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Detecting zombie firms in a sample of Finnish small firms

Erkki K. Laitinen

School of Accounting and Finance, University of Vaasa, Vaasa, Finland

Correspondence
Erkki K. Laitinen, School of Accounting and Finance, University of Vaasa, Wolffintie 34, FI-65200 Vaasa, Finland.
Email: erkki.k.laitinen@uwasa.fi

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Abstract

The objective of the study was to develop a method to detect zombie firms in a sample of mainly very small companies. The original sample consisted of 70,809 active and 134 bankrupt Finnish companies (or firms in insolvency proceedings) for 2018–2020. In the sample firms, the median number of employees was only 2. First, a logistic regression model to measure bankruptcy risk was estimated using three financial ratios as independent variables reflecting profitability, liquidity and solvency. Zombie firms were defined as active companies which are technically bankrupt but are still operating in the market. Second, following this definition, the model was used to assess the bankruptcy risk of active firms, and a zombie company was operationally defined as an active company whose bankruptcy risk exceeds the median for bankrupt companies in three consecutive years. In this way, over 2000 zombie companies were detected making in total 3.5% of the active companies.

1 | INTRODUCTION

The aim of this study is to develop a method to detect zombie firms in a sample of mainly very small companies. It is required that the method can be used to identify zombie companies from a dataset, using only financial statement data, even of small firms.

Zombieism can be regarded as a phenomenon that describes the existence of companies that are technically insolvent but continue to live on due to unusual market conditions, financial institutions and investor or government support (Altman et al., 2024). In recent years, Zombieism has sparked a lot of discussion among economists, which is why several studies have been conducted on the subject from different perspectives (Acharya et al., 2019; Adalet McGowan et al., 2018; Andrews & Petroulakis, 2019; Banerjee & Hofmann, 2022; Caballero et al., 2008; Schivardi et al., 2022). Zombie firms are usually unprofitable, indebted and financially distressed firms that live in this kind of state for years, but neither grow nor die. These unproductive and unviable zombie companies have significant negative macroeconomic implications, as they can receive public support to keep them alive and avoid or delay a necessary creative destruction process (Albuquerque & Iyer, 2023). If lenders fail to properly recognise loans to zombie firms as nonperforming, they can extend credit to these firms to keep them alive. This creates congestion effects on healthier competitors, thus reducing productivity, investment and employment in the economy. Therefore, it is important to develop efficient methods to detect zombie firms whatever size firms have.

This paper has two main challenges for detecting zombie firms. First, in previous studies on zombie companies, the goal has usually been to find out the ratio of zombie companies of all companies and to explain this ratio with the macroeconomic variables of the countries. Researchers have used different methods in their studies to identify zombie companies, but they may not work well for very small companies. For example, Altman et al. (2024) found that democratic accountability, financial market development, creditor rights and debt enforcement efficiency explain cross-country variations in zombie ratios. They also found that the zombie ratio in a country declines after the reform of the bankruptcy code. Albuquerque and Iyer (2023) evidence that the financial performance of non-zombie firms is reduced in industries populated with a higher ratio of zombie firms. However, conducting such studies requires the availability of long time series data from several comparable countries. Altman et al. (2024) compiled a comprehensive data sample that encompasses all publicly traded nonfinancial firms from 1990 to 2020 in the World Bank's top 20 economies. Albuquerque and Iyer (2023) had a sample of listed firms from 63 countries over 2000–2021and private firms from 43 countries over 1997–2020. This study only uses short time series data from Finland, from the period 2018–2020. Therefore, the purpose of this study is not to study the temporal development of the share (ratio) of zombie companies or to compare the shares of different countries.

The second challenge of this paper is focused on small firms. Prior studies are mostly based on data from large public companies which have very informative financial statements and in general little missing information. However, financial behavior and availability of financial data are significantly different in small companies which are often neglected in empirical research. This means that the methods developed for large public firms are generally not applicable in small business sample. In this study, the method for finding zombie companies is primarily based on a statistical model, which is developed in the same material being evaluated, so that its functionality can be verified. In this statistical model, the company's profitability, liquidity and solvency measures are used as variables, so that the company's viability can be measured in a versatile way. The statistical model is based on a comparison between bankrupt companies and operating (active) companies, and as a result, it produces an estimate of the conditional probability of the company's bankruptcy. Then, a company is considered a potential zombie company if its probability of bankruptcy exceeds the probability of a typical bankrupt company (median bankrupt company) for three consecutive years. In this method, a total of 2178 (3.5%) zombie companies were found in the Finnish company database, which consists of a total of 57,821 (non-missing) active companies. This number (ratio) roughly corresponds to the number of zombie companies that Albuquerque and Iyer (2023) identified in their own study from Finnish data.

Therefore, the contribution of this research is twofold. First, the objective is to develop a new method for identifying zombie companies. Second, it is required that the method can be effectively used in a dataset that mainly consists of very small private companies. This is important because, in almost all countries, small businesses play an essential role in the economy of the entire country, according to the World Bank. This study is based on empirical evidence from Finland, where there is a very large number of small micro-companies. In 2021, there were a total of 562,542 companies in Finland, of which 526,150 companies (93.5%) employed only 0–4 employees or entrepreneurs (Statistics Finland, Enterprise Statistics, 2023). Therefore, it is important in countries like Finland to develop a method for identifying zombie companies that is applicable for very small micro-companies.

Policy Implications

- Logistic regression analysis is an effective tool for private and public financiers to detect zombie firms which do not add any value.
- Private and public financiers can develop an efficient model for detecting zombie firms using only financial statement data.
- Private and public financiers can use the logistic regression model also to detect very small zombie firms usually excluded.
- Private and public financiers can use the model to detect firms which should not be financed by any financers.
- Private and public financiers can use the model to detect firms which are misclassified by failure detection models.
- Private and public financiers can use the model to detect firms which should be filed into bankruptcy.

This research report is divided into five different sections. In this introduction, the objective and contribution of the research were briefly explained. In the second section, earlier studies are discussed in more detail and their pros and cons in recognising zombie companies are compared. In the third section, the sample material used in the research is presented in more detail as well as the statistical methods. In the fourth section, empirical results of the application of the model are presented and the characteristics of the detected zombie companies are evaluated. The last section summarises the study and give outlines for future research.

2 | FRAMEWORK FOR THE STUDY

The identification of zombie companies has become an important area of research in recent years, and therefore, a lot of scientific research has been done on it from different perspectives. The aim of the studies has usually been to identify zombie companies either (i) among listed companies from several countries (Altman et al., 2024; Banerjee & Hofmann, 2022; Caballero et al., 2008) or (ii) among listed and private companies using pooled data from several countries (Acharya et al., 2019; Adalet McGowan et al., 2018; Andrews & Petroulakis, 2019; Schivardi et al., 2022). In the latter studies, the material is usually treated as a single sample, and the occurrence of zombie companies is not compared among listed and private companies. However, there are recent studies that provide comparative information about the share of zombie firms in samples of public and private firms (Albuquerque & Iyer, 2023; Favara et al., 2022).

There are several ways to detect zombie firms adopted in prior studies. Albuquerque and Iyer (2023) and Favara et al. (2022) define zombie firms as firms that are likely both in financial distress and unprofitable. Albuquerque and Iyer (2023) selected as zombie firms those that have for at least two consecutive years: (i) an ICR below one, (ii) a leverage ratio above the median firm in the same industry and (iii) negative real sales growth. The authors regarded the first two indicators as somewhat standard in the literature to capture financial distress, but considered the third indicator essential to ensure that only those firms were selected that are also persistently unprofitable. The authors argued that the two-year horizon minimises misclassification from cyclical fluctuations. This definition departs from the original one proposed by Caballero et al. (2008), who focus on a concept of subsidised interest rates for Japanese firms.

Altman et al. (2024) adopted a different procedure to detect zombie firms. They proposed a two-step filtering process to determine zombie firms using (i) an accounting-based measure and (ii) a default predictor. The authors use as an accounting measure ICR due to calculation simplicity and data availability. In their definition, zombie firms refer to those with less-than-one ICR, defined as EBIT/Interest or EBITDA/Interest. Intuitively, a firm that is unable to create sufficient earnings or cash flows to meet its interest payments, but is able to survive for a few years, should be classified as a zombie. However, the authors consider ICR alone too aggressive, since many even B-rated companies have ICR less than 1.0 for several consecutive years meeting the definition. Actually, they found an increasing occurrence of firms with a coverage ratio of less than one over the past 20–30 years. Therefore, they chose for the second filter one of the most popular default/bankruptcy prediction models, the Altman *Z*-score model. This model was aimed to help accurately identify financially distressed firms that are close to being in default. Finally, Altman et al. (2024) designated any firm with a three-year moving average of interest coverage (IC) less than one, and a three-year moving average *Z*-score below zero, as a zombie firm to avoid measurement error resulting from temporary fluctuations of firm performance.

This study uses a method that most closely resembles the approach adopted by Altman et al. (2024) in identifying zombie companies. The fundamental difference between the company samples used in this study and previous studies is that almost all the companies here are private, very small companies, whereas in previous studies, they are larger and often listed. Therefore, the problems identified by the researchers in the use of the ICR measure are significantly emphasised in this study. A particularly difficult problem is the quality of accounting information for small companies, which is often remarkably weak and misleading (Balcaen & Ooghe, 2006; Dirickx & Van Landeghem, 1994; Ooghe & Joos, 1990). There is also a problem with the missing observations, because the financial statements of very small companies are often so aggregated that key ratios cannot be calculated precisely due to the missing details in the financial statements. In this study, missing observation limits the use of several standard financial ratios. The database ORBIS used in this study can also cause problems in this regard (Bureau van Dijk, 2023). Albuquerque and Iyer (2023: 11) who also used the ORBIS database in their research had to calculate the ICR as EBITDA (earnings before interest, taxes, and depreciation) over interest expenses due to the lack of data on EBIT (earnings before interest and taxes). It is clear that the identification of zombie companies is essentially influenced by which concept is used in the identification. Missing observations are difficult to handle and they lead to the situation that the number of observations in a statistical analysis depends on which variables are used. Anyway, the clear advantage of using ORBIS database is that data entries from all types of firms are standardised and easily accessible. However, the disadvantage is that the standardisation comes at the cost of losing information. Due to the classification procedures, ORBIS aggregates financial statement data and only provides a limited number of different line items for asset, capital and income statement (Beuselinck et al., 2023: 51). This is especially limiting when very small firms are considered.

Altman et al. (2024) adopted a failure prediction model (Altman *Z*-score) in the process of selecting zombie firms. This model is based on four ratios referring to liquidity, solidity and profitability. In failure prediction research, small firms are often neglected. This neglecting is a consequence of the fact that annual accounts may especially in small firms be unreliable because of the lack of an internal control system or because of annual account adjustments made by the auditor in the light of a bankruptcy filing. Because of the unreliability of annual account information, small business failure prediction models based on financial ratios may be distorted and their practical usefulness may be limited (Balcaen & Ooghe, 2006: 82). In estimating the original Z-model, Altman (1968: 593) used data from manufacturing companies emphasising the asset-size group to be sampled. Altman eliminated both the small firms (under $1 million in total assets) and the very large companies from the sample essentially due to the asset range of the bankrupt firms. Altman justified this elimination saying that the incidence of bankruptcy in the large asset-size firm is quite rare, while the absence of comprehensive data negated the representation of small firms.

The present study also uses a failure risk model to assess the financial distress of the potential zombie firms. However, the study does not use the (Altman) *Z*-score model, but rather tailors the risk model specific using a statistical method based on the company data of the study, to ensure the performance of the approach. In fact, Altman and Sabato (2007) estimated a specific SME model and showed that its performance in terms of prediction accuracy was clearly higher than that of the generic corporate model. They concluded that small- and medium-sized enterprises are significantly different from large corporates from a credit risk point of view. Later, Altman et al. (2010) confirmed these results. The use of a failure risk model to detect zombie firms is justified, since zombie companies actually closely resemble bankrupt companies whose bankruptcy process takes a long time (Lukason & Laitinen, 2019).

Laitinen (1991) identified three failure process types, which he called acute, chronic and revenue financing failure firms. From these process types, the chronic failure firm was such that all of the company's key indicators were weak for at least 4 years before the bankruptcy. The company was therefore a "zombie" or "walking dead" for at least 4 years before bankruptcy. There were no difficulties in predicting the company's bankruptcy at least 4 years before the bankruptcy, as the high bankruptcy risk was detectable with most of the individual indicators or combination risk measurement models. These chronic failure companies were a total of 32.5% of Laitinen's small sample of Finnish firms. This type of long-lasting failure process has a clear connection with the type presented by D'Aveni (1989), to which the author gives the title "lingeringly failing firm." The failure firms classified as lingerers were non-viable for a long time before bankruptcy declaration. Thus, empirical studies imply that chronically or lingeringly failing firms have much in common with zombie firms. Therefore, it is natural to use a failure risk measurement model to detect zombie firms.

Albuquerque and Iyer (2023) required in their third filter that the potential zombie firm should have a negative real sales growth. Empirical studies that have analysed the relationship between company size and growth have shown that the so-called Gibrat's law, according to which company growth rates are independent and identically distributed in each size classes, does not hold. In size classes of smaller firms, the volatility of the growth rate is systematically clearly higher than in larger size classes (Reichstein & Jensen, 2005). Thus, in very small firms the growth process (as measured by a change in employment, sales, assets or profits) is largely a stochastic process around the origin (zero growth). This is why it is largely a random coincidence if the growth rate of a very small company exceeds or falls below zero for several years in a row. Stochastic growth also means that the key ratios calculated from the financial statements of very small firms have a lot of variation as a time series (volatility is high), which makes it difficult to use them in the company's financial distress analysis (McLeay & Stevenson, 2009).

High volatility is especially related to flow-based financial statement variables calculated from the income statement and its transformations (sales margin, EBIT, EBITDA, cash flow), which do not have a structure that accumulates over time. The structural variables calculated from the balance sheet (asset, liability) accumulate over a long period of time and are not affected as strongly by annual fluctuations. For this reason, the method for identifying zombie companies being developed in this study emphasises key figures calculated from balance sheets, such as quick ratio and equity ratio, which can be used to measure the liquidity (short-term solvency) and (long-term) solvency of the companies in the sample. Albuquerque and Iyer (2023: 10–11) also use ICR and the leverage ratio (debt to total assets) in addition to real sales growth, to assess the constraint of potential zombie firms in raising additional debt.

The basic problem with the use of data from private companies is the clearly lower quality and availability of accounting information than in the data from listed companies. In addition to this, the material of private companies only contains financial statement information published annually, while quarterly materials can be used in the evaluation of listed companies. For these reasons, for example, Altman et al. (2024) used a comprehensive data sample that only encompassed all publicly traded nonfinancial firms from 1990 to 2020 in the World Bank's top 20 economies by GDP in 2019. Their final sample had 431,539 unique firm-year observations. However, Albuquerque and Iyer (2023) assessed and compared the incidence of zombie firms between listed and private firms for a large set of Advanced Economies (AEs) and Emerging Markets (EMs). Their final sample of listed firms covered an unbalanced panel of 42,760 nonfinancial firms over 2000q1–2021q4, resulting in 1,770,521 firm-quarter observations. Their final sample of private firms covered 43 countries (26 AEs and 17 EMs) in an unbalanced panel of 4,394,313 nonfinancial firms over 1997–2020. Thus, the researchers showed that it is possible to compare the share of zombie firms between public and private firms in spite of the differences in information quality, availability, coverage and frequency.

In this study, the second line of recent zombie research is followed so that the data from both public and private firms are used as pooled in the same sample extracted from the ORBIS data base. In this way, it is possible to achieve comparability between companies, as the financial statements of the companies have been prepared according to the same principles and the same indicators (financial ratios) have been calculated for all companies. The research data cover 136 public companies and (approximately) 70,807 private or delisted companies in the years 2018–2020, so there is a total of approximately 212,829 company-year observations. The number of companies is not the same in all statistical analyses, as the database has a relatively large number of missing observations due to the inaccuracy of the financial statements of small firms. The coverage of the observational data is good, as it includes all (corporate) public firms and about 13.5% of all companies in the country. The main limitation is that the sample is restricted to limited companies, whose financial statements are legally public. The size structure of the firms in the data corresponds to the size structure of all companies in Finland, as most of the companies are very small. Due to these limitations, the objective of the research is operationally specified to develop a method for recognising zombie limited companies in the sample where the majority of companies are very small.

In summary of previous studies, it can be stated that most methods used to identify zombie companies are based on the key figure ICR. However, ICR potentially works unreliably in SME samples, especially in very small companies due to missing data and volatility. ICR is based on the company's profitability (EBIT) and solvency (interest rate), which can in the data of small companies be measured more reliably directly with profitability and solvency indicators. The zombie firm detection models have also used company growth as a constraint, which is difficult to apply in very small companies due to volatility in growth. In addition to these indicators, the leverage ratio referring to the long-term solvency has been used as a constraint in the models. Since this indicator is based on the balance sheet (debt, total assets), it is also justified for evaluating the financial distress of very small companies. This indicator is closely related to solvency ratio (equity ratio) leading to parallel results.

The models used in prior zombie studies also include a combined measure (*Z*-score) based on several indicators, which can be used to assess financial distress and failure risk more precisely. Using a combined model is potentially a good idea, because the volatility of the combination is usually lower than the volatility of the individual indicators. However, in order to work effectively in the sample of this study, the combined model should be fresh and tailored specifically for measuring the riskiness of very small companies. In this study, the combined model will be adopted to detect zombie firms. This risk measurement model is to be estimated from the current material of small companies to specify it reliably to reflect risk in the sample firms. Thus, the estimated model assesses specifically the riskiness of target companies in order to identify small zombie companies. This combined model consists of indicators of profitability, liquidity and solvency, which are theoretically and empirically justified, and based on the balance sheet. Since the volatility of very small companies is high, it may be that a 2-year horizon does not minimise misclassification from cyclical fluctuations. Therefore, it is required in this study that the risk of zombie companies in three consecutive years is higher than the risk of a typical (median) bankrupt company. If necessary, this condition can also easily be accompanied with additional filtering conditions, for example for ICR as is done in Altman et al. (2024).

3 | EMPIRICAL DATA AND METHODS

3.1 | Sample

The basic problem with the use of data from private companies in prior literature is the clearly lower quality and availability of accounting information than in the data from listed companies. In addition to this, the material of private companies only contains financial statement information published annually, while quarterly materials can be used in the evaluation of listed companies. For these reasons, for example, Altman et al. (2024) used a comprehensive data sample that only encompassed all publicly traded nonfinancial firms from 1990 to 2020 in the World Bank's top 20 economies by GDP in 2019. However, Albuquerque and Iyer (2023) assessed and compared the incidence of zombie firms between listed and private firms for a large set of Advanced Economies (AEs) and Emerging Markets (EMs). Their final sample of private firms covered 43 countries (26 AEs and 17 EMs) in an unbalanced panel of 4,394,313 nonfinancial firms over 1997–2020. Thus, the researchers showed that it is possible to compare the share of zombie firms between public and private firms in spite of the differences in information quality, availability, coverage and frequency.

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includes all (corporate) public firms and about 13.5% of all companies in the country. The main limitation is that the sample is restricted to limited companies, whose financial statements are legally public. The size structure of the firms in the data corresponds to the size structure of all companies in Finland, as most of the companies are very small. Due to these limitations, the objective of the research is operationally specified to develop a method for recognising zombie limited companies in the sample where the majority of companies are very small.

The sample for the study is extracted from the ORBIS database of Bureau van Dijk (BvD) (Bureau van Dijk, 2023). The selection of the sample was made under the restriction that the selected company must be Finnish and have successive financial statements available for at least 3 years, last year being 2020. The purpose of the study is to develop a model to identify zombie firms in a sample of typical Finnish firms that is mainly consisted of small and micro-firms. Therefore, any restrictions for the size and the industry of the selected enterprises were not set to get as representative sample as possible. The original sample included in all 77,294 firms from all size classes and most NACE Rev. 2 industries. The sample was however in further steps limited to include only (private and public) limited companies (legal form) and corporates (industrial firms). For instance, all partnership firms, proprietorship firms, public authorities and non-profit companies were excluded, mainly due to the lack of comparable financial data. Furthermore, banks and financial institutions, insurance companies, and pension funds were excluded due to the incomparability with industrial firms. The resulted sample included in all 74,854 active firms, one active firm with default of payment, 13 active firms in insolvency proceedings, 123 bankrupt firms, 1612 dissolved firms, seven merger or take-over firms and 684 firms in liquidation.

In order to derive the combined statistical model, two different groups of companies were formed: (i) active companies and (ii) high-risk companies, which were consisted of bankruptcy companies and companies in insolvency proceedings. The definition of insolvency is technically similar to bankruptcy, since an insolvency proceeding is a process taken when an organisation is no longer able to meet its financial obligations and pay its creditors when debts are due. In Finland, restructuring proceedings under the Restructuring of Enterprises Act may be undertaken in order to rehabilitate a distressed debtor's viable business, to ensure its continued viability and to achieve debt arrangements. In practice, bankrupt firms and firms in insolvency proceedings in Finland are similar very high-risk companies. However, the financial risk of companies whose status in ORBIS is default of payment, dissolved or in liquidation is not necessarily high, and they cannot be included either in the high-risk group or the group of operating companies. The final research sample contains 70,809 active firms, 13 firms in insolvency proceedings and 121 bankrupt firms, of which the latter two form the high-risk group (13 + 121 firms).

The companies in the sample of this study are on average very small. Since there are only a few large companies in the sample, the company size distributions are positively skewed. The median net sales of the companies in 2020 are only 142 TEUR, while the average is as high as 5690.59 TEUR. In the same year, the average number of employees in companies is 33.1, but the median is only 2. This means that half of the companies are companies with 1–2 employees. In fact, 17% of the companies are led by a sole entrepreneur without any employees. Due to the skewness of the size distribution, only 5% of the firms have more than 45 employees. The average of total assets in 2020 is 5859.49 TEUR, but the median is only 122 TEUR. In general, the median size of the companies in the risk group is somewhat larger than in operating (active) companies, but the differences are not statistically significant. The median number of employees in 2020 is 2 in active firms, but 3 in the high-risk companies. However, the mean number is clearly higher in active firms (33.2) than in high-risk firms (8.0), because there are a number of active large firms but only few large high-risk companies.

The classification of the sample firms across industries is here made applying the broad structure of NACE Rev. 2 on the main industry of the company. NACE is the statistical classification of economic activities in the European Community being the subject of legislation at the European Union level, which imposes the use of the classification uniformly within the member states (Eurostat, 2021, October 17). The largest frequencies of the companies are found in the NACE industries 13 M Professional, scientific and technical activities (18.3%); 7 G Wholesale and retail trade; repair of motor vehicles and motorcycles (15.6%); and 6 F Construction (13.9%). The proportion of traditional manufacturing enterprises (3 C Manufacturing) is only 7.80%. In the population, the proportion of the firms carrying out professional, scientific and technical activities (13 M) is in the population only 10.2%, while the proportion in the sample is 18.3% (Statistics Finland, 2023, March 29). For 7 G, these proportions are respectively 10.8% and 15.6%. The differences in the industry distributions between the present sample and the population are due to restrictions set to the companies selected into the sample.

3.2 | Model construction

The present approach to detect zombie firms is based on a logistic regression model composed of financial ratios. These ratios are selected using both theoretical justification and results from empirical studies in prior financial risk research (Balcaen & Ooghe, 2006; Bellovary et al., 2007; Shi & Li, 2019). The dimensions of financial risk are usually theoretically classified as profitability, liquidity (short-term solvency) and solidity (long-term solvency). Therefore, the model will be based on three financial ratios reflecting these basic dimensions. Appendix A presents a short list of ORBIS financial ratios that from different perspectives measure these three basic dimensions. However, a challenging problem in this context is that many variables in all three variable groups have a large number of missing observations in the estimation data as is typical for small company samples.

The combined logistic model is estimated on the 2019 data, since it is representative and not yet affected by COVID-19. In the next year, COVID-19 already had an influence on the financial conditions of companies, which could affect the estimation results and make the results biased. The proportions of missing observations in the 2019 data were, for example, for ORBIS variables Gross margin 99.8%, Shareholders liquidity ratio 59.2%, ICR 57.0%, Gearing 50.7%, EBITDA margin 43.3% and Cash flow to operating revenue 38.6%. Therefore, these variables cannot be used in estimating the model due to number of missing observations. The data also include a number of outliers and extreme values due to the large number of very small firms. For the statistical analyses, all model variables were winsorised at the 2.5/97.5 percentiles level to minimise the impact of extreme outliers as is done in Albuquerque and Iyer (2023).

In the present study, (binary) logistic regression analysis (LRA) is applied to estimate the bankruptcy risk measurement model based on a set of three financial ratios as independent variables. In this estimation, the dependent variable $Y=0$ when the firm is active (operating) and $Y=1$ when it is bankrupt (or in insolvency proceedings). LRA can be used to predict a dependent variable on the basis of continuous or categorical independent variables and also to determine the per cent of variance in the dependent variable explained by the independent variables. LRA does not require that independent variables are multivariate normal or that groups have equal covariance matrices that are basic assumptions in linear discriminant analysis (Hosmer & Lemeshow, 1989). LRA creates a linear score (logit) L for every firm. This score is used to determine the conditional probability to become bankrupt as follows:

$$p(Y=1|X) = \frac{1}{1+e^{-L}} = \frac{1}{1+e^{-(b_0+b_1x_1+b_2x_2+b_3x_3)}} \quad (1)$$

where b_i ($i=0,1,2,3$) are estimated coefficients and x_i ($i=1,2,3$) are the three independent variables referring to the basic dimensions of profitability, liquidity and solvency.

The three financial ratios to the logistic regression model were selected by both theoretical and empirical reasons. First, the most important key figure in measuring risk is Solvency ratio (Equity ratio), which alone (in univariate analysis) in this sample correctly classified 77.4% of bankruptcy companies and 78.4% of active companies. This solvency ratio is based on balance sheet items, which makes it more robust than ratios based on a flow concept. Thus, Solvency ratio was selected to the logistic model. Second, the next most important dimension of financial distress is profitability. The indicators of profitability are composed of different margins and return on asset ratios. In the comparison between key ratios, Return on total assets turned out to be the most effective profitability ratio. This indicator has a good theoretical basis, as it is often used as an approximation of real profitability, the internal interest rate (Brief, 2013). In addition, it is not as sensitive to volatility as margins, as its denominator is based on balance sheet items. Thus, Return on total assets was selected to the logistic regression model to reflect profitability.

TABLE 1 Percentiles of relevant variables from 2019 in bankrupt firms and active firms.

		Percentiles						
	Group	**5**	**10**	**25**	**50**	**75**	**90**	**95**
Quick ratio	Active firms	0.11	0.25	0.72	1.60	4.00	10.50	19.86
	Bankrupt firms	0.05	0.08	0.20	0.46	0.97	1.64	3.82
Return on total assets	Active firms	−34.15	−16.67	−1.11	5.98	18.58	35.00	48.28
	Bankrupt firms	−54.53	−54.53	−36.24	−12.24	2.28	15.47	35.48
Solvency ratio	Active firms	−14.29	3.26	26.67	60.00	87.50	98.95	100.00
	Bankrupt firms	−44.44	−44.44	−19.30	5.07	20.11	63.13	79.13
Interest coverage ratio	Active firms	−14.00	−6.00	0.33	4.81	19.00	62.00	117.00
	Bankrupt firms	−25.85	−25.85	−9.00	−2.33	1.15	6.10	10.10
Growth rate in net sales	Active firms	−62.14	−40.82	−14.16	0.57	18.29	58.96	117.31
	Bankrupt firms	−62.30	−43.61	−24.92	−3.03	15.94	53.98	214.74

Note: The maximum number of observations in bankrupt firms is 133. The maximum number of observations in acting firms is 68,853. Median values are shaded.

Third, short-term solvency or liquidity turned out in comparisons to be the least important dimension in the development of the model. Its two measures, Current ratio and Liquidity ratio (Quick ratio), are both based on balance sheet items, but they did not prove to be very significant variables in the tests. Nevertheless, Quick ratio was chosen for the model, because it is not affected by stocks (inventories), which in turn makes Current ratio dependent on the industry. Before the final selection of the variables, the compatibility of the potential variables was examined using a stepwise logistic regression analysis. The selected three key figures were chosen by the stepwise procedure for the final model.

Table 1 shows the percentiles of the three indicators selected for the model in the 2019 data, which was used to estimate the model. In addition to these indicators, the table also contains the percentiles of ICR and the annual Growth rate of net sales. Based on the median test, the medians of the three model indicators and ICR differ statistically significantly (p-value < 0.001) in the groups of bankruptcy companies and active companies, while the difference in Growth rate of net sales is not statistically significant (p-value = 0.178). Thus, growth distributions are relatively similar in bankruptcy companies and active companies. Since there are many missing observations for each variable, only the maximum number of observations is indicated in the table. The table shows that in at least half of the bankruptcy companies, Return on total assets, ICR and Growth rate in net sales are negative. For Quick ratio, a value of 1 or above indicates that the company has sufficient liquid assets to satisfy its short-term obligations. However, according to the table, about 75 per cent of bankruptcy companies have a Quick ratio below this limit. Moreover, almost half of the bankruptcy companies have a negative Solvency ratio, while for active companies, a negative ratio is rare and only occurs in less than 10% of companies.

4 | DETECTING ZOMBIE FIRMS

4.1 | Logistic model

Table 2 shows the results of the logistic regression analysis. Panel 1 shows the model coefficients that can be used to calculate the logit and conditional probability for each firm. The p-values of the coefficients show that Solvency ratio is by far the most statistically significant variable (p-value < 0.001). On the other hand, the coefficient of Quick ratio, the short-term solvency measure, is not statistically significant (p-value = 0.102). The significance of the coefficient of the profitability ratio Return on total assets is statistically very good (p-value < 0.001). The classification ability of the logistic model in the sample where it has been estimated is presented in Panel 2. In the classification of observations, the cut-value 0.002, which corresponds to the relative share of bankrupt companies among all companies, was adopted. Using this value as cut-off, the model correctly classifies 76.4% of the companies in the sample. When measured in this way, the accuracy of the classification remains lower than the classification performed in a univariate analysis solely with the help of Solvency ratio.

The Nagelkerke R Square calculated for the model is only 0.118, because the number of bankrupt companies is very small compared to active companies. This R Square achieves the highest value in the material, where the share of bankrupt companies is 50%. The Hosmer and Lemeshow test of the model is not statistically significant (p-value is 0.057). Figure 1 shows the ROC curve of the model. The area under the curve

TABLE 2 Estimated logistic regression model for bankruptcy and active firms (Year 2019).

Panel 1. Coefficients of the model

Variable	Coefficient	Standard error	Wald test statistics	*p*-value	Exp (*B*)
Quick ratio	−0.102	0.063	2.669	0.102	0.903
Return on total assets	−0.019	0.004	18.497	<0.001	0.981
Solvency ratio	−0.024	0.003	60.347	<0.001	0.976
Constant	−5.456	0.130	1760.825	0.000	0.004

Panel 2. Classification accuracy of the model

	Predicted		
Observed	Active firms	Bankrupt firms	Percentage correct
Active firms	42.998	13.310	0.764
Bankrupt firms	22	78	0.780
Overall percentage			0.764

Note: Cut-value = 0.002.

(AUC) is 0.843. AUC measures the accuracy of the estimated model in relation to the perfect model. For a perfect model, AUC is 1, and for a random model, it is 0.5. AUC in this context refers to very good classification ability. For Solvency ratio alone, AUC is 0.820 so that the accuracy of the combined model as measured in this general way exceeds the accuracy of the univariate model. Although the difference in classification accuracy between the univariate and multivariate models in this case is not significant, the models produce different solutions in terms of factors affecting risk. In this case, in the combined model of three variables, the resulted risk in the sample firms is influenced by Solvency ratio, Return on total assets and also Quick ratio, while in the univariate model, the risk only takes Solvency ratio into account.

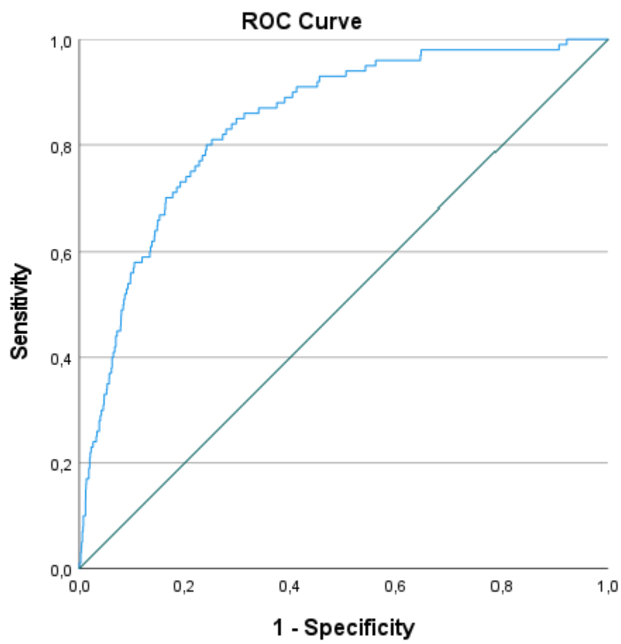

FIGURE 1 The ROC curve of the estimated logistic regression model.

The present sample includes relatively few bankrupt firms (and firms in insolvency proceedings) so that it was not possible to test the performance of the model using an independent dataset test. Therefore, the logistic model was validated using the bootstrap procedure based on 1000 bootstrap samples. Table 3 presents the results of the bootstrap procedure. Panel 1 shows the bootstrap coefficients of the logistic regression model. The coefficients of the three model variables are almost identical to the original model. In the tests performed, the differences in the coefficients had no significance for the results of the study. In the bootstrap procedure, no bias was detected in the coefficients of the variables Return on total assets and Solvency ratio. However, a negative bias was observed in the coefficient of the variable Quick ratio, based on which the coefficient cannot be considered completely reliable. The classification accuracy of the model in the bootstrap procedure is presented in Panel 2 of the table. This accuracy is approximately the same as for the original logistic regression model. For the bootstrapping estimates, total percentage of correct classifications is 0.754, when it was 0.764 for the original model.

4.2 | Zombie firms

The search for the zombie firms was carried out so that an estimate of the conditional bankruptcy risk was first calculated for each company based on the results of the logistic model. Therefore, following the logistic model, the conditional probability of each company was calculated with the help of the linear logit L through a logistic transformation. Thus, the conditional

TABLE 3 Estimated logistic regression model for bankruptcy and active firms (Year 2019).

Panel 1. Bootstrap for the variables in the model

Variable	Coefficient	Bootstrap bias	Standard error	*p*-value	Exp (*B*)
Quick ratio	−0.108	−0.035	0.091	0.114	0.903
Return on total assets	−0.020	0.000	0.005	<0.001	0.981
Solvency ratio	−0.024	0.000	0.003	<0.001	0.976
Constant	−5.467	0.018	0.141	<0.001	0.004

Panel 2. Bootstrap classification accuracy of the model

	Predicted		
Observed	Active firms	Bankrupt firms	Percentage correct
Active firms	44.228	14.402	0.754
Bankrupt firms	21	81	0.794
Overall percentage			0.754

Note: Cut-value = 0.002.

probability is defined as $p(Y=1|X)=1/(1+e^{-L})$ according to Equation (1). The estimated logit is as follows:

$$\text{Logit} = -5.456 - 0.102 \cdot \text{Quick ratio} - 0.019 \cdot \text{Return on total assets} - 0.024 \cdot \text{Solvency ratio} \quad (2)$$

Because of missing observations, logits and the corresponding conditional probabilities could only be calculated for 58,630 operating (active) companies and for 102 high-risk companies.

The median value of the conditional probability for the group of (high-risk) bankrupt firms was 0.0041, whereas the mean of the probability due to the skewness of the distribution was as high as 0.0071. The 25% percentage of the probability was 0.0022, while the 75% percentage was 0.0088. The median is significantly higher than the cut-off value 0.002 that was used in assessing the classification accuracy of the model. In fact, this cut-off value is close to the 25% percentage. Then, the filter that the conditional probability of a zombie company must exceed the median probability of bankrupt companies for each year 2018–2020 was applied to the set of all active companies (firms in insolvency proceedings excluded). In this way, a total of 2078 zombie companies were found. Thus, the share of zombie companies among active companies resulted as 3.5%, which corresponds well to the results obtained by Albuquerque and Iyer (2023: 49) for Finnish private companies in 2018–2020. Using this method, the operational definition of a zombie company is that the conditional bankruptcy risk of a zombie company is higher than the risk of a typical bankrupt company, that is it exceeds the median risk of bankrupt companies, for 3 years in a row.

Table 4 shows the percentiles of the variables of the logistic model in active and zombie firms for the years 2018, 2019 and 2020. The values of Quick ratio in zombie companies are low, and in about 75% of the companies, the value of the indicator falls below the critical value of 1. The values of Return on total assets show that every year more than half of the zombie companies have a negative value of this profitability ratio. However, also about 25% of active companies have a negative profitability ratio. The most important variable of the model, Solvency ratio is generally negative in more than 75% of zombie companies. In active companies, the Solvency ratio is only very rarely negative, which is also affected by Finnish legislation (Finnish Companies Act 20:23 §). The median value of Solvency ratio in active companies is approximately 56–60%, that is a high value even internationally. The development of the solvency is negative in zombie companies perhaps due to the influence of COVID-19 epidemic in the last year. However, the development is anyway positive in active companies. Although some zombie companies have satisfactory level of liquidity, profitability or solvency, it is essential how good the combination of the financial ratios reflecting these dimensions is.

Figure 2 shows the dependence between the indicators Solvency ratio and Return on total assets in the 2019 data of zombie firms. The figure draws attention to at least two things. First, the upper level of the observation points, in a way "the efficient frontier," goes through the origin. The zombie companies on this efficient frontier have the highest Return on total assets (profitability) on a given value of Solvency ratio (solvency). There are, in the sample of zombie firms, factually none companies that have simultaneously positive Return on total assets and positive Solvency ratio. For each company, either profitability or solvency is negative. Second, the efficient frontier is linear along the values of Solvency ratio. This means that the efficient frontier is a straight line that passes through the origin. This line intersects both the vertical axis (Return on total investment) and the horizontal axis (Solvency ratio) at approximately +40. This basically means that the trade-off between profitability and solvency is about one. If we consider that the zombie company moves on the efficient frontier down to the right in such a way that it gradually improves its solvency, then for every percentage unit of solvency that it increases, the company correspondingly loses a percentage unit of profitability. When a company moves forward on the efficient frontier, it reaches a point (origin) where both profitability and solvency are zero. If the company continues on the frontier, it reaches the last point on the frontier, when its Solvency ratio reaches the value +40% and at the same time the Return on total assets is zero. The great majority of zombie firms live outside the efficient frontier, in the rectangular, where both Return on total assets and Solvency ratio are negative.

Appendix B shows the percentiles of ICR, Growth rate in net sales and Net sales for the years 2018, 2019 and 2020. This Appendix shows that the ICR is negative in about half of the zombie companies in each year, but only in slightly more than 10% of the active companies. The median growth in Net sales is low in both company groups and clearly negative in 2020. Zombie companies are very small in terms of net sales, and the median net sales is only slightly over 100 TEUR, around 115–140 TEUR. Active firms are larger, but their median net sales are still less than 200 TEUR. The median number of employees in zombie firms is only 2 (not presented in the Appendix) but 5% of the zombie firms has more than 25 employees. There are no significant differences in the age of company between zombie and active firms. The median age is for zombie companies 12 years and for active firms 14 years. Appendix C shows the distribution of zombie companies by industry. Considerable differences compared to the distribution of active companies can be found in three industries. About 19.5% of the zombie companies are from the G Wholesale

TABLE 4 Percentiles of the model variables in active and zombie firms in 2020, 2019 and 2018.

	Percentiles						
Variable	**5**	**10**	**25**	**50**	**75**	**90**	**95**
Quick ratio 2020							
Active firms	0.20	0.40	0.93	1.89	4.60	12.00	22.50
Zombie firms	0.06	0.06	0.19	0.44	0.85	1.44	2.15
Quick ratio 2019							
Active firms	0.18	0.36	0.84	1.72	4.00	10.00	18.25
Zombie firms	0.05	0.06	0.19	0.46	0.87	1.41	2.14
Quick ratio 2018							
Active firms	0.17	0.34	0.82	1.66	3.75	9.29	16.83
Zombie firms	0.06	0.08	0.20	0.54	1.00	1.80	2.71
Return on total assets 2020							
Active firms	−25.00	−11.11	0.00	7.96	20.00	35.48	47.72
Zombie firms	−55.78	−40.00	−17.31	−4.59	1.80	10.85	18.75
Return on total assets 2019							
Active firms	−22.49	−10.00	0.00	7.86	20.00	35.53	47.37
Zombie firms	−54.53	−50.00	−25.00	−7.44	0.00	8.53	16.39
Return on total assets 2018							
Active firms	−23.44	−10.38	0.00	7.88	20.41	36.91	49.56
Zombie firms	−51.69	−40.33	−17.68	−3.91	2.42	16.04	33.03
Solvency ratio 2020							
Active firms	2.50	10.84	31.64	60.00	83.75	95.01	97.92
Zombie firms	−41.19	−41.19	−41.19	−31.65	−12.29	0.00	4.07
Solvency ratio 2019							
Active firms	1.39	9.30	29.51	57.90	82.75	94.83	98.23
Zombie firms	−44.44	−44.44	−44.44	−23.73	−5.88	3.33	10.35
Solvency ratio 2018							
Active firms	0.00	7.37	27.59	56.25	81.46	94.47	98.25
Zombie firms	−43.48	−43.48	−36.73	−11.71	4.87	24.50	39.90

Note: The maximum number of observations in active firms is 55,734. The maximum number of observations in zombie firms is 2078. Median values are shaded.

and retail trade sector, while only 15.6% of the active companies operate in the sector. Furthermore, about 3.5% of active companies operate in the sector I Accommodation and food service, while the corresponding share of zombie companies is more than this, that is 8.9%. Industry M Professional, scientific and technical activities is only slightly represented in zombie companies, as only 9.2% of companies belong to this industry. In active companies, the share of this industry is as much as 18.3%.

In prior zombie research, filters have been set on ICR and growth to find firms that are "Walking Dead." Table 5 shows the frequency of filled ICR and Net sales growth filters among zombie and other active companies. If we use as the fulfilment of the condition (=1) that ICR is lower than 1 in each of the years 2018, 2019 and 2020, then 430 (35.4%) of the 1216 zombie companies, that have non-missing data to test the filter, fulfil the condition. However, of all (other) active companies (29,463), the condition is fulfilled only by 1037 (3.52%) companies. Thus, the fulfilment of the ICR filter is 10 times more frequent in zombie firms than in other active firms. If as the filter (=1) is used that Growth in net sales is negative every year (3 years in a row), the condition is fulfilled in 285 (15.52%) zombie companies, but only 5077 (9.78%) of all active 51,907 companies. If only the ICR filter is used to identify zombie companies, the share of zombie companies among active firms would be about 4.8%. However, there are many missing observations in the values of ICR, so that it can only be applied to a part of the active companies. In this study, only the conditional bankruptcy risk is used as a filter. Thus, the detected zombies factually are "technically" bankrupt firms.

The unproductive and unviable zombie companies have significant negative macroeconomic implications, if they can receive public support to survive and avoid creative destruction process. Therefore, it is important that

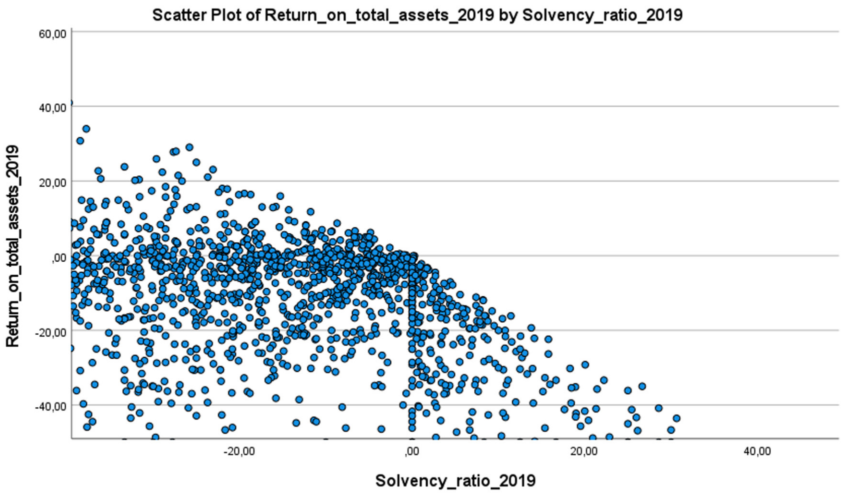

FIGURE 2 The relationship between Return on assets and Solvency ratio in 2019.

TABLE 5 The frequency of filled ICR and growth filters in the sample.

	Active firms	Zombie firms	Total
Panel 1. Effect of ICR filter			
ICR filter = 0	28,426	786	29,212
ICR filter = 1	1037	430	1467
Total	29,463	1216	30,679
Percentage:			
ICR filter = 0	96,480	64,638	95,218
ICR filter = 1	3520	35,362	4782
Total	100,000	100,000	100,000
Panel 2. Effect of growth filter			
Growth filter = 0	46,830	1551	48,381
Growth filter = 1	5077	285	5362
Total	51,907	1836	53,743
Percentage:			
Growth filter = 0	90,219	84,477	90,023
Growth filter = 1	9781	15,523	9977
Total	100,000	100,000	100,000

Note: ICR filter = 1 if ICR <1 for 2018, 2019 and 2020, 0 otherwise. Growth filter = 1 if Growth in net sales negative 2018, 2019 and 2020, 0 otherwise.

zombie firms can be detected by public authorities. In Finland, ELY Centres and Business Finland (BF) granted funding throughout the country to help enterprises to minimise the adverse effects of the COVID-19 pandemic outbreak and to encourage firms to provide employment (ELY Centre, 2020). ELY Centres granted subsidies for micro-firms employing less than five employees (excluding sole entrepreneurs), while BF concentrated on subsidy to larger enterprises. The zombie companies detected in this study also received COVID-19 support from public actors BF and ELY Centres. BF, which gives support to larger companies, granted funding to 111 (5.2%) zombie companies, while ELY Centres, which give support to micro-companies, granted funding to 174 (8.1%) small zombie companies ($n = 2147$). BF granted zombie companies subsidies in the amount of 3.16–110.0 TEUR, and the average subsidy per company was 53.0 TEUR. ELY Centres granted aid packages of 2.4–71.6 TEUR, while the average aid was 13.4 TEUR. In total, BF gave 5880.9 TEUR in aid to zombie companies and respectively ELY Centres granted 2327.2 TEUR. These grant amounts were thus granted to zombie companies whose bankruptcy risk was at least three years higher than the risk of a typical (median) bankrupt company. In total, BF and ELY Centres granted subsidy respectively to 8.6% and 7.5% of the companies in the present sample ($n = 70{,}943$). These percentages are not significantly higher than those for the zombie firms.

5 | CONCLUSIONS, LIMITATIONS AND FUTURE RESEARCH

Altman et al. (2024) define Zombieism as a phenomenon that describes the existence of companies that are technically insolvent but continue to live on due to unusual market conditions, financial institutions and investor or government support. Zombie firms are usually unprofitable, indebted and financially distressed firms which live in this kind of state for years, but neither grow nor die. Zombie companies may have significant negative macroeconomic implications, as they can receive public support to keep them alive and avoid or delay a necessary creative destruction process (Albuquerque & Iyer, 2023). Due to the negative meaning of zombie companies, it is important to be able to reliably identify them using methods that are in general use. Empirical studies on zombie companies have used many different approaches and methods to identify them. Factors such as ICR, leverage, profitability, growth and (Altman) *Z*-score have been used as measures and filters. The samples used in these studies mostly include large and listed companies. In identifying zombie companies, it has usually been assumed that the filter is filled in 2 or 3 years in a row to eliminate random variation. Studies have also often tried internationally to explain the relative share of zombie companies with macroeconomic, business and legal factors.

The objective of this research was to develop a simple method that can be used to reliably identify zombie companies in small business data. Thus, the study does not make any international comparison, nor does it look for factors affecting the share of zombie companies. In this case, small business data refer to a sample from Finnish companies where the median size of companies is only 2 employees. Most of the companies in the material are therefore micro-companies. The starting point for the development of the method is the definition of a zombie company, where it means a company that is technically a bankrupt company, but is still alive for one reason or another ("Walking Dead"). Zombie companies must therefore have values of key indicators that are typical for bankrupt companies, as for the "chronic" failure firms or "lingerers." In order to recognise zombie companies, profitability, liquidity and solvency indicators can be used, as has been done in previous studies. The problem with small business data is that individual key figures have very high volatility, so it is difficult to use them in univariate analysis for effective and reliable measurement. If the key figures are combined into one common key figure, a combination of variables, the measurement will become significantly more robust. In this way, Altman et al. (2024) used the *Z*-score developed by Altman in the 1960s as a filter for identifying zombie companies.

From the perspective of the performance of the combined model, it is important that (i) the model is fresh and (ii) it has been estimated in a similar (or same) material where the target companies live. Therefore, the starting point for the search for zombie companies was a statistical model reflecting bankruptcy risk. In this study, the model was estimated by means of logistic regression analysis from the same sample of companies where it is used to measure risk. In this study, the indicators of profitability, liquidity and solvency selected on theoretical and empirical grounds were used as the independent variables of the regression analysis. The model thus considers profitability and solvency, as do ICR and Leverage used in previous zombie detection approaches.

The model did not include growth, because its volatility in very small companies is significantly high, and it did not bring additional information to measure risk. The model was used in such a way that zombie companies were considered to be operating (active) companies whose bankruptcy risk is higher than for the median bankrupt company for 3 years in a row. Thus, as a result, the method used detected zombie companies that are still active (operating), but technically bankrupt. The share of zombie companies identified in this way was about 3.5% of the active companies, which corresponds to the results obtained in previous studies. The use of the multivariate model is illustrated in the results by the fact that there is not a single zombie company in the material with positive indicators of both profitability and solvency in 2019. Identifying zombie companies is important, because some of the zombie companies tend to get public support. The present sample of zombie firms also included a number of firms that got financial support in 2020.

The method developed in this study for identifying zombie companies works well, but the study has shortcomings that can be resolved in future studies. In the future, the research can be expanded to use material that includes companies from different countries. Like in previous studies, at the same time, factors affecting the share of zombie companies in different countries could be explained. The approach can also be developed using other risk measurement tools, statistical methods than logistic regression analysis, for example neural networks. In future studies, it is also good to use samples with more bankrupt companies than in this study. Moreover, it should be investigated which is the best cut-off value of bankruptcy risk to identify a zombie firm. It is also worth paying more attention to the selection of variables for the multivariate model. In addition to that, it is advisable to use databases with fewer missing observations in the sampling. The main idea of this study was to develop an approach that can be used to identify zombie companies in small business data. In future studies, the approach should be used and tested in sample from larger companies. It is also worth investigating in the future how well public authorities are able to identify zombie companies when evaluating their support applications.

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CONFLICT OF INTEREST STATEMENT

There are no conflicts of interest to declare.

DATA AVAILABILITY STATEMENT

The data that support the findings will be available by request in Orbis at https://www.uwasa.fi/fi/henkilo/1041551 following an embargo from the date of publication to allow for commercialization of research findings.

ORCID

Erkki K. Laitinen https://orcid.org/0000-0002-9169-7709

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APPENDIX A

Relevant financial ratios in ORBIS

1. Profit margin (%) (Profit before tax/Operating revenue) * 100
2. Gross margin (%) (Gros profit/Operating revenue) * 100
3. EBITDA margin (%) (EBITDA/Operating revenue) * 100
4. EBIT margin (%) (EBIT/Operating revenue) * 100
5. Cash flow/Operating revenue (%) (Cash flow/Operating revenue) * 100
6. ROA (%) (Profit (Loss) for period/Total Assets) * 100
7. Return on total assets (%) (Profit before tax/Total assets) * 100
8. ROE (%) (Profit (Loss) for period/Shareholders funds) * 100
9. Current ratio (x) Current assets/Current liabilities
10. Liquidity ratio (x) (Current assets Stocks)/Current liabilities
11. Shareholders liquidity ratio (x) Shareholders funds/Non-current liabilities
12. Solvency ratio (%) (Shareholders funds/Total assets) * 100
13. Gearing (%) ((Non-current liabilities + Loans)/Shareholders funds) * 100

APPENDIX B

Percentages of relevant variables in active and zombie firms in 2020, 2019, and 2018

	Percentiles						
Variable	**5**	**10**	**25**	**50**	**75**	**90**	**95**
Interest coverage ratio 2020							
Active firms	–11.50	–4.43	1.07	6.61	23.67	70.00	135.00
Zombie firms	–25.71	–14.32	–4.50	–0.33	1.67	4.50	8.12
Interest coverage ratio 2019							
Active firms	–11.00	–4.00	1.07	6.00	22.34	69.00	128.91
Zombie firms	–25.85	–19.00	–7.00	–1.51	1.03	4.00	6.67
Interest coverage ratio 2018							
Active firms	–12.00	–4.50	1.00	6.00	22.00	69.00	132.01
Zombie firms	–27.84	–19.40	–6.00	–0.50	2.00	6.00	12.07
Growth rate in net sales 2020							
Active firms	–60.00	–42.64	–19.37	–1.84	14.03	49.02	100.00
Zombie firms	–72.22	–55.50	–26.99	–6.90	10.63	46.73	106.40
Growth rate in net sales 2019							
Active firms	–51.45	–33.33	–11.25	1.80	18.64	56.34	108.99
Zombie firms	–62.36	–41.60	–17.11	0.00	16.91	57.94	128.75
Growth rate in net sales 2018							
Active firms	–51.03	–32.31	–10.32	2.95	21.96	66.67	136.29
Zombie firms	–58.42	–41.36	–14.88	0.00	25.00	88.22	200.00
Net sales TEUR 2020							
Active firms	8.00	17.00	60.00	186.00	686.00	2592.00	6372.00
Zombie firms	3.00	7.00	31.00	114.00	384.00	981.50	1879.50
Net sales TEUR 2019							
Active firms	9.00	19.00	66.00	198.00	696.50	2565.40	6321.70
Zombie firms	4.00	10.00	36.00	134.00	429.00	1070.00	2042.00
Net sales TEUR 2018							
Active firms	8.00	19.00	65.00	194.00	670.00	2452.10	6026.00
Zombie firms	4.00	8.92	36.00	137.00	419.25	1025.73	1995.85

Note: The maximum number of observations in active firms is 55,734. The maximum number of observations in zombie firms is 2078. Median values are shaded.

APPENDIX C

Industrial distribution of zombie and all firms

	Zombie firms		All firms	
	Frequency	Percent	Frequency	Percent
A Agriculture, forestry and fishing 01–03	86	4.3	1670	2.4
B Mining and quarrying 05–09	8	0.4	247	0.3
C Manufacturing 10–33	184	9.1	5543	7.8
D Electricity, gas, steam and air conditioning supply 35	13	0.6	353	0.5
E Water supply; sewerage, waste management and remediation activities 36–39	46	2.3	728	1
F Construction 41–43	260	12.9	9859	13.9
G Wholesale and retail trade; repair of motor vehicles and motorcycles 45–47	394	19.5	11090	15.6
H Transportation and storage 49–53	135	6.7	3749	5.3
I Accommodation and food service activities 55–56	180	8.9	2493	3.5
J Information and communication 58–63	92	4.6	4270	6
K Financial and insurance activities 64–66	7	0.3	599	0.8
L Real estate activities 68	156	7.7	7111	10
M Professional, scientific and technical activities 69–75	185	9.2	12979	18.3
N Administrative and support service activities 77–82	91	4.5	3455	4.9
O Public administration and defence; compulsory social security 83–84	0	0	20	0
P Education 85	23	1.1	1002	1.4
Q Human health and social work activities 86–88	44	2.2	2748	3.9
R Arts, entertainment and recreation 90–93	74	3.7	1707	2.4
S Other service activities 94–96	41	2	1111	1.6
X Other industries	1	0	209	0.3
Total	2020	100	70943	100

Note: Most important industries are shaded.

AUTHOR BIOGRAPHY

Erkki K. Laitinen is Professor Emeritus of the University of Vaasa. He was a professor at the Faculty of Economics, the Department of Accounting and Finance. Laitinen is a well-known researcher of bankruptcies and defaults, who has created several statistical (linear and logistic) models used in banks and other organisations to predict financial disruptions in companies. Laitinen has written dozens of international articles and several textbooks on the topic.