen map to design different trajectories. In addition, du Jardin (2021) employed an ensemble of self-organizing neural networks to design trajectories. In their early approach, the map was used to delineate boundaries between areas representing various stages of a company's financial health. Subsequently, the authors analyzed how companies moved over time within these areas to estimate a typology of behavior (trajectories). This typology was then used to forecast financial failure for horizons of one, two, and three years. Du Jardin & Severin designed six super-classes and six trajectories per super-class, resulting in a total of thirty-six trajectories. This trajectory-based prediction method yielded better accuracy than traditional methods. The models in these studies were based on financial ratios collected over seven consecutive years. In addition, Du Jardin (2015) developed models that rely on a set of "terminal failure processes". These processes represent prototype behaviors of companies measured over a span of only three years.

Lukason & Laitinen (2019) reviewed prior research on failure processes and found support for the existence of three distinct basic processes, consistent with the findings of Laitinen (1991) and D'Aveni (1989). They used data from 1234 bankrupt manufacturing firms across different European countries. Financial variables were calculated using the re-estimated Z''-model from Altman, Iwanicz-Drozdowska, Laitinen, & Suvas (2017), and clustering analyses were conducted to identify three theory-driven failure processes. These processes were classified as short-range, medium-range, and long-range failure processes, based on the timing of failure risk emergence. The most common process (73.0%) was the short-range failure process, which aligns with the acute failure firm (Laitinen) and the suddenly failing firm (D'Aveni). In this type of process, the failure risk is not clearly observable until one year before bankruptcy is declared, making long-term predictions unreliable. In their international data, 16.0% of the processes were medium-range processes, and only 11.0% were long-range processes. The medium-range processes resemble the revenue-financing or gradually failing processes, while the long-range processes resemble chronic or lingeringly failing processes. Lukason & Laitinen also demonstrated that the most significant contributor to failure risk in the short-range was negative annual profitability, while in the longer-range, annual profitability is accompanied by accumulated profitability. Finally, the authors concluded that the best predictors of impending failure are annual and accumulated profitability.

Laitinen (2021) explored both accounting and managerial aspects in his recent study on failure process risk. Using path dependence theory, Laitinen sought to explain the failure or bankruptcy process. He described failure processes as those where similar stages recur due to strong path dependence. Path dependence leads companies into serious financial difficulties when management attempts to break the cycle. The actions taken by management to break this cycle can either increase or, if successful, decrease the risk of bankruptcy. Successful actions can prolong the survival of a failing firm. Laitinen argued that the failure process begins with organizational decline, which is followed by a financial distress process characterized by a decline in key financial ratios. The accounting system is mechanistic, as the income statement and the balance sheet are interconnected through the double-entry bookkeeping system, which is based on mechanistic accounting rules. A major dependency in the financial system is that losses reduce equity, making it difficult to obtain financing. This type of negative development leads the company into financial difficulties related to profitability, solvency, and liquidity. The mechanistic nature of the accounting system reinforces path dependence, creating a "straitjacket" effect that causes failing companies to follow similar financial failure processes, with only variations in the duration of the process. Consequently, the failure process itself generates systematic risk. This systematic risk is common to all companies where the failure process has begun.

Laitinen also presented a simplified model that assumes a constant growth rate of failure risk during the failure process to highlight the characteristics of systematic risk. In his approach, the systematic risk of a failing company is reflected by a beta coefficient, which is constructed between the time series of the failure risk of this company and the median failing company. Laitinen defined the last-period systematic risk as the product of the beta coefficient and the last-period failure risk of the median failing company. While the last-period failure risk is influenced by systematic risk, it is also affected by the risk created by managerial actions, which can either decrease or increase the risk.

In summary, the relevant prior studies can be summarized as follows. Argenti (1976) developed a typology, based on his own case studies, that includes three failure processes. Based on this research, Argenti (1983) created the A-score model to assess a company's bankruptcy risk. The variables in this model are structured in a way that logically follows the failure process. Laitinen (1991) applied factor analysis and demonstrated that there are three failure processes, the most common of which are the acute and chronic failure processes. His research also highlighted how the failure process affects bankruptcy predictability: in acute failure firms, key figures only deteriorate about a year before bankruptcy, making earlier predictions difficult. D'Aveni (1989) hypothesized the existence of three failure processes. Empirical research based on his D-value supported this hypothesis, identifying three types: suddenly, gradually, and lingeringly failing firms. These process types can be used to anticipate and avoid corporate crises. While these types correspond to those found by Laitinen, D'Aveni focused more on the managerial and strategic aspects of companies, while Laitinen used accounting concepts.

Du Jardin & Severin (2011, 2012) applied complex and detailed statistical methods to leverage the information contained in failure processes for bankruptcy prediction. The researchers identified six super-classes of failure processes, each containing six different processes (versions). Using the statistical methods, Du Jardin and Severin achieved better prediction accuracy than traditional approaches. Lukason & Laitinen (2019) studied failure processes using data from several countries and demonstrated, through cluster analysis, that three basic processes can generally be identified. Among these, the so-called short-range process was by far the most common, followed by the long-range process. These processes correspond to the acute and chronic failure processes, respectively. The researchers also emphasized the central role of profitability in initiating the failure process and predicting bankruptcy. Laitinen (2021) offered an intriguing perspective on how the failure process and associated risk emerge due to path dependence: path dependence forces companies to follow a similar trajectory, which can be modified by management actions. The median risk of bankrupt companies can serve as a risk index, which can be used to estimate the systematic risk of the process (beta coefficient) for a given company.

2.2. Taking Account of the Process Information

Previous research on the bankruptcy process suggests that it contains important information that can improve bankruptcy prediction. However, this information is difficult to measure and relate to the variables in the prediction model. Additionally, incorporating process information makes the model more complex and requires the use of advanced statistical methods (du Jardin & Severin, 2011, 2012; du Jardin, 2021). The contribution of this research is to present a model that allows the information related to the failure process to be measured simply and incorporated into the model as a standard variable. Another contribution is that the method provides additional insights into how the process and its factors affect financial failure forecasting. The aim is for process information not to complicate prediction statistically, but rather to allow prediction using a simple, standard multivariate method. In this study, binary logistic regression analysis is applied. The basic model (benchmark) is one in which the variables are limited to key ratios calculated from the last financial statements of bankrupt companies and from the corresponding financial statements of active companies. Variables describing the process are then added to this basic model, and their significance for prediction is assessed. In this way, the expectations for the contribution of the process variables are realistic, since the financial ratios from the last financial statements generally contain most of the information about impending bankruptcy (Laitinen, 1993). Compared with previous models, the current approach generalizes the traditional financial-ratio model by including variables that reflect the process of the financial ratios as well.

To measure the variables describing the failure process, the dimensions of the process are divided into two categories: process form and process level. In this context, the form of the process refers to how the key figures in the basic model behave as a time series, without regard to the level of the process. According to empirical studies, key financial ratios can evolve in various ways during the process, depending on the specific trajectory (Argenti, 1976; Laitinen, 1991; D'Aveni, 1989; Lukason & Laitinen, 2019). However, a common feature in the development of key ratios is that, regardless of the process, the values of financial ratios weaken as bankruptcy approaches. At the same time, processes tend to behave similarly, as path dependence forces distressed companies to follow a similar trajectory (Laitinen, 2021). Although different failure processes occur in practice, the declining behavior of key figures as bankruptcy nears is common to all. This means that the median of financial ratios for bankrupt companies serves as a useful rough descriptor (index) of the financial development of the average bankrupt company. In this study, this descriptor, or index, plays a key role in the development of the process-describing variables.

The development of the median value of the financial ratios of bankrupt companies over the years roughly describes the standard form of the failure process as an index (Laitinen, 2021). Since the distributions of financial ratios are generally skewed, the non-parametric median works better as an index than, for example, the mean. The median is a simple measure that, however, does not oversimplify the process. If the development of a firm's financial ratio perfectly corresponds to the development of the index, the correlation between the ratio and the bankruptcy index over time will be equal to unity. The higher the time correlation, the more similar the forms of the processes for the ratio and the index are. Therefore, in this study, the form of the process of a financial ratio is reflected by its time correlation (COR) with the index process, as follows:

$$Form\left(F\left(i\right)\right)=COR\left(F\left(i\right),M\left(i\right)\right) \quad (1)$$

In this formula, $F(i)$ refers to the financial ratio i ($i = 1, 2, \ldots, m$) and $M(i)$ is the median of this ratio i for bankrupt firms. Time correlation is calculated for each m financial ratio using observations from the previous years ($t = 1, 2, \ldots, n$) as observations. If the correlation coefficient is 1, the form of the financial ratio perfectly corresponds to the development of the median for bankrupt companies. For active companies, the development of financial ratios is usually flat or increasing. If the value of the financial ratio remains stable, the time correlation is close to zero. If the ratio's development is upward, the correlation is typically negative. However, for bankrupt companies, the correlation is positive if the development is downward, as hypothesized. Thus, it can be hypothesized that the time correlation (form of the process) is higher for bankrupt companies than for active companies.

In this study, the level of the process refers to the height of the financial ratio time series. When using the model, it is essential that the level of the process is independent of its form, which ensures that the correlation between the predictors remains low. The form of the process (time correlation) can be high, but the level can still be low, and vice versa. The time correlation of a financial ratio in an active company can be high, but it does not necessarily indicate bankruptcy if the level of the process is also high. The development of a bankrupt company is most typically characterized by a high form and a low level. In this study, the level of the process for a financial ratio is measured as its average difference from the median (index) of bankrupt companies, as follows:

$$Level\left(F\left(i\right)\right)=\sum_{t=1}^{n}\frac{F\left(i\right)-M\left(i\right)}{n}=\sum_{t=1}^{n}\frac{F\left(i\right)}{n}-\sum_{t=1}^{n}\frac{M\left(i\right)}{n} \quad (2)$$

The level of the financial ratio process can be represented as the difference between the cumulative averages of the financial ratio and the median of bankrupt companies. If a company's financial ratio equals the index in each of the n years, the level of this ratio is zero, indicating bankruptcy risk. Thus, it can be hypothesized that the level of the financial ratio process is higher in active companies than in bankrupt companies. A high level of the financial ratio process (cumulative margin) and a negative correlation with the bankruptcy index (median) indicate a low bankruptcy risk. The importance of cumulative financial ratios in process analysis has been highlighted in previous failure research (Lukason & Laitinen, 2019).

The process metrics presented here (form and level of the process) can be applied in bankruptcy prediction by adding three values from each financial ratio to the prediction model: the ratio value from the last financial statement, the time correlation with the bankruptcy index (form), and the cumulative average difference from the index (level). Based on the obtained results, it can then be assessed how strongly the process variables, in relation to the value of the financial ratio from the last financial statement, affect bankruptcy risk. These process indicators are easily calculated and simply interpreted. There are two extreme cases of companies in terms of their processes. First, an excellent active company, characterized by a high ratio value from the last financial statement, a negative time correlation with the index, and a high cumulative margin compared to the index. Second, a risky company, whose financial ratio value from the last financial statement is low, the time correlation with the index is positive, and the level of the process is low. Most companies fall somewhere between these extremes.

In summary, it is expected that the process variables will significantly differ between active and bankrupt firms. Furthermore, it is hypothesized that these variables will improve the performance of the benchmark financial ratio model. Therefore, the following three hypotheses can be presented for empirical testing:

Hypothesis 1 (*H*1): The time correlation of financial ratios in bankrupt companies with their sample median (index) is higher than the time correlation of these ratios in active companies (form of the process).

Hypothesis 2 (*H*2): The cumulative margin of financial ratios in bankrupt companies, calculated as the margin from their sample median (index), is lower than the cumulative margin in active companies (level of the process).

Hypothesis 3 (*H*3). The process variables (form and level of the process) improve the performance of the bankruptcy prediction model based only on financial ratios.

3. Empirical Analysis

3.1. Empirical Data and Variables

The purpose of the empirical part of this study is to illustrate the novel process measures (the form and level of the process) introduced in the theoretical section and to test the research hypotheses *H*1, *H*2, and *H*3. Empirical studies have shown that failure processes can last more than five years in practice, although their duration may vary. This means that the empirical data used to assess the contribution of the process measures must include long time series of consecutive financial statements from both bankrupt (failed) and active (non-bankrupt) companies. In this context, a long time series means that there is a 5 - 6-year time series of financial statement data, which covers, according to bankruptcy statistics, the most significant stages of the longest bankruptcy processes. In this study, empirical data were extracted from the ORBIS database of Bureau van Dijk (BvD) (see https://www.bvdinfo.com/en-gb/).

The data were retrieved under several restrictions. It was required that the selected companies be Finnish, industrial (non-financial) firms, limited liability companies, either active or bankrupt, and that they have at least six consecutive years of financial statements, with the last year being either 2023 or 2022. No industry restrictions were imposed during the sample selection. However, companies with fewer than five employees were excluded, as their data typically contain many missing or biased observations. Furthermore, the financial ratios for such micro-companies tend to be unstable due to their small business volume. Initially, the database contained 25,618 firms meeting the selection criteria. However, the original sample included companies with missing data, so after excluding these companies, the number of usable observations was reduced to 23,533. Among these, 23,386 were active (non-bankrupt) companies, and only 147 were bankrupt companies, which generally declared bankruptcy less than one year after publishing their last financial statements. The last financial statements of these companies are from 2022 and 2023, with almost all of the statements originating from 2023.

The size distribution of the sample companies aligns with the population of Finnish industrial firms. The distribution is highly right-skewed, with an average company size of 72 employees in the last year, while the median size is only 12 employees. The average total assets of the companies in the final year were 9223.4 thousand euros (Teur), with the median being only 1197.0 Teur. The firms in the final sample represent various industries. However, the industrial distribution of active companies differed from that of bankrupt firms. The most frequent industries for active firms were wholesale & retail trade (18.1%), construction (16.5%), and manufacturing (15.7%). For bankrupt companies, the most frequent industries were construction (27.2%), wholesale & retail trade (17.0%), and manufacturing (14.3%). The sample of bankrupt companies had an exceptionally high percentage of construction firms, indicating the high bankruptcy risk in this industry. The average age of the active firms was 23.2 years, while it was 18.9 years for the bankrupt companies. The final sample mainly consisted of private limited companies, but it also included 183 public limited companies.

The empirical part of this study compares the basic (benchmark) model with the process model. The basic model includes only the selected financial ratios, whereas the process model also incorporates the process variables, i.e., two variables (form and level of the process) for each financial variable. Three financial ratios were selected to represent the three main dimensions of financial distress, which have been proven to be efficient in previous bankruptcy prediction studies (Balcaen & Ooghe, 2006; Bellovary, Giacomino, & Akers, 2007; Shi & Li, 2019; Lukason & Laitinen, 2019). These important dimensions and their traditional measures (financial ratios) are as follows: 1) profitability (return on total assets, ROA), 2) liquidity (liquidity ratio, LRA), and 3) solvency (solvency ratio, SRA). These fundamental dimensions are relatively independent of each other, so the model does not exhibit multicollinearity, which would undermine the reliability of the results. The three selected traditional financial ratios are calculated in the ORBIS database as follows:

1. Return on total assets (%) = (Profit/Loss Before Tax/Total Assets)·100
2. Liquidity ratio = (Current Assets − Stocks)/Current Liabilities
3. Solvency ratio (%) = (Shareholders' Equity/Total Assets)·100

Thus, the basic model will include only these three financial ratios ($m = 3$), while the process model will include these ratios along with their process measures (form and level), resulting in a total of nine (3 × 3) variables. The length of the failure process is, according to bankruptcy statistics, set to 6 years, so n = 6. In traditional financial statement analysis, the liquidity ratio is also known as the quick ratio, and the solvency ratio is also referred to as the equity ratio. It is expected that the relationship between these three financial ratios and the failure risk is negative: the lower the ratios, the higher the risk.

There are two questions worth considering when selecting financial ratios for the basic benchmark model. First, empirical research has indicated that cash-flow ratios may form a distinct dimension of their own (Aziz, Emanuel, & Lawson, 1988; Keasey & Watson, 1987). However, their contribution to the prediction accuracy of financial models is often marginal. The predictive ability of the cash-flow ratio was tested before selecting the final data, using the average year of 2020 in the failure process and selecting a set of Finnish firms from ORBIS without any size restrictions. In total, 77,297 firms were found in the database. However, ORBIS aggregates financial statement data and provides only a limited number of different line items, which is particularly limiting for small firms and cash-flow measures (Beuselinck, Elfers, Gassen, & Pierk, 2023: p. 51). As a result, the number of missing observations was 9.7% for ROA, 18.1% for LRA, 9.2% for SRA, and as high as 42.8% for the cash-flow ratio. These four ratios were used in a logistic regression model to predict bankruptcy over a one-year horizon, leading to the following p-values for the model coefficients: ROA < 0.001, LRA = 0.196, SRA < 0.001, and the cash-flow ratio = 0.854. The coefficient of the cash-flow ratio in the model was 0.000. Consequently, the cash-flow ratio was excluded from the present basic model, and a size limit for the firms entering the final sample was set.

The second consideration in variable selection is associated with earnings management (EM). Previous research on EM in failing firms is limited and inconclusive, as several studies show that there are incentives that can lead to upward earnings management before filing for insolvency, as well as incentives for downward earnings management (Dutzi & Rausch, 2016; Campa & Camacho-Miñano, 2014). The behavior of earnings over the failure process is an interesting issue from the perspective of process variables. Most quantitative empirical studies use aggregate unexpected accruals to detect earnings management. In Finland, Kallunki & Martikainen (1999) concluded that income-increasing earnings management is an important variable for predicting financial failure. Kallunki & Martikainen measure the extent of EM prior to failure by the difference between reported earnings and adjusted earnings. These adjusted earnings are directly calculated from the income statement, meaning that the reported earnings are adjusted for depreciation in excess of the plan, changes in reserves, and changes in pension fund liabilities. In ORBIS, the data for small firms necessary to measure EM in these ways is very limited. Therefore, the intriguing question of the effect of EM on failure process variables is left for future research. This study focuses solely on reported traditional financial ratios.

3.2. Statistical Methods

In this study, binary logistic regression analysis is applied to first estimate the basic model of bankruptcy risk based on the three financial ratios as independent variables. Second, logistic regression analysis is used to estimate the process model with nine variables. In logistic regression analysis, the binary dependent variable $Y = 0$ when the firm is active (operating) and $Y = 1$ when it is bankrupt. Logistic regression analysis is useful in this study in several ways. It is simple and transparent, showing the separate effects of predictors on the conditional risk. It also has efficient statistical characteristics. The independent variables used to predict the dependent variable can be either continuous or categorical. Logistic regression analysis can also determine the percentage of variance in the dependent variable explained by the predictors. Additionally, it is a more general method than linear discriminant analysis, as it does not rely on the restrictive assumptions of multivariate normality and equal covariance matrices in both groups (Hosmer & Lemeshow, 1989). Logistic regression analysis creates a linear score (logit) L for each firm. In this study, this score is used in both the basic model and the process models to determine the conditional probability of bankruptcy as follows:

$$p(Y=1|X)=\frac{1}{1+e^{-L}}=\frac{1}{1+e^{-(b_0+b_1x_1+b_2x_2+\cdots+b_mx_m)}} \quad (3)$$

where b_i ($i=0, 1, 2, \ldots, m$) are the estimated intercept and the coefficients whereas x_i ($i=1, 2, \ldots, m$) are the independent variables. In the basic model, $m = 3$ which refers only to the basic dimensions of profitability, liquidity, and solvency whereas in the process model $m = 9$ referring to these three basic dimensions but also to their six (2×3) process variables. It is expected that the coefficients of significant form variables will be positive, while for significant level variables, negative coefficients are expected.

The three research hypotheses are tested using simple statistical methods. The analysis of the distributions of the tested variables showed that the variables are skewed and not normally distributed. Therefore, the statistical significance of the differences in the hypothesized variables between bankrupt and active firms is tested using the nonparametric median test. The nonparametric median test is applied to assess whether the medians from two independent populations are equal. The median test (Brown-Mood median test) is a special case of Pearson's chi-squared test.

Firstly, hypothesis $H1$ assumes that the time correlations of the financial ratios with the median of bankrupt companies (forms of the process) are higher in bankrupt companies than in active firms. This hypothesis is tested by first calculating the Pearson correlation coefficients for the time series of the three financial ratios used in the basic model (ROA, LRA, and SRA) for each firm separately. The median test is then used to test the significance of the difference in the median of the correlations between bankrupt and active firms.

Secondly, hypothesis $H2$ assumes that the cumulative differences between the financial ratios and their median value for the bankrupt companies (levels of the process) are higher for active companies than for bankrupt firms. The significance of the differences in the median of the cumulative differences is statistically tested again by the nonparametric independent-samples median test.

Thirdly, hypothesis $H3$ assumes that the inclusion of the process variables (forms and levels) in the model improves the performance of the prediction model. The improvement in performance is first assessed by the goodness-of-fit measures: Cox & Snell R^2, Nagelkerke R^2, and the Hosmer & Lemeshow test. Then, the classification abilities of the models are compared by the classification accuracy when the theoretically selected threshold value of conditional bankruptcy probability (the share of bankrupt companies in the sample) is used as the cutoff value.

Furthermore, the differences in the median probabilities yielded by the basic model and the process model for bankrupt and active companies were tested using the non-parametric related-samples (Wilcoxon) signed-rank test. The model's performance is considered improved by the contribution of the process variables if the estimated bankruptcy probabilities given by the process model are lower for active companies and higher for bankrupt firms. Finally, the ROC curve was calculated for both models for comparison. However, especially in cases where the number of bankrupt firms is very small compared to the number of active firms (imbalanced sample), ROC analysis can be skewed and may not provide reliable results, potentially leading to misleading conclusions (Lobo, Jiménez-Valverde, & Real, 2008). Therefore, only limited attention is given to the ROC analysis. The main focus of the assessment is on how including process variables in the model affects the differences in bankruptcy probabilities between active and bankrupt companies.

3.3. Empirical Results

Table 1 presents the time series of the three financial ratios for both bankrupt and active companies. Panel 1 shows the series for bankrupt companies. The medians of these time series are used as benchmarks when calculating the failure process variables: the correlation of the ratios to the median of bankrupt firms (form of the process) and the accumulated margin between the ratio and the median of bankrupt firms (level of the process). The downward trend in ROA (profitability) is strong and clear. However, the decline in LRA (liquidity) is not significant, except in the last year. The decline in SRA (solvency) is particularly pronounced in the last two years. Panel 2 presents the time series for active firms. The development of ROA is stable in the first three years but declines thereafter. The time series for LRA is stable across all six years. However, SRA gradually increases each period, indicating that Finnish companies are continuously improving their financial structure. For each year, the three ratios are consistently higher in active companies than in bankrupt companies. This suggests that these ratios contain significant information for predicting bankruptcy.

Table 1. Medians and quartiles of the three financial ratios in the process years 1 - 6.

Panel 1. Bankrupt companies (N = 147) in years 1 - 6 before the bankruptcy.									
	Return on assets (ROA)			Liquidity ratio (LRA)			Solvency ratio (SRA)		
Year	25	50	75	25	50	75	25	50	75
1	−36.870	−12.214	0.802	0.393	0.698	1.012	−28.234	4.324	16.756
2	−13.021	−1.135	6.465	0.455	0.803	1.099	−6.566	8.000	25.736
3	−9.510	0.438	10.927	0.489	0.903	1.276	−1.742	12.389	33.385
4	−7.574	2.500	8.047	0.547	0.815	1.209	2.083	14.797	36.142
5	−4.118	3.393	12.036	0.550	0.922	1.212	1.069	18.571	40.409
6	−3.218	3.075	10.145	0.618	0.990	1.304	2.128	16.524	40.728
Panel 2. Active firms (N = 23.386) in successive years 1 - 6.									
	Return on assets (ROA)			Liquidity ratio (LRA)			Solvency ratio (SRA)		
Year	25	50	75	25	50	75	25	50	75
1	0.622	7.793	17.203	0.793	1.283	2.124	26.466	46.932	67.166
2	1.167	8.513	18.052	0.802	1.284	2.098	25.555	45.805	65.601
3	1.667	9.385	18.992	0.827	1.311	2.142	25.559	45.598	65.723
4	1.750	9.449	19.811	0.824	1.325	2.170	24.883	45.095	65.385
5	1.704	9.168	19.534	0.772	1.255	2.090	22.901	43.447	64.276
6	1.796	9.570	20.276	0.779	1.250	2.057	21.351	42.135	63.331

Table 2 presents the medians and quartiles of the three financial ratios and the six process variables for the last year (for failed firms, the last year before bankruptcy). The table also shows the median test statistics and p-values to assess the research hypotheses H1 and H2. The form measures (FROA, FLRA, and FSRA) are significantly higher in bankrupt companies than in active companies, indicating that the financial ratios of bankrupt companies more closely follow the form of the benchmark process. For active companies, the median of FROA is positive, which may be due to the decline in profitability over the last two years. The statistical tests show that the median values of the process form measures (FROA, FLRA, and FSRA) are significantly higher in bankrupt companies than in active companies, supporting *H*1. Similarly, the median values of the process level variables (LROA, LLRA, and LSRA) are significantly lower in bankrupt companies than in active companies, supporting *H*2. The significance of the median tests is particularly high for the financial ratios and process level variables. The highest test statistics were obtained for SRA, LSRA, and LROA, indicating the high importance of long-term and annual profitability. However, LRA also reports a high value of the test statistic, indicating significant differences in liquidity between the groups.

Table 2. Medians and quartiles of the three financial ratios (last financial statements) and the six process measures.

	Bankrupt companies			Active companies				
Variable	25	50	75	25	50	75	Median test	*p*-value
ROA	−36.870	−12.214	0.802	0.622	7.793	17.203	78.365	0.000
LRA	0.393	0.698	1.012	0.793	1.283	2.124	90.443	0.000
SRA	−28.234	4.324	16.756	26.466	46.932	67.166	121.078	0.000
FROA	−0.023	0.477	0.818	−0.319	0.111	0.503	19.233	<0.001
FLRA	−0.079	0.474	0.733	−0.577	−0.047	0.492	28.928	<0.001
FSRA	−0.030	0.530	0.846	−0.736	−0.231	0.501	49.466	<0.001
LROA	−6.819	−1.051	4.996	3.507	9.591	17.079	90.561	0.000
LLRA	−0.274	0.023	0.380	0.020	0.495	1.283	61.821	<0.001
LSRA	−13.774	0.981	16.850	13.408	31.684	50.519	103.576	0.000

Legend: ROA = Return on assets ratio; LRA = Liquidity ratio; SRA = Solvency ratio; FROA = Time correlation of ROA with the median ROA of bankrupt companies (form); FLRA = Time correlation of LRA with the median LRA of bankrupt companies (form); FSRA = Time correlation of SRA with the median SRA of bankrupt companies (form); LROA = Average cumulative difference between ROA and the median of ROA of bankrupt companies (level); LLRA = Average cumulative difference between LRA and the median of LRA of bankrupt companies (level); LSRA = Average cumulative difference between SRA and the median of SRA of bankrupt companies (level).

Table 3 presents the logistic regression estimates for both the basic model and the (full) process model. Panel 1 shows the results for the basic model. The Wald test statistics indicate that SRA (solvency) is the most important ratio among the three financial variables, followed by ROA (profitability). LRA (liquidity) has the lowest test statistic, but its coefficient is still statistically very significant. The panel also includes the results of bootstrapping, which estimates the accuracy of the measurements by repeatedly sampling (1000 samples) from the original data.

These results suggest that the coefficients of the model are accurate, although there may be a slight negative bias in the coefficient of LRA. Panel 2 reports the estimation results for the process model, which includes nine independent variables. The results show only a few statistically significant coefficients. The Wald test statistics indicate that the most significant variable statistically is LSRA (level of solvency), followed by ROA (profitability). Additionally, almost statistically significant coefficients were found for LRA (liquidity), FROA (form of ROA), and FSRA (form of SRA). The bootstrap results in this panel show that the estimates of the coefficients are generally not accurate. However, the coefficients for ROA and LSRA appear to be clearly unbiased.

Table 3. Estimated logistic regression models for the basic model and for the full process model.

Panel 1. The basic model of three financial ratios.								
					Bootstrap (1.000 samples)			
Variable	*b* (expected sign)	Standard error	Wald test	*p*-value	*b*	Bias	Standard error	*p*-value
ROA	−0.023 (−)	0.004	41.645	<0.001	−0.023	0.000	0.004	<0.001
LRA	−0.483 (−)	0.168	8.278	0.004	−0.483	−0.011	0.148	0.002
SRA	−0.025 (−)	0.003	90.448	<0.001	−0.025	0.000	0.003	<0.001
Constant	−3.957	0.163	586.312	<0.001	−3.957	0.004	0.152	<0.001
Panel 2. The full process model of nine variables.								
					Bootstrap (1.000 samples)			
Variable	*b* (expected sign)	Standard error	Wald test	*p*-value	*b*	Bias	Standard error	*p*-value
ROA	−0.023 (−)	0.007	11.900	<0.001	−0.023	0.000	0.007	<0.001
LRA	−0.368 (−)	0.188	3.829	0.050	−0.368	0.009	0.184	0.053
SRA	−0.006 (−)	0.006	0.862	0.353	−0.006	0.000	0.006	0.311
FROA	0.540 (+)	0.275	3.845	0.050	0.540	0.002	0.269	0.036
FLRA	0.327 (+)	0.205	2.556	0.110	0.327	0.018	0.195	0.095
FSRA	0.385 (+)	0.211	3.315	0.069	0.385	0.004	0.187	0.045
LROA	−0.006 (−)	0.010	0.386	0.535	−0.006	0.001	0.010	0.542
LLRA	0.092 (−)	0.084	1.209	0.272	0.092	−0.055	0.151	0.324
LSRA	−0.028 (−)	0.007	14.111	<0.001	−0.028	0.000	0.007	<0.001
Constant	−4.357	0.207	443.280	<0.001	−4.357	−0.040	0.205	<0.001

Legend: See Table 2 for variables.

The inaccuracy of the coefficient estimates in the full process model may be due to the inclusion of several variables that may be correlated with each other. For example, ROA is strongly correlated with its form version (FROA), while LRA and SRA are significantly correlated with their level versions (LLRA and LSRA). To reduce the number of variables and their mutual correlations, a forward selection procedure was applied in the logistic regression. Table 4 presents the results for the logistic model estimated stepwise in this way. The forward selection model includes only five variables: ROA and SRA (financial ratios), FROA and FLRA (form variables), and LSRA (level variable). Bootstrap results suggest a small positive bias in FROA and FLRA. The findings show that the level of solvency (LSRA) is statistically more important than the financial ratio (SRA). For liquidity, the form of LRA (FLRA) is the only significant variable. In the regression model, ROA (profitability), LSRA (level of solvency), and FLRA (form of liquidity) are statistically the most significant variables.

Table 4. Forward selection logistic regression model with finally selected five variables.

					Bootstrap (1.000 samples)			
Variable	*b* (expected sign)	Standard error	Wald test	*p*-value	*b*	Bias	Standard error	*p*-value
ROA	−0.024 (−)	0.005	25.448	<0.001	−0.024	0.000	0.005	<0.001
SRA	−0.013 (−)	0.005	8.058	0.005	−0.013	0.000	0.005	0.003
FROA	0.504 (+)	0.239	4.459	0.035	0.504	0.005	0.236	0.029
FLRA	0.615 (+)	0.181	11.521	<0.001	0.615	0.000	0.179	<0.001
LSRA	−0.023 (−)	0.006	14.432	<0.001	0.023	0.000	0.006	<0.001
Constant	−4.617	0.123	1398.560	<0.001	−4.617	−0.016	0.130	<0.001

Legend: See Table 2 for variables.

Table 5 reports the performance measures for each logistic regression model. The full process model has the highest Cox & Snell and Nagelkerke R-squares, followed by the forward selection model. However, the improvement in the R-squares of the basic model is not very significant. The Hosmer & Lemeshow test shows clearly better results for the process models, as the p-values for these models are significantly higher. For the theoretical cutoff probability of 0.006 (the share of bankrupt companies in the sample), the percentage of correct classifications (for all companies) is highest for both the forward selection and full process models. However, for this cutoff value, the basic model gives the highest percentage of correct classifications for bankrupt companies. The table also indicates that the area under the ROC curve (AUC) is almost identical for each model. In this case, where the sample is strongly imbalanced, the importance of the AUC is limited. Figure 1 shows the ROC curves for the basic and process models, with only small differences between the curves.

Table 5. Performance of the estimated logistic regression models.

				Percentage of correct classifications§			
Cox & Snell R Square	Nagelkerke R Square	Hosmer & Lemeshow test	*p*-value	Active companies	Bankrupt companies	All companies	Area under ROC curve (AUC)
The basic model of three financial ratios							
0.015	0.205	11.145	0.194	77.9	83.7	77.9	0.891
The full process model of nine variables							
0.016	0.218	5.006	0.757	79.3	80.3	79.3	0.891
Forward selection logistic regression model with finally selected five variables							
0.016	0.213	7.021	0.534	79.6	82.3	79.6	0.890

Legend: §: Cut-off probability = 0.006; §: Cut-off probability = 0.006.

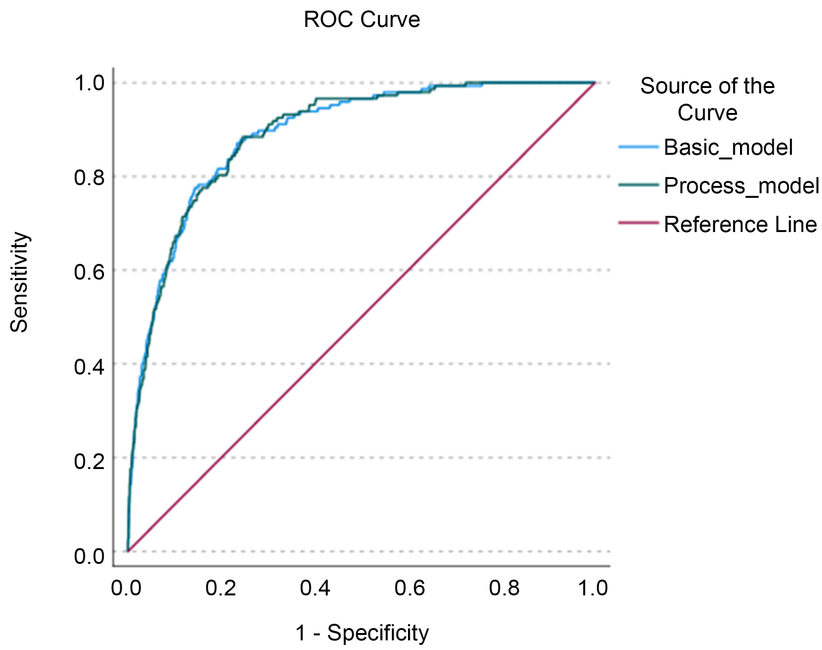

Figure 1. The ROC curve of the basic model and the process model.

Table 6 reports the distributions of the predicted bankruptcy probabilities from the three logistic regression models. Panel 1 shows the medians and quartiles of the bankruptcy probabilities. For the bankrupt companies, the median probability is clearly highest for the process model, followed by the five-variable (forward selection) model. The basic model yields the lowest probabilities. However, in the tails of the distributions (quartiles), the differences in probabilities between the models are smaller. Similarly, the bankruptcy probabilities for the active companies are lowest for the process model and the forward selection model. Panel 2 presents the results of the related-samples Wilcoxon signed-rank test. First, the test indicates that the difference between the paired observations in the bankrupt firms is not zero when comparing the probabilities from the basic model and the process model. Second, this result also holds for the probabilities from the basic model and the forward selection model. In summary, empirical evidence supports research hypothesis *H*3, which states that the process variables (form and level of the process) improve the performance of the bankruptcy prediction model based solely on financial ratios.

Table 6. Distributions of the predicted bankruptcy probabilities for the three models.

Panel 1. Medians and quartiles of the conditional bankruptcy probabilities.						
	Bankrupt companies			Active companies		
Model	25	50	75	25	50	75
Basic model	0.00913	0.01591	0.04969	0.00093	0.00250	0.00574
Process model	0.00879	0.01981	0.05475	0.00065	0.00188	0.00518
Forward selection model	0.00839	0.01823	0.05337	0.00086	0.00205	0.00518

Continued

Panel 2. Comparison of the medians of the probability distributions.			
Related-Samples Wilcoxon Signed Rank Test Summary			
Bankruptcy companies		Active companies	
Basic model versus full process model			
Standardized Test	3.761	Standardized Test	−40.440
p-value§	<0.001	*p*-value§	0.000
Basic model versus forward selection model			
Standardized Test	2.404	Standardized Test	−18.514
p-value§	0.016	*p*-value§	0.000

§: Asymptotic significance (2-sided test).

Thus, the empirical evidence is consistent with previous studies, which highlight the crucial role of profitability as a predictor for the performance of a failure prediction model. Moreover, long-term profitability, as reflected by the solvency ratio, plays a central role in predicting failure. The results of this research are novel in that they demonstrate the effect of the process of financial ratios on failure risk. For prediction, the form of the return on assets ratio process is relevant, in addition to the value of the ratio in the last year. Similarly, the importance of the solvency ratio is emphasized by the high significance of the level of the ratio process in prediction. The results also show the relatively minor importance of the liquidity ratio in a financial ratio model but reveal a novel finding: the form of the liquidity ratio process is highly significant. This clearly shows that the liquidity ratio for a single year is not as important in assessing bankruptcy risk as the dynamics of the ratio. This explains why the liquidity ratio has not been a particularly significant predictor in previous traditional studies. To conclude, in bankruptcy prediction, the form of the process is important for both the return on assets and liquidity ratios, whereas the level of the process is important for the solvency ratio.

4. Summary of the Study

Previous studies have found that, as bankruptcy approaches, financial ratios in distressed companies follow a specific trajectory due to strong path dependence. These studies indicate that there are generally three types of failure paths or processes. However, all of these processes share the common feature that the most important financial ratios weaken as bankruptcy approaches, although there are differences in the timing and intensity of the deterioration. In this study, a simple method was developed to account for the failure process. First, the median failure process (benchmark process) was constructed over time using the medians of the key financial ratios of bankrupt companies. Second, the development of financial ratios in bankrupt and active firms was compared to this median process. The variables describing the failure process were divided into two categories: the first measures the form of the process, and the second measures the level of the process. By adding these variables to the model along with the financial ratios, a hybrid model was created that considers both the ratios and the form and level of their processes. The form of the process was measured by the time correlation of the financial ratios with their benchmark process (the median of bankrupt companies), while the level of the process was measured by the cumulative difference of the ratios from their benchmark median values.

The process model developed in this study was tested with empirical data consisting of 147 bankrupt Finnish companies and 23,386 active companies. The results supported the hypotheses, as the development of the key financial ratios of bankrupt companies more clearly corresponded to the form of the benchmark process (H1), and their level was higher in active companies (H2). The hybrid model, which included both financial ratios and process variables, also performed statistically more efficiently than the basic model based solely on the ratios, although the differences between the models were not large (H3). In addition to improving forecasting accuracy, the hybrid model also provides qualitative results that offer an interpretive understanding of which factors affect bankruptcy risk. Using the forward selection logistic regression model, it was shown that the profitability of the last financial statement and the form of its process, solvency and its process level, and the form of the liquidity process primarily affect failure risk. The importance of solvency is significantly influenced by the level of its process, while the importance of profitability and liquidity is complemented by the form of their processes (temporal development). In summary, the process information of financial ratios can be used to improve the quality of bankruptcy prediction.

The present research has several implications for failure prediction research. It shows that, although some financial ratios are not statistically significant predictors of failure, their process can provide important information that is useful in prediction. The liquidity ratio is a good example of such a financial ratio. For prediction, it is important to consider how the liquidity ratio behaves over time (the form of the process), whereas the pure (last-year) value of the ratio may play a minor role. However, for the solvency ratio, the difference in its level between failing and active firms is so significant that the level of the ratio process plays an important role in prediction. Thus, in failure prediction, it is important to assess the significance of the process variables in addition to the pure values of the financial ratios.

This study thus provides new and interesting insights into the importance of the process in predicting bankruptcy. However, the study has several limitations that could be addressed in future research. In this study, only two types of simple process metrics (form and level) were used, but these could be developed into more complex measures in future studies. Additionally, there are other options besides the median of bankrupt companies to describe the benchmark process. The length of the process in this study was six years, but it could be extended or shortened in future research to test the effect of the process length. Financial ratios other than those used in this study, such as cash flow ratios, could also be included in the model. Moreover, other statistical methods besides logistic regression analysis could be applied in modelling. The empirical data could be diversified by considering non-Finnish companies, and the sample could be made more balanced, in which the use of the ROC curve to assess classification ability would be more meaningful than in this study. Finally, it would be interesting to analyze how earnings management (EM), such as through accruals, influences the significance of the process in failure prediction.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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