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Carlos Serrano-Cinca, Begoña Gutiérrez-Nieto, Martha Bernate-Valbuena

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The use of accounting anomalies indicators to predict business failure

Carlos Serrano-Cinca
Department of Accounting and Finance
University of Zaragoza, Spain

Begoña Gutiérrez-Nieto
(corresponding author)
Department of Accounting and Finance
Universidad de Zaragoza, Spain, bgn@unizar.es

Martha Bernate-Valbuena
Department of Accounting and Finance
University of Bucaramanga, Colombia

Abstract

Most of the studies that try to predict business failure assume that accounts give a true and fair view of the financial position of a company, without considering that managers can discretionarily apply accounting rules or even perform accounting fraud. This paper takes a set of financial ratios especially designed to detect accounting anomalies as bankruptcy predictors. These ratios are not very common in bankruptcy prediction studies, but they come from creative accounting studies. The ratios try to identify abnormal depreciation figures, exaggerated receivables or deteriorating financial conditions preceding aggressive accounting practices. The empirical study has been performed from a sample of 51,337 public and private European companies, during the period 2012–2016. The analysis techniques applied were logistic regression and decision trees, allowing to obtain rules to predict the status of failed or non-failed. It is found that several indicators proposed in the literature as earnings management indicators present statistically significant differences between failed and non-failed firms, but they do not have enough predictive power to incorporate them into prediction models. However, an index developed to measure accounting anomalies exhibits high discriminatory power, similar to that of the classical financial ratios. The construction of the index and its application to private firm sample provide the main contribution of the paper, as the results suggest slightly better forecast accuracy only for the private firm sample. The inclusion of indicators to detect accounting anomalies should be considered when developing new models to predict bankruptcy, especially in private companies.

Keywords: Bankruptcy, insolvency, financial ratios, earnings management, creative accounting.

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Abstract

Most of the studies that try to predict business failure assume that accounts give a true and fair view of the financial position of a company, without considering that managers can discretionarily apply accounting rules or even perform accounting fraud. This paper takes a set of financial ratios especially designed to detect accounting anomalies as bankruptcy predictors. These ratios are not very common in bankruptcy prediction studies, but they come from creative accounting studies. The ratios try to identify abnormal depreciation figures, exaggerated receivables or deteriorating financial conditions preceding aggressive accounting practices. The empirical study has been performed from a sample of 51,337 public and private European companies, during the period 2012–2016. The analysis techniques applied were logistic regression and decision trees, allowing to obtain rules to predict the status of failed or nonfailed. It is found that several indicators proposed in the literature as earnings management indicators present statistically significant differences between failed and nonfailed firms, but they do not have enough predictive power to incorporate them into prediction models. However, an index developed to measure accounting anomalies exhibits high discriminatory power, similar to that of the classical financial ratios. The construction of the index and its application to private firm sample provide the main contribution of the paper, as the results suggest slightly better forecast accuracy only for the private firm sample. The inclusion of indicators to detect accounting anomalies should be considered when developing new models to predict bankruptcy, especially in private companies.

1. Introduction

Most of the studies that try to predict business failure assume that accounts give a fair and realistic appraisal of the financial situation of a company. Very often the focus is on selecting the best statistical techniques, as shown by the literature revisions by Olson et al (2012), Sun et al (2014), or Tian et al (2015). Financial ratios measuring aspects such as profitability, solvency or liquidity are the most frequent inputs to develop bankruptcy prediction models since the pioneer works by Beaver (1966) and Altman (1968), although some studies also include stock market information and proxies for changes in the macro-economic environment (Tinoco and Wilson, 2013) or corporate governance structures (Manzaneque et al, 2016). However, these models do not always consider the presence of accounting anomalies caused by managers applying discretionally accounting rules, which influences annual statements and traditional financial ratios. The aim of this paper is to use a set of alternative financial ratios especially designed to detect accounting anomalies and analyzing whether including them in bankruptcy models improves their predictive power.

The idea of the paper came to us when analyzing the annual statements of firms applying for loans in crowdlending electronic platforms, or P2B lending. One of these new P2B lending platforms had a very high write off ratio (close to 30%). Firms applying for loans to this platform, all of them SME without audited accounts, presented acceptable annual profits and adequate values of their classical financial ratios, such as profitability, liquidity, or debt level, but we did recognize a clear pattern in many of the failed companies: “stagnant sales figures although high and growing receivables figures,” indicating that the companies did sell but they did not collect their money, perhaps owing to the fact that their clients themselves had failed payments and their accountants did not write off the losses from nonrecoverable trade debts. Although it is not the only explanation, this is a suspicious case of manipulation of accounts and we started our research to test this anecdotal evidence empirically. Among the previous literature proposing earnings management indicators, we focused on Beneish (1999) and Beneish et al (2013), but we also reviewed other proposals, such as Eckel (1981), Imhoff (1981), Leuz et al (2003), Peasnell et al (2005), Roychowdhury (2006), Beaver et al (2012) and Vladu et al (2017). When carrying out the literature review, we acknowledged that although the link between earnings management and bankruptcy was clear, few papers included such indicators in bankruptcy prediction models (Beaver et al, 2012). In other words, bankruptcy researchers implicitly have assumed that the annual accounts have given a fair and true view of the financial situation of companies, but it is clear that many annual accounts are unreliable (Balcaen and Ooghe, 2006).

According to a survey conducted with 400 chief financial officers, a remarkable 20% of the companies intentionally distort earnings, due to accounting choice (Dichev et al 2016). This fact lowers the quality of accounting information, as studied by Beaver et al (2005 and 2012). They find a slight decline in the predictive ability of the financial ratios, justified by the presence of creative accounting. The study by Chen and Schoderbek (1999) provides indirect evidence on the feasibility of earnings management in the presence of possible punitive actions by regulators. Cheng et al (2010) investigate both accounting and real earnings management measures and find that loss firms use less accruals management than real earnings management. Beyond creative accounting, some companies commit accounting fraud, and forensic accounting skills have become crucial to untangling the maneuvers that obscure financial statements (Ramaswamy, 2005). Other companies apply accounting conventions that may lead to distortions on the income earning capacity of the economy and are likely to lead to corporate failures (Robb, 1987).

Persons (1995), Beneish (1999), Wells (2001) and Kaminski et al (2004) wonder if financial ratios can detect fraudulent financial reporting. Wells (2001) affirms that auditors can frequently detect signs of financial statement frauds because such frauds can be visible when certain numbers do not make sense because the balance sheet, income statement and statement of cash flows are interrelated. Beneish's (1999) model correctly identified, in advance of public disclosure, a large majority (71%) of the most famous accounting fraud cases that surfaced after the estimation period of the model. However, Kaminski et al (2004) find limited empirical evidence of the ability of financial ratios to detect fraudulent financial reporting. Sometimes the same indicators that capture deteriorating financial conditions are used to detect fraud, since those companies experiencing financial difficulties are precisely those more prone to manipulating accounting statements (Roychowdhury, 2006). Thus, financial leverage, capital turnover, asset composition, and firm size are significant factors influencing the likelihood of fraudulent financial reporting, according to Persons (1995). DeAngelo et al (1994) study accounting choice in 76 NYSE troubled companies and found that managers' accounting choices primarily reflect the financial difficulties of their firms rather than attempts to inflate income.

There is not a list of generally accepted indicators to measure the likelihood of fraudulent financial reporting or to detect signs of creative accounting; rather, the indicators proposed by Eckel (1981), Beneish (1999), Leuz et al (2003), Peasnell et al (2005), Roychowdhury (2006), Beaver et al (2012), Beneish et al (2013), and Vladu et al (2017) deserve attention. Creative accounting may affect the models of bankruptcy prediction based on classical financial ratios. For example, let us think about the working capital ratio, which measures the ability of the firm to pay off its current liabilities with current assets. Usually, the higher the value of the working capital ratio is, the higher the liquidity of the company is. However, in companies engaging in accounting manipulation, the receivables figure that belongs to the category of current assets may have been inflated with doubtful receivables, and consequently, the working capital ratio will show a surprisingly high value. Hence, an index measuring if the percentage of receivables to sales has increased from year to year can detect sales not paid and then pointing out the anomaly, as shown by Beneish (1999). Other indicators related to accounting anomalies measure if the depreciation figures changed from the previous year, or measure the propensity to capitalize and defer costs, or check if the ratio of debt to assets in the year t relative to the corresponding ratio in the year t-1has grown.

This paper presents novelties with respect to the existing literature. We mostly employ the financial ratios proposed by Beneish et al. (2013) to detect accounting anomalies; however, the authors used them to predict stock returns, whereas we use them to predict bankruptcies. Other authors relate earnings management and bankruptcy (DeAngelo et al, 1994; Rosner, 2003; Leach and Newsom, 2007; García-Lara et al, 2009; and Campa and Camacho-Miñano, 2014); however, their goal is not to predict bankruptcies but to describe them. Dutzi and Rausch (2016) revise the recent literature on earnings management practices before bankruptcy, finding that the results are ambiguous, since there are upwards earnings management incentives and incentives which may lead to downwards earnings management. García-Lara et al (2009) affirm that further research on failure prediction models is needed to explicitly control for earnings management practices. Beaver et al (2012) relate discretionary behavior and bankruptcy. They use two proxies for discretionary behavior: the magnitude of discretionary accruals and the restatement of the financial statements; however, our paper uses financial ratios as variables. Our study extends the literature on bankruptcy prediction by focusing on the inclusion of financial ratios specifically designed to detect accounting anomalies and obtaining a set of rules to feed decision support systems.

The empirical study uses a sample of 51,337 public and private European companies, during the period 2012–2016. The test sample comes from a later period; it is a holdout sample allowing intertemporal validation. This fact tries to resemble a real-world situation where the financial analyst knows past financial information and uses it to predict future failures. Logistic regression and decision trees have been used as prediction techniques, the last one to obtain rules easy to incorporate to decision support systems. The CHAID decision tree algorithm by Kass (1980) was chosen because of its simplicity, transparency, descriptive and predictive power (Delen et al, 2013). An index to measure the accounting distortion degree has been built from the financial ratios used to identify accounting anomalies (EM-index). A simple rule obtained from the decision tree assigns the highest probability of default to those companies engaging in manipulation practices, having losses, with liquidity problems and without enough retained earnings to face financial difficulties.

The contribution of the paper is threefold. First, it is found that several indicators proposed in the literature as earnings management indicators present statistically significant differences between failed and nonfailed firms. However, we have found that they do not have enough predictive power to incorporate them into prediction models. This result seems coherent. The fact that an indicator proposed to detect some kind of manipulation in annual accounts, such as depreciation or assets quality, had more predictive power than debt ratios or lack of profits and would only be possible in a world where accounting were very far from the true and fair situation of the company. Second, an index was created by aggregating indicators associated to earnings management. Results show that this index is a good bankruptcy predictor, as good as any of the frequently used financial ratios measuring aspects such as profitability, liquidity or solvency. The construction of the index and its application to private firm sample provide the main contribution of the paper, as the results suggest slightly better forecast accuracy only for the private firm sample. It seems reasonable that companies experiencing financial difficulties would have incentives to manipulate their accounts, as modeled theoretically by Akerlof et al (1993) and with sufficient empirical evidence (Vladu et al, 2017). Third, the information provided by this index is different from those of classical financial ratios, such as profitability or debt ratios, as shown by its low correlation with the rest of indicators.

The remainder of the paper is organized as follows. Section 2 presents the literature review and hypothesis development. Section 3 presents the empirical study. Finally, conclusions are presented.

2. Literature review

Predicting bankruptcy of companies from financial ratios is a widely studied issue since the pioneer works by Beaver (1966) and Altman (1968). Ravi Kumar and Ravi (2007), Olson et al (2012), Sun et al (2014), Tian et al (2015), and Alaka et al (2018) provide a literature review of financial distress prediction. Sun et al (2014) analyze first the definition of the financial distress concept, finding that there is not a consensus but many different points of view. Given that financial distress is a dynamic ongoing process, they conclude that it would be interesting to explore a metric that can classify the distressed companies into different degrees such as mild, intermediate, and bankrupt. A different point of view is considering "time to failure" as dependent variable, instead of "failure" (Shumway, 2001). In this case, instead of a logistic regression, alternative techniques such as Cox regressions, based on survival analysis, are used, which exhibit a good performance in comparative studies (Bauer and Agarwal, 2014).

There are many financial distress prediction modeling methods, from traditional statistical methods to machine learning methods based on artificial intelligence. The literature review by Alaka et al (2018) focuses on the choice of the most adequate tool according to 13 criteria: accuracy, interpretability of results, sample size or the presence of multicollinearity, among others. Overall, they find that no single tool is predominantly better than the other tools because it depends on the choice of the criterion; at this point, they agree with Caruana and Niculescu-Mizil (2006). They conclude that the techniques with the best predictive power, such as neural networks or support vector machines, have the worst interpretability. Even the classical linear discriminant analysis is optimal assuming certain conditions (Briggs and MacLennan, 1983). However, in the financial ratios case, these conditions are not satisfied, which justifies the use of sophisticated statistical techniques. This paper uses two complementary techniques: logistic regression and decision trees. Logistic regression is the most widely used technique and is also commonly used as a benchmark to compare the performance of rival techniques (Demyanyk and Hasan, 2010). Decision trees are used to analyze the financial distress problem since the early work by Srinivasan and Kim (1987). Decision trees are becoming increasingly more popular because they are expressed in easily understood terms, handle both numerical and categorical data, have the capacity of modeling nonlinear complex situations, and they perform well with a large data set (Delen et al, 2013). The study by Amani et al (2017) shows that 14% of the applications of data mining in accounting use decision trees. Several studies compare data mining methods for bankruptcy prediction obtaining mixed evidence. For example, Olson et al (2012) found decision trees to be relatively more accurate compared to neural networks, but Chen (2012) found the opposite. There are several algorithms to implement decision trees, being the most commonly employed CHAID, C5.0, QUEST, and C&RT. Delen et al (2013) compare their performance, finding that CHAID overcomes the other.

As for the variables used, financial ratios have been prevalent in the literature, following the pioneer papers by Beaver (1966), Altman (1968), Ohlson (1980), and Taffler (1983). One of the major criticisms received by these empirical models is their perceived lack of theory. These statistical models are not explanatory theories of failure but pattern recognition devices (Agarwal and Taffler, 2007). However, Scott (1981) develops a coherent theory of bankruptcy arguing that bankruptcy prediction is both empirically feasible and theoretically explainable. There are other variables intricately related to bankruptcy: market-based variables such as market size, past stock returns and idiosyncratic returns variability (Shumway, 2001 and Campbell et al, 2008). A key innovation is the use of measures of distance to default, which are based on Merton's (1974) bond pricing model, such as Bharath and Shumway (2008) and Campbell et al (2008), who find a remarkable improvement over previous studies. But Tian et al (2015), analyzing 39 bankruptcy predictors, find that classical financial ratios provide significant additional information about future failures beyond market-based variables. Other bankruptcy models propose the inclusion of alternative indicators, for example, Cooper et al (1994) incorporating qualitative information using measures of general human capital, Liang et al (2016) including corporate governance variables, and Ooghe and De Prijcker (2008) including as predictors variables errors made by management, errors in the corporate policy and external factors. Despite the efforts to find new predictors of bankruptcy of firms, financial ratios exhibit a good predictive capacity. Agarwal and Taffler (2007) evaluated the performance of the Taffler (1983) model over the 25-year period since it was originally developed, thus demonstrating the predictive ability of the published accounting numbers and their associated financial ratios. The paper by Altman et al (2017) also shows the resilience of the five financial ratios from his Z-score model (Altman, 1968), thus finding that 50 years later the model is still valid.

The quality of the financial information is a key aspect that can be influenced by aspects such as earnings management, creative accounting, income smoothing, and accounting fraud. Earnings management and fraudulent financial reporting are both subsets of earnings manipulation, but while earnings management may not technically violate generally accepted accounting principles, fraud does (Rosner, 2003). Earnings management is a purposeful intervention by managers in the earnings determination process usually to satisfy selfish objectives (Schipper, 1989). This can be done by means of creative accounting, which is the transformation of financial accounting figures, given the existence of loopholes in the accounting rules (Naser, 1993). Income smoothing is a particular case:

It is the process of manipulating the time profile of earnings reports to make the reported income stream less variable (Fudenberg and Tirole, 1995). Financial statement fraud occurs when managers use accounting practices that do not conform to accounting standards to alter financial reports (Healy and Wahlen, 1999).

Braswell and Daniels (2017) review a variety of techniques that managers may use to influence current period earnings, like deferring discretionary expenditures such as research and development or general and administrative expenses to the following accounting period, the sales of profitable assets, or excesses in the production activity before the fiscal year ends. Among the symptoms characterizing the companies that manage their earnings, we can underline relatively high levels of inventory and larger net operating assets (Roychowdhury, 2006) or high levels of debt (Herrmann et al, 2003). Some authors use abnormal accruals as a proxy for earnings management (Peasnell et al 2005). Estimating the discretionary component of accruals is usually done by means of regression models (Aerts and Zhang, 2014). Imhoff (1981), Eckel (1981), and Leuz et al (2003) propose indicators to measure income smoothing, based on the coefficients of variation of sales and profits. Kaminski et al (2004) propose a series of analytical procedures to detect fraud. They claim that identifying the population of firms involved in fraudulent financial reporting is problematic because fraud samples are limited to just discovered fraud, and undiscovered fraud is never available for study. Nieschwietz et al. (2000) and Sharma and Panigrahi (2012) review the literature on detecting financial statement fraud and find a lack of relevant articles given the difficulty of obtaining sufficient research data. Beneish (1999) and Beneish et al (2013) propose a set of financial ratios to detect earnings management. These indicators can be classified into two groups: direct or indirect earnings management indicators. The latter are indicators specifically designed to capture deteriorating economic conditions because those companies experiencing financial difficulties are more prone to manipulate their financial statements (Roychowdhury, 2006).

3. Our empirical study

The empirical study uses a sample of large and very large European firms, taken from the Amadeus database owned by Moody's Corporation. Amadeus companies are considered to be large and very large if they match at least one of the following conditions: (a) operating revenue is not less than EUR 10 million, (b) total assets is not less than EUR 20 million, or (c) employees are not less than 150. The sample contains 51,337 firms, during the period 2012–2016. The data were split into train and test sets because a data splitting strategy is considered superior to a full data strategy for prediction purposes (Faraway, 2016). Moreover, we do split the training and test sets into chronological order to ensure intertemporal validation, a highly recommended procedure (Kraus and Feuerriegel, 2017). Joy and Tollefson (1975) are in favor of using such intertemporal validation; they highlight that many failure prediction studies use cross validation (ex-post discrimination in a validation sample) and argue that the predictive abilities of many bankruptcy prediction models tend to be overstated because the authors confuse ex-post classification results with ex-ante predictive abilities. According to Balcaen and Ooghe (2006), the model needs to be tested on data subsequent to its construction to have confidence in the predictive abilities of a failure prediction model. Lau (1987) also criticized some of the early studies because holdout samples were drawn from the same time period as original samples.

Amadeus database not only provides the accounting data but also the company status, that is, if the company is bankrupt, together with its status change date. Hence, a firm is considered as failed if it had entered statutory bankruptcy proceedings. Bankruptcy studies suffer from a problem of imbalanced samples (when the number of instances in each category of the target variable is not equal), and in real-life, the number of bankrupt firms is much smaller than the number of nonbankrupt firms (Crone and Finlay, 2012). Some techniques perform badly with unbalanced samples; a possibility to solve this problem is to follow a matching procedure, with some advantages, but also concerns (Zmijewski 1984, and Roberts and Whited, 2013). The samples were paired by size and sector in the pioneer paper by Altman (1968) and other papers such as Jain and Nag (1977), Daily and Dalton (1994) and Iturriaga and Sanz (2015); this is precisely what was done here. However, authors such as Ohlson (1980) did not use the matching technique to avoid biases existing from oversampling bankrupt firms. For each failed firm, a comparable healthy company was chosen, taking into account that (1) they belong to the same industry, as measured by the first four digits of the International Standard Industrial Classification (ISIC) and (2) they have a similar size, measured by total assets and net sales. Outliers were removed from the sample because the train sample is used to estimate the model, and logistic regression is sensitive to outliers, or more exactly, to influential data (Chatterjee and Hadi, 1986). Finally, the train sample comprises a balanced subsample of 182 public nonfailed firms and 182 public failed firms in 2012, hence, in year -1 prior to the bankruptcy; and a balanced subsample of 389 private nonfailed firms and 389 private failed firms in 2012, again, in year -1 prior to the bankruptcy.

Our test sample contains all the available data from the Amadeus database. The test sample is a holdout sample taken from two periods later than the train sample, 2014, and comprises 10,507 public firms, where 269 are failed firms and 10,238 are nonfailed firms, and 39,688 private firms, where 707 are failed firms and 38,981 are nonfailed firms. Taking the sample test from posterior years resembles a real-world case, but the accuracy can be lowered as the more the horizon increases, the more these models are not able to capture the different patterns that characterize firms which will go bankrupt (du Jardin, 2015). Sung et al (1999) find that financial ratios preceding bankruptcy are different in crisis periods compared to stability periods. In this sense, it must be remarked that the period analyzed matches a time of European recovering, after a crisis. Companies classified as solvent in 2014 could fail in the following years, thus we checked that the 2014 nonfailed firms were still active in 2016. We have decided to consider as failed those companies that went bankrupt one or two years later, a prudent point of view that tries to ensure a reliable sample of nonfailed firms. However, the analysis was also performed using the traditional way, considering that a firm is failed only in the last year of bankruptcy filing, otherwise is still healthy. In this case, the test sample included 37 companies that were solvent in 2014 but failed in 2015 or 2016. When this test was performed, the results hardly changed. In order to ensure that statistical results were not heavily influenced by outliers, we winsorized the data, by setting all observations higher than the 99th percentile of each variable to that value; all values lower than the first percentile of each variable were winsorized in the same manner, following Bharath and Shumway (2008).

The paper benchmarks the classical financial ratios models by Beaver (1966) and Altman (1968), updated by Altman and Sabato (2007) and by Beaver et al (2012). Most of the companies in the sample are not listed, so models such as Merton distance to default (Bharath and Shumway, 2008), which is based on Merton's (1974) bond pricing model, could not be used. Other bankruptcy models propose the inclusion of new indicators, for example from corporate governance (Liang et al, 2016), but these data were not available. Table 1 shows the predictive variables and their definition. The first nine independent variables are traditional financial ratios measuring profitability (ROA), retained earnings (RE/TA), equity strength (EQ/TL), working capital ratio (WC/TA), asset turnover (ROTA), short-term liquidity (CASH), presence of profits (PROFIT), financial expenses coverage (INT/S), and the increase in sales (ΔSALES). The first five variables are the financial ratios from

Altman (1968). The others are common ratios in bankruptcy studies, taken from Rose and Giroux (1984).

The following 11 variables are indicators designed to detect anomalies in annual accounts, and they follow Beneish (1999) and Beneish et al (2013) because of their good results when predicting stock returns, however not previously used to predict bankruptcy. Notwithstanding, we have revised other proposals, such as Eckel (1981), Imhoff (1981), Leuz et al (2003), Peasnell et al (2005), Roychowdhury (2006), Beaver et al (2012) and Vladu et al (2017). Some of these ratios detect aggressive accounting practices while other ratios capture deteriorating fundamentals. The first index is days' sales in receivable index (DSRI), which measures whether receivables and revenues are in or out of balance in two consecutive reporting periods. A material increase in the index could indicate that the receivables of the company are phony (Wells, 2001). However, a high value of this index can simply reflect a lax credit policy in the company because of a strategy to gain customers. Beneish (1999) determined that companies that had not manipulated sales had a mean index of 1.031 while companies that had manipulated sales had a mean index of 1.465, a 42% increase.

*** Table 1 ***

Several variables are specifically designed to capture deteriorating economic conditions because firms experiencing financial stress tend to manipulate annual statements (Roychowdhury, 2006). An example is the LEVI ratio, defined as the ratio of leverage (debt to assets) in year t divided by the same ratio in year t-1. According to Beneish (1999), increasing leverage tightens debt constraints and predisposes companies to manipulate earnings. The asset quality ratio (AQI) measures the proportion of total assets for which future benefits may be less certain; an increase in the asset quality index may indicate a propensity of company to capitalize costs (Wells, 2001) since the ratio captures distortions in other assets that can result from excessive expenditure capitalization (Beneish, 1999). SGAI denotes the ratio of sales, general, and administrative expenses to sales in period t divided by the same ratio in period t-1. Decreasing administrative and marketing efficiency predisposes companies to manipulating earnings.

Distortions in depreciation figures are a classical issue in accounting choice. If the company intends to appear profitable, a possible way is to lower depreciation, whereas if the company wishes to defer taxes, it can increase depreciation. Some other times the company wishes to smooth profits because the stakeholders detest abrupt movements. DEPI denotes the ratio of depreciation to depreciable base in year t-1 divided by the same ratio in year t. DDI, or depreciation decay index, is calculated by dividing the depreciation in year t-1 into the depreciation in year t.

TATA is defined as total accruals to total assets. The ratio tries to capture where accounting profits are not supported by cash profits. Zach (2007) found that low accrual firms have a higher bankruptcy probability than high accrual firms. But, according to Wells (2001), the presence of higher accruals and a corresponding decrease in cash often can be an attempt by a manager to internally finance its losses. Some authors use abnormal accruals as a proxy for earnings management (Peasnell et al 2005) and DeFond and Park (2001), while Jones (1991) uses total accruals as a measure of managers' earning manipulations.

Beneish (1999) tried to identify companies with sales figures artificially inflated. He employed the sales growth index (SGI), which is computed by dividing the sales of the current period by the sales of the last period. Wells (2001) points out that an increase in the index reflects a rise in sales, which may or may not be legitimate. However, in our case, the context involves firms experiencing financial difficulties so the expected pattern is just the opposite, a drop in sales. For this reason, we propose the use of another indicator, i.e., the coefficient of variation of sales (CvSALES). The idea of using the coefficients of variation was taken from Imhoff (1981), Eckel (1981), and Leuz et al (2003). Any distortion or shift in this indicator can raise suspicions, and a high coefficient of variation could be a symptom preceding bankruptcy. Deteriorating margins can also predispose companies to manipulating earnings (Beneish et al, 2013), and the gross margin index (GMI) ratio measures whether gross margins of an entity on sales shrink from one period to the next (Wells, 2001). Finally, we have calculated the coefficient of variation of profits (CvPRO); a higher probability of default is expected for those companies having a high coefficient.

Table 2 presents the exploratory analysis of the classical financial ratios for public companies, whereas table 3 shows the exploratory study for private companies. The descriptive statistics refer to years 2009–2013 and shows the results from the test sample, which is the sample of companies whose status we want to predict, and for this reason it is more interesting than the train sample. The tables show the mean and the median for failed and nonfailed firms. They also show the results from a nonparametric Wilcoxon test for means, a nonparametric test for medians and their significance levels. As expected, failed companies present worse values for the nine financial ratios compared to nonfailed firms. Differences are statistically significant for all the ratios except for the asset turnover ratio (ROTA) in the subsample of public firms. Assets turnover is not always a good bankruptcy predictor because many companies with low turnover can have high margins, being profitable.

*** Table 2 and 3***

Figure 1 and Figure 2, following Beaver (1966), allow visualizing failed and nonfailed companies and their time evolution of up to 5 years before bankruptcy, for both public and private companies. Differences between failed and nonfailed companies are clear in the classical financial ratios.

*** Figure 1 and 2 ***

Table 4 presents the exploratory analysis of the earnings management ratios containing the mean and median for nonfailed and failed public firms. Table 5 is equivalent to the previous one but made with private companies. There are differences among failed and nonfailed firms in most of the indicators, and some of them are statistically significant, but this time differences are not as acute as in the case of the classical financial ratios. The indicators presenting the highest differences between failed and nonfailed firms are the CvSALES and the CvPRO. The leverage index (LEVI) is also relevant, higher for failed firms. The assets quality index (AQI) is also higher for failed firms than that for nonfailed firms, as well as the SGAI and the DSRI. Except for this last index, all of them can be considered as indirect indicators associated to accounting anomalies. Five years before bankruptcy, the depreciation figures for failed firms are lower than the previous year (DDI), although the percentage of depreciation to assets remains the same (DEPI). From year to year, the depreciation figures converge, but the percentage of depreciation to assets grows. Five years before bankruptcy, failed companies present a similar or even a higher value of the accruals ratio (TATA) than that of nonfailed companies. But this value lowers from year to year in the case of failed firms. SGI reveals a drop in sales for failed companies. No statistically significant differences are found in the GMI. Figures 3 and 4 show the time evolution of up to 5 years before bankruptcy for private and public firms, respectively.

*** Table 4 and 5 ***

*** Figure 3 and 4 ***

An aggregated bankruptcy index was built from the indicators associated to earnings management (EM-index), following Anderson et al (2009) procedure, applied to the bankruptcy case by Liao and Mehdian (2016). In order to develop the EM-index, 1) indicators with low discriminatory power were discarded, using the following six indicators: DSRI, LEVI, AQI, SGAI, CvSALES and CvPRO; 2) to avoid distortion of extreme values, we recoded the data into their rank ordering from smallest to largest; 3) the six previously obtained rankings were then standardized to mean 0 and variance 1; and 4) the EM-index was obtained by adding the values of the new variables. Notice that with this procedure all the variables weigh equally. Differences between failed and nonfailed firms were statistically significant and very sharp in the EM-index.

Tables 6 and 7 display the Spearman correlation coefficients among the EM-index, the financial ratios and the variables associated to accounting anomalies. The most relevant data are the correlation between the EM-index and the financial ratios. The highest Spearman correlation is –0.37 with the ROA variable for the public companies and –0.26 for the private companies. It can be concluded that the information provided by the EM-index is different from those of classical financial ratios, as shown by its low correlation with the rest of indicators. Many financial ratios share a common numerator or denominator, so high correlations arise naturally between them. The level of multicollinearity was measured by means of the variance inflation factor (VIF), which is based on the proportion of variance the ith independent variable shares with the other independent variables in the model. If all the variables are uncorrelated with each other, the VIF is 1. As a rule of thumb, a VIF of 10 or greater reveals multicollinearity, considering the cautions stated by O’Brien (2007). The VIF value for Index-EM is 1.77, which is very low.

*** Table 6 and 7 ***

Once the statistically significant differences were contrasted, we analyzed the predictive power of each variable. A total of 21 univariate logistic regressions were performed, taking as predictors each of the 9 classical financial ratios and each of the 12 creative accounting indicators, including the EM-index. Tables 8 and 9 show the confusion matrices and three performance measures: accuracy, true negative rate, and true positive rate, for both public and private firms. Accuracy measures how often the classifier is correct. The true negative rate is defined as 1-Type 1 error rate, that is, when a firm is actually "failed," how often the technique predicts "failed." The true positive rate is defined as 1-Type II error rate, that is, when a firm is actually "solvent," how often the technique predicts "solvent." Some of the models present very high accuracies. For example, in the case of private firms, the test sample contains 39,688 firms, where 707 are failed firms, so, there is a 98.22% of solvent firms and a 1.78% of failed firms. This is a very unbalanced sample; hence, a naïve model "classifying all the companies as solvent" would have 98.22% accuracy. That is why some of the models present such high accuracies. However, this naïve model would classify 707 failed companies as solvent ones (Type I error), which has a high cost. Ferri et al. (2009) analyze the behavior of 18 performance measures; being accuracy, area under the ROC curve (AUC), and F-score the most popular. Not one of them outperforms the rest because they measure different aspects. In fact, the best measure will be the most useful one for decision making (Armstrong and Collopy, 1992), and in bankruptcy studies, the true negative rate is especially important, given the high cost of Type I errors, or false positives, facing Type II errors, or false negatives. According to Altman et al (1977), the cost of Type I errors is 35 times greater than that of a Type II error.

*** Table 8 and 9***

The tables confirm the previous exploratory findings and, as expected, show that classical financial ratios are good univariate predictors. However, some financial ratios present a high true positive rate but a low true negative rate. The contrary also happens, that is, high true negative rates but low true positive rates. The most balanced financial ratio is the retained earnings ratio (RE/TA), with a 74.7% true negative rate and a 77.6% true positive rate in the case of public firms and a 66.5% true negative rate and a 68.1% true positive rate in the case of private firms. As for the accounting anomalies indicators, most of them present very unbalanced values in Type I and Type II errors. None of them approaches the values got by the best performing financial ratios. This result seems comprehensible: debt ratios or profitability ratios have more predictive power than any indicator proposed to detect accounting anomalies. The opposite would only be possible if the financial statements are very far from the true and fair image of the company. However, the EM-index obtains percentages rather high, with a 67.7% true negative rate and a 69.6% true positive rate in the case of public companies; and a 52.3% true negative rate and a 70.1% true positive rate in the case of private companies.

Tables 10 and 11 show the results of several multivariate logistic regression analyses for predicting bankruptcy, for both public and private firms. The tables present the Nagelkerke's R^2 and –2 log likelihood as measures of goodness of fit. The tables display accuracy, true negative rate, true positive rate, AUC, and F_{β}-score. The tables also display the confusion matrices because they allow knowing exactly the number of errors, and from them, obtaining new performance measures. The ROC curve is very interesting because it plots the true positive rate against the false positive rate at various threshold settings. It is more complete than accuracy because it is a curve and not a single number statistic, thus providing a visual representation that allows extracting important conclusions. For example, if two ROC curves do not intersect, one model dominates the other; but if two ROC curves intersect, one model is better in some circumstances and the other is better in different circumstances. Although they are gaining popularity in bankruptcy studies, it should not be forgotten that, in their conventional design, ROC curves treat the costs of a type I error and a type II error the same (Agarwal and Taffler, 2008). Figures 5 and 6 display the ROC curves for each of the five models, for both public and private firms. The full model clearly outperforms the rest of the models. F_β-score is a harmonic average that combines both Type I and II errors, considering their different costs (van Rijsbergen, 1979). It is defined as

$$F_\beta = \frac{(1+\beta^2)\times\text{true positive}}{(1+\beta^2)\times\text{true positive}+\beta^2\times\text{true positive}+\text{false positive}}$$

$$\text{being } \beta = \frac{\text{Importance of Type II error}}{\text{Importance of Type I error}}$$

Thus, the higher the F_β-score, the better it is. If $\beta = 1$, both costs are considered as being of equal importance and the measure is the F-score. In our case, we have considered that the cost of a Type II error is 35 times lesser than that of a Type I error, and hence β equals 1/35, trusting Altman et al (1977)'s findings.

*** Table 10 and 11 ***

*** Figure 5 and 6 ***

Five multivariate models have been tested. The first model incorporates the five ratios of the Altman model, obtaining a test sample accuracy of 80.0%, a true negative rate of 76.6%, a true positive rate of 80.1%, a F_β-score of 99.22%, and an AUC of 0.800 in the case of public firms. Model 2 adds to the Altman model 4 financial ratios, entering nine classical financial ratios. Model 3 adds to the nine classical financial ratios the EM-index. Model 4 just includes the accounting anomalies variables. The results of models 2, 3, and 4 are very similar to those obtained by the Altman model, without increasing the predictive power. Model 5 is a full model including the 21 variables, and obtains the best performance, with an 83.7% accuracy, an 82.1% true negative rate, an 83.7% true positive rate, an F_{β}-score of 99.51%, and an AUC of 0.860. Altman's model performs well for public companies, with similar results compared to the full model including the accounting anomalies variables. In fact, the results of the full model only slightly improve those obtained by Altman's model.

However, analyzing the results of the models in the case of private companies, it can be seen that Altman's model performs not so well for these companies (accuracy of 70.7%; true negative rate of 66.5%; true positive rate of 70.8%, F_{β}-score of 99.12%, and AUC of 0.725); while the full model including the accounting anomalies variables is very useful here (accuracy of 81.3%; true negative rate of 74.4%; true positive rate of 81.4%, F_{β}-score of 99.52%, and AUC of 0.837). The results show that it should be very convenient to include variables that detect accounting anomalies in models developed for private companies.

Tables 12 and 13 show the results of a CHAID decision tree, for both public and private firms. As for its performance, the test sample accuracy is 79.0%, the true negative rate is 75.5% and the true positive rate is 79.1% in the subsample of public firms. The test sample accuracy is 70.3%, the true negative rate is 68.8% and the true positive rate is 70.3% in the subsample of private firms. These are worse results than that of logistic regressions results; however, this decision trees offer rules easy to interpret. The tables include two panels, the first containing the rules to predict whether a firm will be solvent and the second to predict whether a firm will go bankrupt. The tables show the train and the test results, being the latter the most important. The first row serves as a benchmark because it shows the results of forecasting that "all firms will be nonfailed." In the case of public firms, the percentage of correctly classified firms is 97.4%, which is the percentage of solvent firms in the test sample. The rule corresponding to node 1 predicts that 'firms with an EM-index below -0.152 will be solvent'; in this case, the percentage of correctly classified firms rises to a 99.2%. The next node adds a new condition: “the presence of profits,” that is, to have a PROFIT=1. In this case, the percentage of firms correctly classified rises to a 99.5%. By adding complexity to the rules, the percentage of correctly classified firms increases. For example, the next node, number 12, adds the rule “enough retained earnings,” with RE/TA values over 0.12; in this case, the percentage of correctly classified firms rises to a 99.7%. Similar rules can be obtained for the case of private companies.

As for the prediction of bankruptcy, the first row shows the results of forecasting that “all firms will be failed.” In the case of public firms, the percentage of correctly classified firms is 2.6%, which is the percentage of failed firms in the test sample. Node 3 predicts that “firms with an EM-index over 3.670 will go bankrupt” getting a 7.2% of companies correctly classified. Node 10 establishes that “firms with an EM-index over 3.670, without profits will go bankrupt.” The percentage of companies correctly classified is 10.5%. Similar rules can be obtained for the case of private companies.

*** Tables 12 and 13 ***

To sum up, according to the logistic regression, the predictive power of each one of the variables associated to accounting anomalies is low, although some of them present certain discriminatory power, finding statistically significant differences between failed and nonfailed firms. However, the index designed to measure the degree of accounting anomalies, obtained by aggregating six variables, does present a remarkable predictive power, comparable to classical financial ratios. This index is also included in the set of rules obtained by the decision tree, assigning the maximum likelihood of failure to those firms with high values of the accounting anomalies index, without profits, with cash tensions and without retained earnings to face difficulties. The inclusion of variables to detect accounting anomalies is especially useful for private companies. This fact is not surprising since private firms exhibit higher levels of earnings management than public companies (Burgstahler et al, 2006) because listed companies have a public interest obligation, which leads to more intensive regulation of financial disclosure (Weetman, 2018). Incentives for earnings management change from public to private companies, and Beneish (1999) and Beneish et al (2013) models are intended for public companies. As a future research line, we propose the inclusion of more variables especially designed for private companies, such as the ones used by Prencipe et al (2008). We think that the analysis of other indicators related to accounting anomalies, like real activities earnings management measures by Roychowdhury (2006) or the use of abnormal accruals as a proxy for earnings management (Peasnell et al 2005), and the development of new indexes such as the one proposed in this paper is a promising research avenue in the field of bankruptcy prediction models.

4. Conclusions

Annual accounts do not always reflect a true and fair view of the financial situation of a company, given the presence of creative accounting practices, earnings management, profits smoothing and accounting fraud. The situation is worsened among companies experiencing financial difficulties, those precisely more prone to develop such practices distorting accounting figures. However, with some exceptions, most of the models developed to predict bankruptcy do not incorporate indicators to detect accounting anomalies. These indicators try to measure distortions in depreciation, detect exaggerated receivables or abnormal accruals, among others. Other indicators are indirect and measure variations in debt, sales or profits because these companies experiencing financial difficulties have a tendency to manipulate annual accounts.

The empirical study has been performed from a sample of failed and nonfailed 51,337 European companies. The robustness of the study was enhanced by 1) splitting the training and test sets into chronological order to ensure intertemporal validation, a procedure more robust than cross validation; 2) using different statistical techniques, in our case logistic regression and decision trees; 3) proposing several performance measures, including the F_β-score, a harmonic average that combines both Type I and II errors, considering their different costs; and 4) splitting the sample into public and private companies. It is found that earnings management indicators present statistically significant differences between failed and nonfailed firms, but they do not have enough predictive power to incorporate them into prediction models. However, the paper has designed an index to detect distortions in accounting built from several financial ratios that try to measure accounting anomalies, based on the creative accounting literature, and it is found that this index is a good bankruptcy predictor, as good as any of the classical financial ratios measuring profitability, liquidity or solvency. The construction of the index and its application to private firm sample provide the main contribution of the paper, as the results suggest slightly better forecast accuracy only for the private firm sample, which stimulates future research in this line. Simple rules, obtained from a decision tree, assign the maximum bankruptcy likelihood to those companies with high values of the accounting anomalies index, without profits, with cash tensions and without retained earnings to face difficulties. We have found that bankruptcy prediction models based on classical financial ratios perform better for public companies than for private ones, whereas variables detecting accounting anomalies are especially useful for private companies. As a practical implication, the paper proposes that when developing new models to predict bankruptcy, the inclusion of indicators to detect accounting anomalies should be considered, not assuming that the annual accounts always give a fair and true view of the financial situation of the companies. Financial analysts who develop decision support systems to predict bankruptcies would do well in examining such indicators capturing creative accounting practices. The inclusion of these variables to detect accounting anomalies is especially useful for private companies.

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Variable	*Definition*
ROA	Return on assets: Earnings Before Interest and Taxes/Total Assets
RE/TA	Retained earnings ratio: Retained Earnings/Total Assets
EQ/TL	Equity strength: Equity/Total Liabilities
WC/TA	Working capital ratio: (Current assets - Current liabilities)/Total Assets
ROTA	Asset turnover: Sales/Total Assets
CASH	Cash ratio: Cash/Total assets
PROFIT	Dummy variable equals to 1 if the return on assets (ROA) is positive
INT/S	Financial expenses coverage: Interest Expenses/Sales
ΔSALES	Increase in sales ratio: $\frac{\text{Sales}_t - \text{Sales}_{t-1}}{\text{Sales}_{t-1}}$
DSRI	Days' sales in receivable index: $\frac{\text{Receivables}_t}{\text{Sales}_t} / \frac{\text{Receivables}_{t-1}}{\text{Sales}_{t-1}}$
LEVI	Leverage index: $\frac{\text{Total Debt}_t}{\text{Total Assets}_t} / \frac{\text{Total Debt}_{t-1}}{\text{Total Assets}_{t-1}}$
AQI	Assets quality index: $\left(1 - \frac{\text{Current Assets}_t + \text{Property, Plant and Equipment}_t}{\text{Total Assets}_t}\right) / \left(1 - \frac{\text{Current Assets}_{t-1} + \text{Property, Plant and Equipment}_{t-1}}{\text{Total Assets}_{t-1}}\right)$
SGAI	Sales, general, and administrative expenses index: $\frac{\text{Sales, general, and administrative expenses}_t}{\text{Sales}_t} / \frac{\text{Sales, general, and administrative expenses}_{t-1}}{\text{Sales}_{t-1}}$
DEPI	Depreciation index: $\frac{\text{Depreciation rate}_{t-1}}{\text{Depreciation rate}_t}$
DDI	Depreciation decay index: $\frac{\text{Depreciation}_{t-1}}{\text{Depreciation}_t}$
TATA	Total accruals to total assets ratio: $\frac{\text{Total accruals}_t}{\text{Total assets}_t}$

SGI	Sales growth index: $\frac{\mathrm{Sales}_t}{\mathrm{Sales}_{t-1}}$
CvSALES	Coefficient of variation of sales: $\frac{\sigma(\mathrm{Sales}_t,\mathrm{Sales}_{t-1})}{\lvert\mu(\mathrm{Sales}_t,\mathrm{Sales}_{t-1})\rvert}$
GMI	Gross margin index: $\frac{\mathrm{Sales}_{t-1}-\mathrm{Cost\ of\ goods\ sold}_{t-1}}{\mathrm{Sales}_{t-1}} / \frac{\mathrm{Sales}_t-\mathrm{Cost\ of\ goods\ sold}_t}{\mathrm{Sales}_t}$
C_VPRO	Coefficient of variation of profits: $\frac{\sigma(\mathrm{Net\ Profit}_t,\mathrm{Net\ Profit}_{t-1})}{\lvert\mu(\mathrm{Net\ Profit}_t,\mathrm{Net\ Profit}_{t-1})\rvert}$
EM-index	Earnings management index: $\sum(z(\mathrm{DSRI}), z(\mathrm{LEVI}), z(\mathrm{AQI}), z(\mathrm{SGAI}), z(\mathrm{CvSALES}), z(\mathrm{CvPRO}))$, being z the standardized variable

Table 1. Variables employed and their definition.

		2013		2012		2011		2010		2009	
		Nonfailed	Failed	Nonfailed	Failed	Nonfailed	Failed	Nonfailed	Failed	Nonfailed	Failed
	N	11,446	270	11,255	266	11,445	269	11,438	270	11,433	269
ROA	Mean	0.04	-0.08	0.04	-0.04	0.04	-0.01	0.05	0.00	0.04	0.01
	Median	0.03	-0.03	0.03	0.00	0.03	0.01	0.03	0.01	0.03	0.01
	Wilcoxon Z	(-15.43)***		(-11.84)***		(-8.85)***		(-7.73)***		(-5.95)***	
	Median X^2	(138.3)***		(92.43)***		(56.63)***		(63.09)***		(23.15)***	
RE/TA	Mean	0.21	-0.22	0.22	-0.04	0.22	0.03	0.21	0.06	0.21	0.10
	Median	0.21	-0.05	0.21	0.01	0.21	0.03	0.20	0.04	0.20	0.07
	Wilcoxon Z	(-15.72)***		(-12.26)***		(-10.63)***		(-9.62)***		(-7.78)***	
	Median X^2	(138.3)***		(102.22)***		(94.98)***		(88.75)***		(56.63)***	
EQ/TL	Mean	5.03	4.81	4.57	3.63	5.00	2.64	4.62	2.28	4.75	2.21
	Median	0.58	0.04	0.57	0.11	0.56	0.15	0.56	0.19	0.56	0.24
	Wilcoxon Z	(-15.91)***		(-13.49)***		(-11.96)***		(-11.11)***		(-9.5)***	
	Median X^2	(141.21)***		(117.85)***		(87.88)***		(77.53)***		(69.1)***	
WC/TA	Mean	0.15	-0.09	0.16	0.00	0.16	0.05	0.16	0.09	0.16	0.11
	Median	0.14	-0.02	0.14	0.01	0.14	0.05	0.14	0.06	0.14	0.08
	Wilcoxon Z	(-9.37)***		(-7.6)***		(-5.83)***		(-3.85)***		(-2.87)***	
	Median X^2	(43.4)***		(42.41)***		(25.58)***		(12.32)***		(6.71)***	
ROTA	Mean	1.51	1.35	1.52	1.24	1.53	1.25	1.50	1.28	1.47	1.26
	Median	1.17	0.84	1.19	0.86	1.19	0.98	1.15	1.02	1.12	0.97
	Wilcoxon Z	(-3.31)***		(-3.58)***		(-2.67)***		(-2.57)**		(-1.97)**	
	Median X^2	(5.19)**		(3.7)*		(6.09)**		(2.76)*		(2.98)*	
CASH	Mean	0.090	0.055	0.088	0.046	0.090	0.051	0.093	0.058	0.095	0.061
	Median	0.036	0.013	0.035	0.015	0.034	0.015	0.036	0.017	0.037	0.017
	Wilcoxon Z	(-6.06)***		(-6.71)***		(-5.75)***		(-5.45)***		(-4.8)***	
	Median X^2	(20.2)***		(33.27)***		(24.35)***		(17.02)***		(10.29)***	
PROFIT	Mean	0.70	0.27	0.68	0.35	0.72	0.50	0.73	0.51	0.70	0.53
	Median	1.00	0.00	1.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00
	Wilcoxon Z	(-15.14)***		(-11.43)***		(-7.6)***		(-8.18)***		(-6.34)***	

	Pearson X^2	(229.239)***		(130.57)***		(57.73)***		(66.85)***		(40.19)***	
INT/S	Mean	-0.041	0.222	-0.007	0.021	-0.092	0.022	-0.084	-0.031	-0.026	0.017
	Median	0.007	0.015	0.008	0.014	0.008	0.012	0.007	0.010	0.008	0.011
	Wilcoxon Z	(-3.54)***		(-3.04)***		(-2.62)***		(-1.53)		(-1.18)	
	Median X^2	(17.43)***		(10.62)***		(8.25)***		(4.54)**		(2.31)	
ΔSALES	Mean	0.04	-0.16	0.04	-0.06	0.12	0.14	0.14	0.19	0.03	0.00
	Median	0.00	-0.19	0.00	-0.08	0.05	0.04	0.05	0.04	-0.05	-0.13
	Wilcoxon Z	(-11.79)***		(-5.91)***		(-1.02)		(-1.25)		(-4.01)***	
	Median X^2	(76.89)***		(11.35)***		(1.27)		(0.4)		(11.89)***	

Table 2. Public firms. Exploratory analysis of the classical financial ratios containing the mean and median for nonfailed and failed firms, for the test sample. The table also shows the results from a nonparametric Wilcoxon test for means, and a nonparametric test for medians and significance levels. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

		2013		**2012**		**2011**		**2010**		**2009**	
		Nonfailed	**Failed**	**Nonfailed**	**Failed**	**Nonfailed**	**Failed**	**Nonfailed**	**Failed**	**Nonfailed**	**Failed**
	N	38,981	707	38,614	695	38,942	706	38,904	706	38,713	701
ROA	Mean	0.05	-0.02	0.05	0.01	0.06	0.03	0.06	0.03	0.05	0.03
	Median	0.03	0.00	0.03	0.01	0.03	0.01	0.03	0.02	0.02	0.02
	Wilcoxon Z	(-14.78)***		(-8.66)***		(-5.99)***		(-4.5)***		(-1.84)*	
	Median X^2	(100.37)***		(32.95)***		(11.94)***		(4.36)**		(0.02)	
RE/TA	Mean	0.28	-0.04	0.28	0.05	0.27	0.08	0.27	0.10	0.26	0.12
	Median	0.26	0.01	0.25	0.04	0.24	0.06	0.23	0.07	0.22	0.07
	Wilcoxon Z	(-19.45)***		(-16.5)***		(-14.26)***		(-12.92)***		(-11.5)***	
	Median X^2	(214.57)***		(194.05)***		(173.64)***		(143.1)***		(118.8)***	
EQ/TL	Mean	7.48	5.63	6.46	4.27	6.77	5.08	6.14	3.47	6.13	3.60

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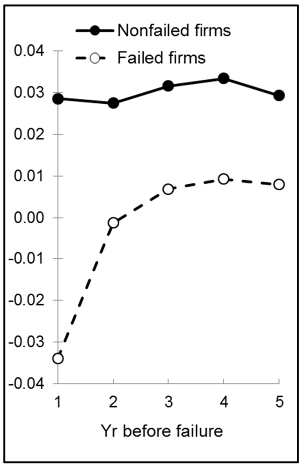
	Median	0.56	0.08	0.55	0.14	0.53	0.17	0.52	0.18	0.50	0.20
	Wilcoxon Z	(-20.44)***		(-17.86)***		(-16.28)***		(-14.97)***		(-13.11)***	
	Median X^2	(235.04)***		(210.08)***		(199.27)***		(163.48)***		(135.37)***	
WC/TA	Mean	0.22	0.02	0.22	0.10	0.22	0.13	0.21	0.14	0.22	0.15
	Median	0.19	0.03	0.19	0.07	0.19	0.08	0.19	0.10	0.19	0.10
	Wilcoxon Z	(-11.94)***		(-9.2)***		(-8.05)***		(-6.41)***		(-6.21)***	
	Median X^2	(87.15)***		(72.18)***		(67.91)***		(40.22)***		(32.68)***	
ROTA	Mean	1.58	2.05	1.55	1.92	1.51	1.78	1.44	1.74	1.23	1.62
	Median	1.08	1.09	1.03	1.22	0.96	1.21	0.87	1.10	0.61	1.01
	Wilcoxon Z	(-4.34)***		(-4.62)***		(-4.97)***		(-5.13)***		(-7.48)***	
	Median X^2	(0.02)		(3.37)*		(8.55)***		(6.87)***		(16.32)***	
CASH	Mean	0.104	0.058	0.103	0.049	0.105	0.061	0.110	0.067	0.112	0.072
	Median	0.038	0.007	0.037	0.007	0.038	0.010	0.041	0.012	0.042	0.013
	Wilcoxon Z	(-14.17)***		(-14.21)***		(-11.9)***		(-10.56)***		(-9.98)***	
	Median X^2	(151.17)***		(165.35)***		(99.75)***		(76.95)***		(75.5)***	
PROFIT	Mean	0.59	0.39	0.58	0.49	0.59	0.58	0.59	0.61	0.55	0.60
	Median	1.00	0.00	1.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00
	Wilcoxon Z	(-10.88)***		(-4.84)***		(-0.74)		(-1)		(-2.66)***	
	Pearson X^2	(118.35)***		(23.39)***		(0.55)		(0.99)		(7.05)***	
INT/S	Mean	-0.018	0.027	-0.003	0.015	-0.009	0.016	-0.002	0.019	-0.004	0.006
	Median	0.004	0.009	0.005	0.010	0.005	0.008	0.005	0.007	0.006	0.008
	Wilcoxon Z	(-5.72)***		(-4.96)***		(-3.39)***		(-3.22)***		(-1.83)*	
	Median X^2	(14.92)***		(19.81)***		(7.62)***		(6.92)***		(4.81)**	
ΔSALES	Mean	0.05	-0.03	0.07	0.11	0.13	0.24	0.15	0.27	0.04	0.10
	Median	0.02	-0.11	0.02	0.01	0.06	0.03	0.07	0.10	-0.02	-0.06
	Wilcoxon Z	(-12.57)***		(-1.86)*		(-2.4)**		(-2.94)***		(-1.33)	
	Median X^2	(85.22)***		(2.08)		(4.89)**		(3.45)*		(5.59)**	

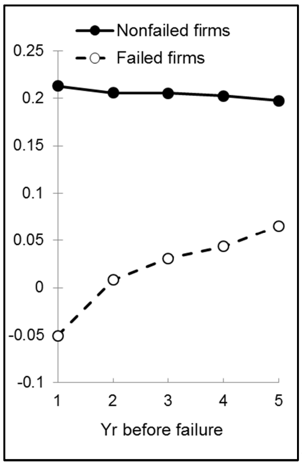
Table 3. Private firms. Exploratory analysis of the classical financial ratios containing the mean and median for nonfailed and failed firms, for the test sample. The table also shows the results from a nonparametric

Wilcoxon test for means, and a nonparametric test for medians and significance levels. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

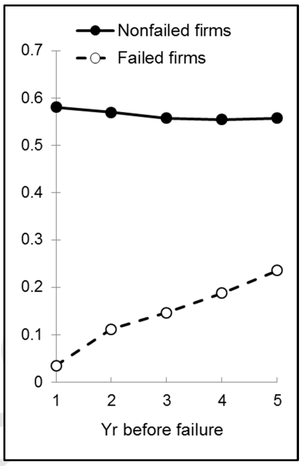
ROA



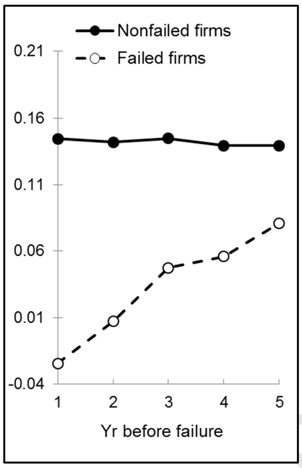
RE/TA



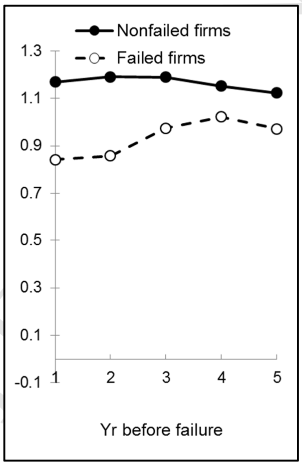
EQ/TL



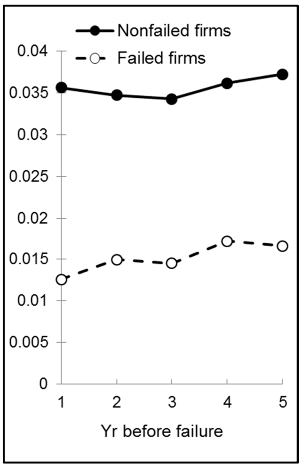
WC/TA



ROTA



CASH



PROFIT

INT/S

ΔSALES

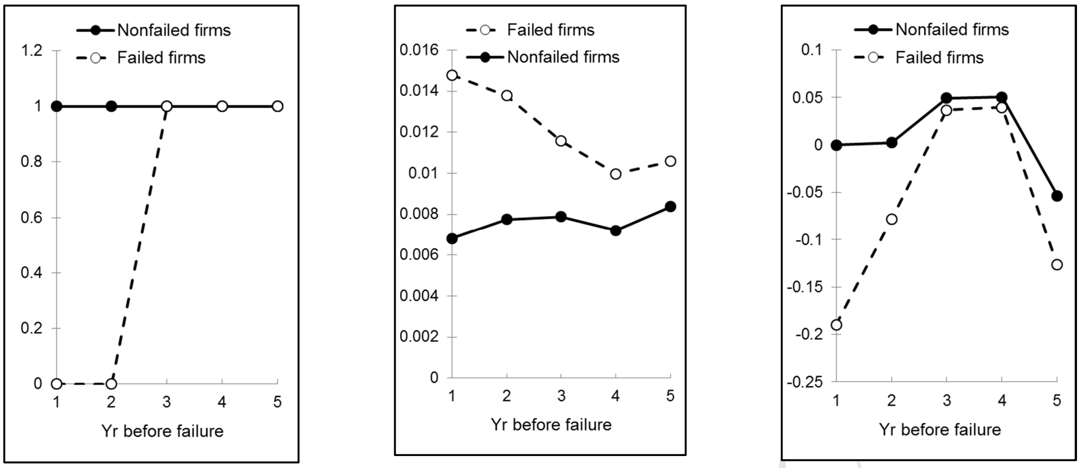
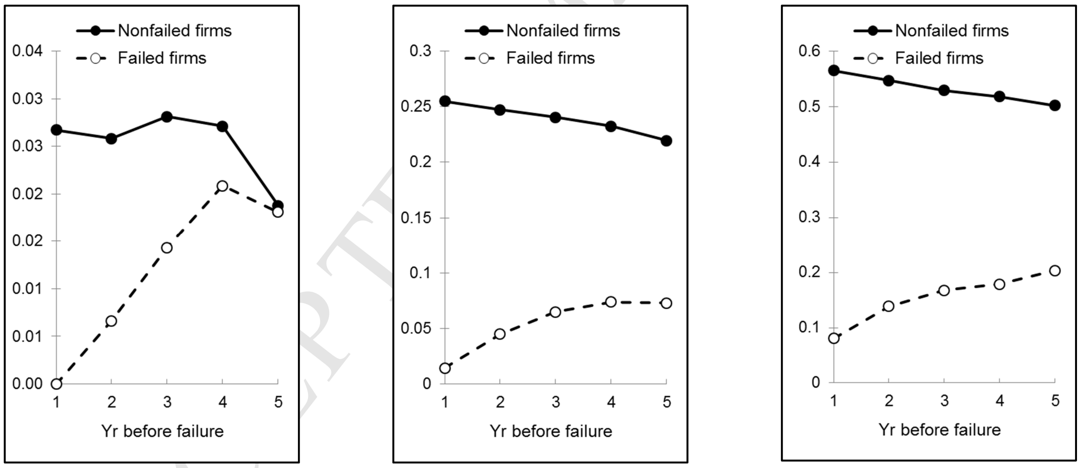


Figure 1. Public firms. Comparison of median values for failed and nonfailed firms using classical financial ratios.

ROA **RE/TA** **EQ/TL**



WC/TA **ROTA** **CASH**

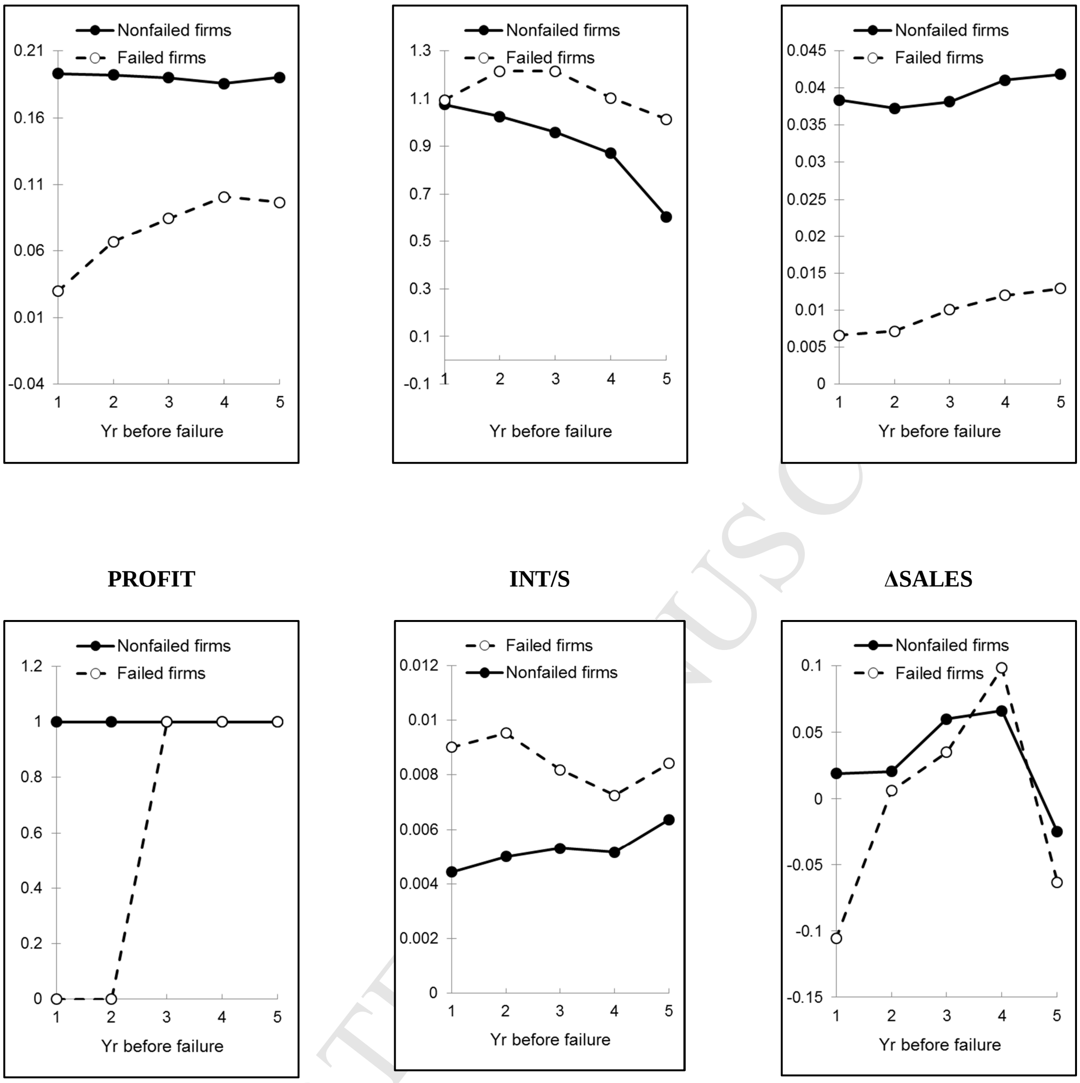


Figure 2. Private firms. Comparison of median values for failed and nonfailed firms using classical financial ratios.

		2013		2012		2011		2010		2009	
		Nonfailed	**Failed**	**Nonfailed**	**Failed**	**Nonfailed**	**Failed**	**Nonfailed**	**Failed**	**Nonfailed**	**Failed**
	N	11,446	270	11,255	266	11,445	269	11,438	270	11,433	269
DSRI	Mean	1.20	1.68	1.16	1.36	1.18	1.50	1.19	1.49	1.25	1.37
	Median	1.00	1.01	0.99	0.98	0.99	1.01	1.00	1.08	1.03	1.02
	Wilcoxon Z	(-0.98)		(-0.23)		(-2.06)**		(-3.59)***		(-0.2)	
	Median X^2	(0.04)		(0)		(1.68)		(9.78)***		(0.21)	
LEVI	Mean	1.02	1.21	1.03	1.09	1.03	1.07	1.05	1.08	1.02	1.05
	Median	1.00	1.05	1.00	1.02	1.00	1.01	1.00	1.01	0.98	1.00
	Wilcoxon Z	(-9.74)***		(-6.26)***		(-4.14)***		(-3.14)***		(-4.2)***	
	Median X^2	(74.38)***		(40.21)***		(10.3)***		(9.63)***		(23.85)***	
AQI	Mean	2.27	2.93	1.92	1.53	2.07	3.78	2.21	2.55	2.38	2.54
	Median	1.00	1.04	1.00	1.01	0.99	1.00	0.98	0.99	1.01	1.01
	Wilcoxon Z	(-2.97)***		(-0.22)		(-1.35)		(-0.78)		(-0.23)	
	Median X^2	(3.04)*		(0.54)		(2.28)		(0.35)		(0)	
SGAI	Mean	1.06	1.37	1.14	1.38	1.05	1.15	1.02	1.02	1.14	1.22
	Median	1.00	1.05	1.01	1.02	0.99	1.00	0.99	1.00	1.02	1.01
	Wilcoxon Z	(-5.4)***		(-2.65)***		(-1.82)*		(-1.12)		(-0.7)	
	Median X^2	(23.03)***		(1.91)		(4.05)**		(0.68)		(3.49)*	
DEPI	Mean	1.09	0.99	1.06	1.11	1.06	1.14	1.07	1.16	1.03	1.05
	Median	0.98	0.91	0.98	1.00	0.98	0.98	0.98	0.96	0.95	0.97
	Wilcoxon Z	(-4.38)***		(-0.16)		(-1.21)		(-0.33)		(-0.51)	
	Median X^2	(7.29)***		(0.47)		(0)		(0.19)		(0.76)	
DDI	Mean	1.08	1.15	1.04	1.10	1.04	1.05	1.03	1.09	1.02	1.01
	Median	1.01	1.02	1.00	1.00	1.00	0.96	1.00	0.99	0.99	1.00
	Wilcoxon Z	(-0.5)		(-0.26)		(-2.57)**		(-0.83)		(-0.58)	
	Median X^2	(0.35)		(0.15)		(4.27)**		(0.33)		(0.43)	
TATA	Mean	-0.03	-0.11	-0.03	-0.10	-0.03	-0.09	-0.03	-0.05	-0.02	0.00
	Median	-0.02	-0.04	-0.02	-0.03	-0.02	-0.07	-0.03	-0.05	-0.02	-0.02
	Wilcoxon Z	(-3.37)***		(-3.15)***		(-5.07)***		(-1.99)**		(-0.96)	
	Median X^2	(3.64)*		(1.11)		(11.09)***		(2.76)*		(0.06)	
SGI	Mean	1.04	0.84	1.04	0.94	1.12	1.14	1.14	1.19	1.03	1.00
	Median	1.00	0.81	1.00	0.92	1.05	1.04	1.05	1.04	0.95	0.87

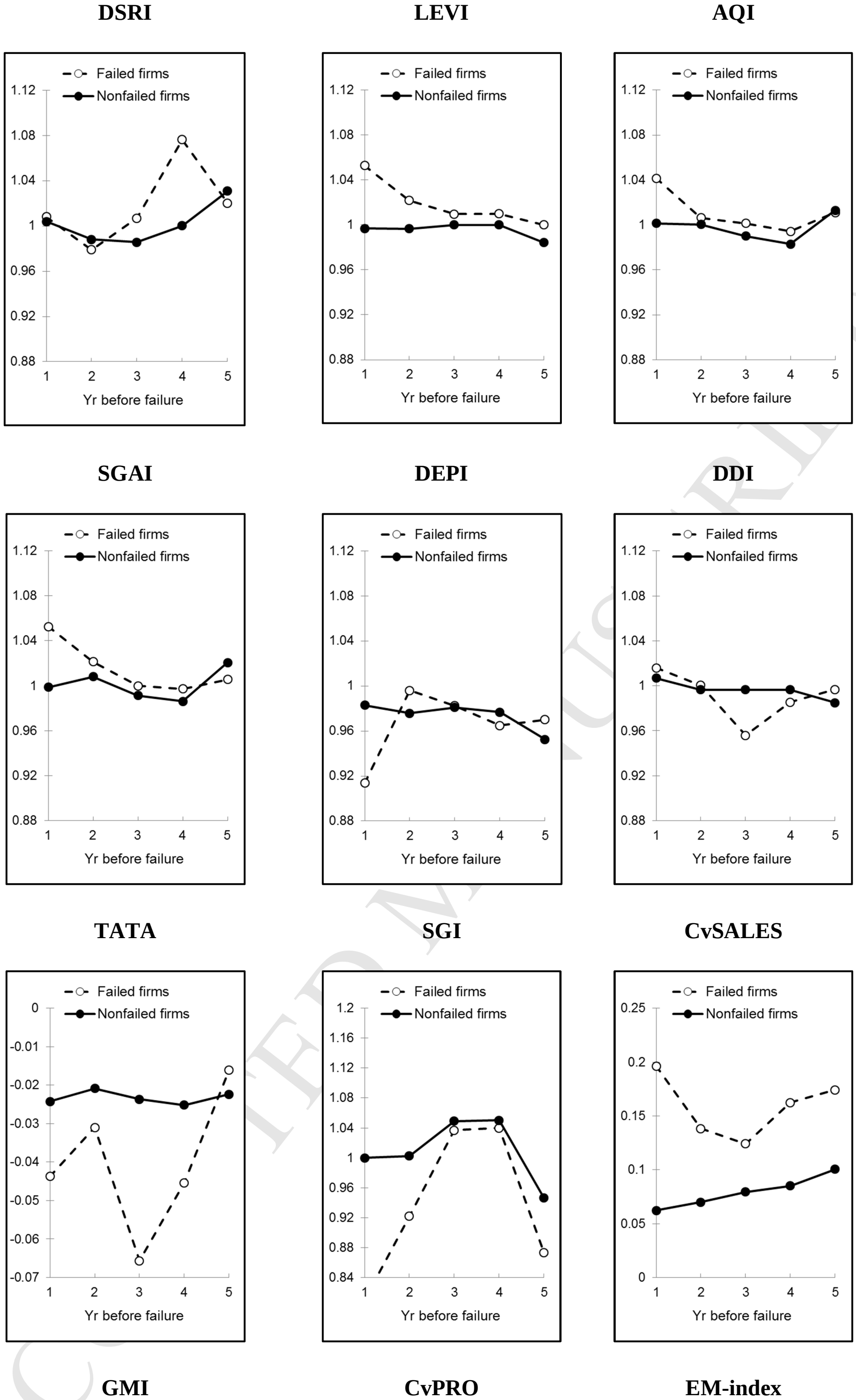
	Wilcoxon Z	(-11.79)***		(-5.91)***		(-1.02)		(-1.25)		(-4.01)***	
	Median X^2	(76.89)***		(11.35)***		(1.27)		(0.4)		(11.89)***	
CvSALES	Mean	0.14	0.36	0.15	0.29	0.16	0.24	0.17	0.26	0.20	0.28
	Median	0.06	0.20	0.07	0.14	0.08	0.12	0.09	0.16	0.10	0.17
	Wilcoxon Z	(-13.26)***		(-8.01)***		(-5.45)***		(-6.33)***		(-6.29)***	
	Median X^2	(107.25)***		(37.69)***		(22.66)***		(26.25)***		(31.58)***	
GMI	Mean	1.01	1.06	0.99	0.96	1.02	1.00	1.04	1.01	0.96	0.97
	Median	1.00	1.00	1.00	0.99	1.01	1.00	1.00	1.01	0.98	1.00
	Wilcoxon Z	(-1.63)		(-1.97)**		(-1.81)*		(-0.49)		(-1.83)*	
	Median X^2	(0.99)		(1.14)		(2.09)		(0.21)		(2.62)	
C_VPRO	Mean	1.16	1.17	1.23	1.16	1.17	1.57	1.27	1.49	1.38	1.56
	Median	0.44	0.88	0.45	0.83	0.43	0.77	0.48	0.76	0.53	0.86
	Wilcoxon Z	(-6.2)***		(-5.87)***		(-5.91)***		(-4.78)***		(-4.37)***	
	Median X^2	(59)***		(43.74)***		(35.81)***		(22.65)***		(23.36)***	
EM-index	Mean	0.27	2.39	0.31	1.82	0.18	1.55	0.19	1.54	0.29	1.20
	Median	0.19	2.35	0.09	1.76	0.00	1.34	0.01	1.35	0.09	0.93
	Wilcoxon Z	(-12.96)***		(-8.3)***		(-7.19)***		(-7.54)***		(-4.7)***	
	Median X^2	(105.73)***		(38.67)***		(30.03)***		(41.8)***		(22.48)***	

Table 4. Public firms. Exploratory analysis of earning management ratios containing the mean and median for nonfailed and failed firms, for the test sample. The table also shows the results from a nonparametric Wilcoxon test for means, and a nonparametric test for medians and significance levels. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

		2013		2012		2011		2010		2009	
		Nonfailed	Failed	Nonfailed	Failed	Nonfailed	Failed	Nonfailed	Failed	Nonfailed	Failed
	N	38,981	707	38,614	695	38,942	706	38,904	706	38,713	701
DSRI	Mean	1.16	1.54	1.16	1.34	1.18	1.68	1.19	1.33	1.22	1.45
	Median	0.99	1.00	1.00	1.00	0.97	1.08	1.00	0.99	1.02	1.07
	Wilcoxon Z	(-1.04)		(-0.07)		(-5.54)***		(-0.89)		(-3.02)***	
	Median X^2	(0.33)		(0)		(13.51)***		(0.6)		(3.02)*	
LEVI	Mean	1.01	1.12	1.02	1.06	1.03	1.06	1.03	1.08	1.02	1.03
	Median	0.99	1.02	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00
	Wilcoxon Z	(-10.29)***		(-7.07)***		(-5.3)***		(-5.41)***		(-4.89)***	
	Median X^2	(87.22)***		(45.37)***		(33.08)***		(24.41)***		(24.07)***	
AQI	Mean	2.14	2.80	1.74	2.50	1.93	3.74	1.97	3.30	2.36	2.57
	Median	0.98	0.98	0.98	1.00	0.97	0.98	0.95	0.93	0.99	0.94
	Wilcoxon Z	(-0.94)		(-0.09)		(-0.83)		(-2)**		(-3.08)***	
	Median X^2	(0.02)		(2.62)		(0.88)		(1.33)		(7.35)***	
SGAI	Mean	1.05	1.25	1.11	1.18	1.05	1.10	1.01	1.07	1.18	1.17
	Median	1.00	1.02	1.00	1.01	1.00	1.00	0.99	1.00	1.01	1.00
	Wilcoxon Z	(-6.98)***		(-2.83)***		(-1.91)*		(-4.21)***		(-0.44)	
	Median X^2	(47.01)***		(15.79)***		(11.02)***		(20.57)***		(4.7)**	
DEPI	Mean	1.02	0.96	1.02	1.07	1.04	1.01	1.05	1.08	1.00	1.02
	Median	0.97	0.91	0.97	0.93	0.98	0.95	0.97	0.95	0.96	0.94
	Wilcoxon Z	(-4.96)***		(-2.9)***		(-3.01)***		(-0.86)		(-1.79)*	
	Median X^2	(16.69)***		(7.64)***		(8.35)***		(1.21)		(1.09)	
DDI	Mean	0.99	1.05	0.99	1.05	0.99	1.01	0.98	1.03	0.99	0.98
	Median	0.98	0.98	0.97	0.96	0.97	0.94	0.97	0.95	0.97	0.92
	Wilcoxon Z	(-0.29)		(-0.39)		(-1.79)*		(-0.85)		(-2.7)***	
	Median X^2	(0.04)		(0.14)		(3.42)*		(1.7)		(7.84)***	
TATA	Mean	-0.03	-0.11	-0.02	-0.04	-0.02	-0.04	-0.03	-0.05	-0.03	-0.01
	Median	-0.02	-0.04	-0.02	-0.02	-0.01	-0.02	-0.02	-0.02	-0.02	-0.01
	Wilcoxon Z	(-4.87)***		(-1.86)*		(-3.01)***		(-1.17)		(-1.34)	
	Median X^2	(5.9)**		(0.84)		(5.02)**		(1.05)		(0.84)	
SGI	Mean	1.05	0.97	1.07	1.11	1.13	1.24	1.15	1.27	1.04	1.10
	Median	1.02	0.89	1.02	1.01	1.06	1.03	1.07	1.10	0.98	0.94

	Wilcoxon Z	(-12.57)***		(-1.86)*		(-2.4)**		(-2.94)***		(-1.33)	
	Median X^2	(85.22)***		(2.08)		(4.89)**		(3.45)*		(5.59)**	
CvSALES	Mean	0.13	0.32	0.14	0.25	0.15	0.26	0.17	0.26	0.19	0.28
	Median	0.06	0.17	0.06	0.13	0.08	0.12	0.09	0.16	0.10	0.17
	Wilcoxon Z	(-17.22)***		(-12.45)***		(-8.43)***		(-9.56)***		(-8.72)***	
	Median X^2	(173)***		(128)***		(39.95)***		(68.85)***		(51.09)***	
GMI	Mean	1.01	1.01	0.99	1.01	1.02	1.05	1.06	1.03	0.96	0.96
	Median	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.00	0.98	0.98
	Wilcoxon Z	(-0.17)		(-0.49)		(-0.51)		(-1.96)**		(-0.44)	
	Median X^2	(0.67)		(0.07)		(0.02)		(4.89)**		(0)	
C_VPRO	Mean	1.14	1.29	1.13	1.44	1.12	1.41	1.27	1.65	1.43	1.59
	Median	0.41	0.85	0.41	0.75	0.41	0.70	0.47	0.65	0.53	0.76
	Wilcoxon Z	(-9.36)***		(-9.09)***		(-8.69)***		(-5.14)***		(-5.14)***	
	Median X^2	(86.75)***		(64.3)***		(63.38)***		(27.14)***		(23.6)***	
EM-index	Mean	-0.13	1.32	-0.15	1.08	-0.13	1.08	-0.09	0.77	-0.08	0.65
	Median	-0.14	1.05	-0.19	0.89	-0.22	0.93	-0.11	0.50	-0.13	0.44
	Wilcoxon Z	(-14.00)***		(-11.83)***		(-11.96)***		(-8.14)***		(-6.76)***	
	Median X^2	(111.3)***		(100.37)***		(90.01)***		(35.05)***		(32.4)***	

Table 5. Private firms. Exploratory analysis of earning management ratios containing the mean and median for nonfailed and failed firms, for the test sample. The table also shows the results from a nonparametric Wilcoxon test for means, and a nonparametric test for medians and significance levels. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.


DSRI
LEVI
AQI
SGAI
DEPI
DDI
TATA
SGI
CvSALES
GMI
CvPRO
EM-index
Failed firms
Nonfailed firms
Yr before failure

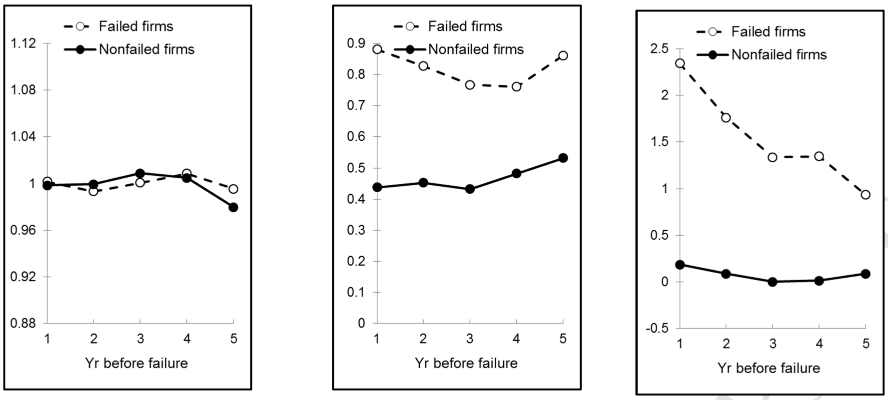
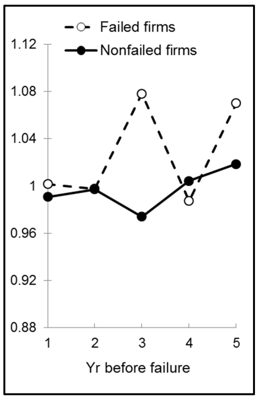
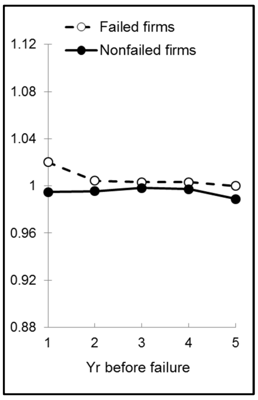
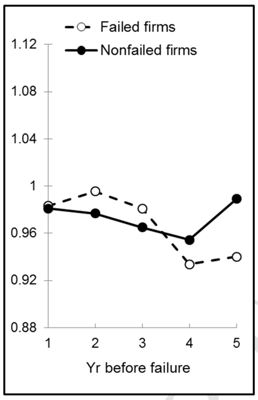

Failed firms
Nonfailed firms
1.12
1.08
1.04
1
0.96
0.92
0.88
1 2 3 4 5
Yr before failure
Failed firms
Nonfailed firms
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1 2 3 4 5
Yr before failure
Failed firms
Nonfailed firms
2.5
2
1.5
1
0.5
0
-0.5
1 2 3 4 5
Yr before failure

Figure 3. Public firms. Comparison of median values using earnings management ratios.

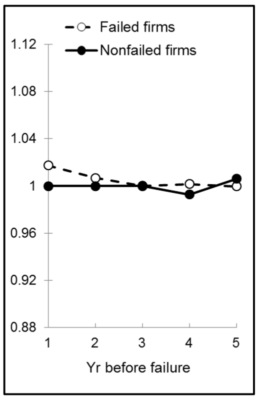
DSRI **LEVI** **AQI**

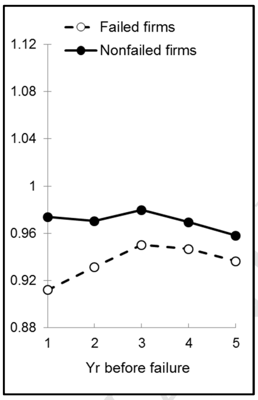


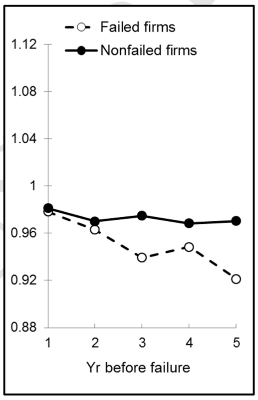




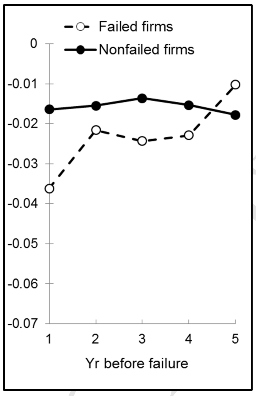
SGAI **DEPI** **DDI**

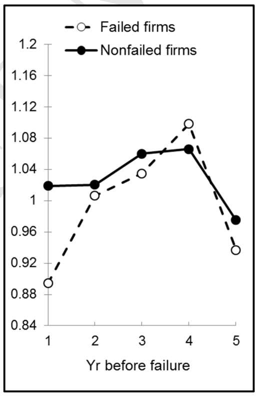


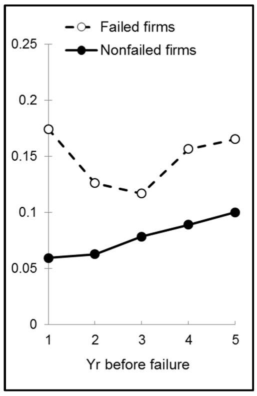




TATA **SGI** **CvSALES**







GMI **CvPRO** **EM-index**

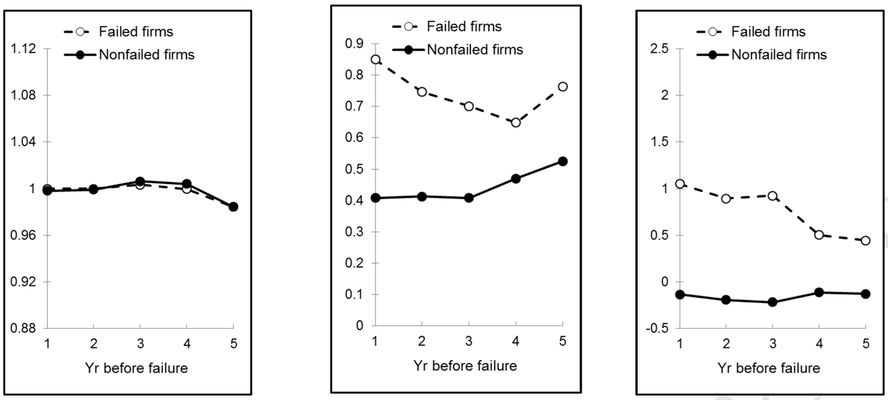

Failed firms
Nonfailed firms
1.12
1.08
1.04
1
0.96
0.92
0.88
1 2 3 4 5
Yr before failure
Failed firms
Nonfailed firms
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1 2 3 4 5
Yr before failure
Failed firms
Nonfailed firms
2.5
2
1.5
1
0.5
0
-0.5
1 2 3 4 5
Yr before failure

Figure 4. Private firms. Comparison of median values using earnings management ratios.

	ROA	RE/TA	EQ/TL	WC/TA	ROTA	CASH	PROFIT	INT/S	ΔSALES	DSRI	LEVI	AQI	SGAI	DEPI	DDI	TATA	SGI	CvSALES	GMI	CVPRO	EM-index
ROA	1	.39**	.22**	.31**	.33**	.30**	.66**	-.23**	.28**	-.05**	-.29**	-.07**	-.13**	.03**	-.06**	.11**	.28**	-.20**	-.08**	-.30**	-.37**
RE/TA		1	.74**	.47**	.02*	.24**	.38**	-.18**	.10**	-.03**	-.24**	.01	-.00	-.02	-.07**	.10**	.10**	-.14**	-.02	-.19**	-.23**
EQ/TL			1	.47**	-.16**	.13**	.27**	-.11**	.05**	-.03**	-.23**	.00	-.04**	.00	-.01	.11**	.05**	-.08**	.01	-.11**	-.17**
WC/TA				1	.13**	.35**	.27**	-.25**	.05**	-.00	-.17**	-.06**	-.02*	-.00	.01	.23**	.05**	-.05**	-.02*	-.12**	-.16**
ROTA					1	.30**	.25**	-.50**	.18**	-.08**	-.09**	.03**	.03**	-.03**	-.03**	-.00	.18**	-.28**	.00	-.07**	-.19**
CASH						1	.24**	-.28**	.11**	-.08**	-.09**	-.03**	.00	.00	-.03**	-.06**	.11**	-.13**	-.02*	-.12**	-.19**
PROFIT							1	-.22**	.24**	-.03**	-.30**	-.04**	-.10**	.01	-.05**	.12**	.24**	-.17**	-.04**	-.22**	-.30**
INT/S								1	-.10**	.02*	.09**	.01	.01	.02	.03**	-.05**	-.10**	.15**	-.02	.12**	.16**
ΔSALES									1	-.25**	-.01	-.08**	-.24**	-.04**	-.20**	.01	1.00**	-.08**	.13**	-.06**	-.19**
DSRI										1	.14**	-.12**	.07**	.04**	.04**	.07**	-.25**	.02	-.01	.01	.47**
LEVI											1	-.09**	.08**	.01	-.03**	-.30**	-.01	.08**	.10**	.04**	.46**
AQI												1	.03**	-.08**	.05**	-.05**	-.08**	-.02*	.01	.01	.33**
SGAI													1	-.11**	-.13**	-.06**	-.24**	.01	-.39**	-.02*	.06**
DEPI														1	.60**	-.03**	-.04**	-.00	.01	-.02	-.02*
DDI															1	.06**	-.20**	.01	.02	.04**	.05**
TATA																1	.01	.02*	-.02	-.02*	-.10**
SGI																	1	-.08**	.13**	-.06**	-.19**
CvSALES																		1	.00	.18**	.53**
GMI																			1	-.01	.03**

C_VPRO	1	.54**
EM-index		1

Table 6. Public firms. Spearman's correlation coefficients among variables for the test sample.

** correlation is significant at the 0.10 level (2-tailed)

* correlation is significant at the 0.05 level (2-tailed)

	ROA	RE/TA	EQ/TL	WC/TA	ROTA	CASH	PROFIT	INT/S	ΔSALES	DSRI	LEVI	AQI	SGAI	DEPI	DDI	TATA	SGI	CvSALES	GMI	CVPRO	EM-index
ROA	1	.19**	.14**	.20**	.28**	.23**	.70**	-.04**	.21**	-.02*	-.22**	-.06**	-.14**	.07**	-.02**	.02**	.21**	-.04**	-.09**	-.35**	-.26**
RE/TA		1	.81**	.35**	-.07**	.16**	.19**	-.16**	.04**	-.01	-.19**	.03**	-.01	.02**	-.03**	.10**	.04**	-.07**	.00	-.17**	-.16**
EQ/TL			1	.37**	-.14**	.14**	.17**	-.15**	.00	-.01*	-.22**	.05**	-.02**	.03**	-.00	.11**	.00	-.08**	.01	-.15**	-.16**
WC/TA				1	.15**	.35**	.11**	-.35**	.00	.00	-.13**	-.08**	-.01	.01*	.04**	.25**	.00	-.07**	-.02*	-.14**	-.16**
ROTA					1	.20**	.25**	-.49**	.17**	-.05**	-.030**	-.02**	-.00	.02**	.040**	-.03**	.17**	-.14**	-.00	-.04**	-.09**
CASH						1	.18**	-.27**	.08**	-.04**	-.07**	-.04**	-.00	.02**	.00	-.10**	.08**	-.08**	-.02*	-.13**	-.13**
PROFIT							1	.04**	.16**	.00	-.20**	-.01**	-.09**	.10**	.01*	.00	.16**	.01*	-.03**	-.30**	-.18**
INT/S								1	-.10**	.03**	.04**	.08**	.02**	.00	.03**	-.08**	-.10**	.09**	-.01	.11**	.13**
ΔSALES									1	-.18**	.02**	-.10**	-.19**	-.03**	-.23**	-.01*	1.00**	.16**	.15**	-.06**	-.04**
DSRI										1	.12**	-.08**	.03**	.04**	.04**	.06**	-.18**	-.01	-.02*	-.00	.47**
LEVI											1	-.09**	.08**	.04**	-.04**	-.26**	.02**	.04**	.09**	.08**	.50**
AQI												1	.03**	-.04**	.06**	-.06**	-.10**	-.03**	-.01	.01	.41**
SGAI													1	-.08**	-.11**	-.03**	-.19**	-.01	-.43**	-.01	.04**
DEPI														1	.55**	-.03**	-.03**	-.03**	.00	-.03**	-.01
DDI															1	.07**	-.23**	-.06**	.01	.04**	.01
TATA																1	-.01*	.01	-.02*	-.04**	-.12**
SGI																	1	.16**	.15**	-.06**	-.04**
CvSALES																		1	.02*	.18**	.53**
GMI																			1	-.00	.03**
C_VPRO																				1	.57**

Table 7. Private firms. Spearman's correlation coefficients among variables for the test sample.

** correlation is significant at the 0.10 level (2-tailed)

* correlation is significant at the 0.05 level (2-tailed)

	Beta and significance	Train sample: Confusion matrix		Train sample: Accuracy (%)	Train sample: True negative rate (%)	Train sample: True positive rate (%)	Test sample: Confusion matrix		Test sample: Accuracy (%)	Test sample: True negative rate (%)	Test sample: True positive rate (%)
ROA	18.568***	134	48				206	63			
		33	149	77.7%	73.6%	81.9%	2,720	7,518	73.5%	76.6%	73.4%
RE/TA	6.770***	147	35				201	68			
		41	141	79.1%	80.8%	77.5%	2,289	7,949	77.6%	74.7%	77.6%
EQ/TL	0.461***	166	16				229	40			
		97	85	69.0%	91.2%	46.7%	4,585	5,653	56.0%	85.1%	55.2%
WC/TA	3.439***	127	55				165	104			
		45	137	72.5%	69.8%	75.3%	3,076	7,162	69.7%	61.3%	70.0%
ROTA	0.328***	125	57				160	109			
		89	93	59.9%	68.7%	51.1%	5,451	4,787	47.1%	59.5%	46.8%
CASH	15.264***	155	27				189	80			
		88	94	68.4%	85.2%	51.6%	5,431	4,807	47.5%	70.3%	47.0%
PROFIT	2.789***	136	46				195	74			
		28	154	79.7%	74.7%	84.6%	2,333	7,905	77.1%	72.5%	77.2%
INT/S	-0.153	27	152				37	227			
		9	171	55.2%	15.1%	95.0%	733	9,077	90.5%	14.0%	92.5%
ΔSALES	0.527**	117	61				202	58			
		65	116	64.9%	65.7%	64.1%	5,256	4,381	46.3%	77.7%	45.5%
DSRI	-0.104	46	125				74	168			
		18	153	58.2%	26.9%	89.5%	1,356	7,888	83.9%	30.6%	85.3%
LEVI	-3.346***	87	95				111	154			
		33	149	64.8%	47.8%	81.9%	1,597	8,450	83.0%	41.9%	84.1%
AQI	-0.015	10	153				18	209			
		12	157	50.3%	6.1%	92.9%	416	8,951	93.5%	7.9%	95.6%
SGAI	-1.093***	77	101				86	171			
		20	159	66.1%	43.3%	88.8%	1,268	8,300	85.4%	33.5%	86.7%

DEPI	0.401**	69	93				71	110			
		26	149	64.7%	42.6%	85.1%	1,636	7,260	80.8%	39.2%	81.6%
DDI	0.239	62	101				55	130			
		19	156	64.5%	38.0%	89.1%	1,140	7,914	86.3%	29.7%	87.4%
TATA	2.560***	93	89				110	159			
		41	141	64.3%	51.1%	77.5%	2,028	8,210	79.2%	40.9%	80.2%
SGI	0.527***	117	61				202	58			
		65	116	64.9%	65.7%	64.1%	5,256	4,381	46.3%	77.7%	45.5%
CvSALES	-1.702***	74	105				115	145			
		35	147	61.2%	41.3%	80.8%	1,299	8,327	85.4%	44.2%	86.5%
GMI	-0.826**	115	51				97	77			
		97	60	54.2%	69.3%	38.2%	3,844	3,614	48.6%	55.7%	48.5%
C_VPRO	-0.163*	89	92				107	147			
		42	140	63.1%	49.2%	76.9%	2,556	7,206	73.0%	42.1%	73.8%
EM-index	-0.358***	116	66				182	87			
		60	122	65.4%	63.7%	67.0%	3,116	7,122	69.5%	67.7%	69.6%

Confusion matrix

True negative	*Type I error*
Type II error	*True positive*

Train sample comprises 364 public firms, where 182 are failed firms and 182 are nonfailed firms in 2012. Test sample comprises 10,507 public firms, where 269 are failed firms and 10,238 are nonfailed firms in 2014. Accuracy = (True negative + True positive) / (True negative + True positive + False negative + False positive). True negative rate = 1 - Type 1 error rate. True positive rate = 1 - Type II error rate.

Table 8. Public firms. Univariate logistic regressions analysis for predicting bankruptcy, showing Beta coefficients and significance levels. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

	Beta and significance	Train sample: Confusion matrix		Train sample: Accuracy (%)	Train sample: True negative rate (%)	Train sample: True positive rate (%)	Test sample: Confusion matrix		Test sample: Accuracy (%)	Test sample: True negative rate (%)	Test sample: True positive rate (%)
ROA	6.199***	265	124	70.1%	68.1%	72.0	474	233	53.8%	67.0%	53.6%
		109	280				18,105	20,876			
RE/TA	3.008***	286	103	71.7%	73.5%	69.9	470	237	68.1%	66.5%	68.1%
		117	272				12,433	26,548			
EQ/TL	0.021*	370	19	56.4%	95.1%	17.7	620	87	25.6%	87.7%	24.4%
		320	69				29,453	9,528			
WC/TA	1.974***	255	134	65.8%	65.6%	66.1	392	315	65.5%	55.4%	65.7%
		132	257				13,377	25,604			
ROTA	-0.019	136	253	47.4%	35.0%	59.9	244	463	69.6%	34.5%	70.2%
		156	233				11,615	27,366			
CASH	8.018***	337	52	66.5%	86.6%	46.3	566	141	43.5%	80.1%	42.9%
		209	180				22.275	16.706			
PROFIT	1.954***	238	151	71.5%	61.2%	81.7	431	276	59.4%	64.0%	59.3%
		71	318				15,848	23,133			
INT/S	-0.509***	51	320	53.3%	13.7%	92.1	90	528	14.6%	92.9%	91.3%
		30	348				2,086	27,393			
ΔSALES	-0.182*	80	281	56.6%	22.2%	89.4	58	543	92.4%	9.7%	94.2%
		40	339				1,675	27,087			
DSRI	-0.093*	47	286	53.1%	14.1%	89.8	83	437	92.6%	16.0%	94.2%
		36	318				1,378	22,518			
LEVI	-1.057***	133	255	57.5%	34.3%	80.7	216	479	82.2%	31.1%	83.1%
		75	314				6,515	32,051			
AQI	0.003	259	15	49.8%	94.5%	4.8	440	34	5.6%	92.8%	4.1%
		259	13				27,176	1,169			
SGAI	-0.456***	100	259	59.0%	27.9%	88.8	115	473	91.5%	19.6%	93.0%
		42	334				1,960	25,917			

DEPI	0.249*	43	253	58.9%	14.5%	96.3	52	308	93.6%	14.4%	94.6%
		13	338				1,449	25,539			
DDI	-0.200*	33	266	56.7%	11.0%	95.5	41	332	95.3%	11.0%	96.4%
		16	336				974	26,281			
TATA	1.379***	180	209	56.3%	46.3%	66.3	317	390	66.8%	44.8%	67.2%
		131	258				1,2791	26,190			
SGI	-0.182*	80	281	56.6%	22.2%	89.4	58	543	92.4%	9.7%	94.2%
		40	339				1,675	27,087			
CvSALES	-2.655***	167	198	65.2%	45.8%	84.0	249	348	86.7%	41.7%	87.6%
		60	316				3,460	24,521			
GMI	-0.149	294	0	56.4%	100.0%	0.0	217	0	1.4%	100.0%	0.0%
		227	0				15,360	0			
C_VPRO	-0.072**	56	313	51.1%	15.2%	85.9	92	531	86.1%	14.8%	87.6%
		54	328				3,571	25,254			
EM-index	-0.246***	237	152	62.6%	60.9%	64.3	370	337	69.8%	52.3%	70.1%
		139	250				11,660	27,321			

Confusion matrix

True negative	*Type I error*
Type II error	*True positive*

Train sample comprises 778 private firms, where 389 are failed firms and 389 are nonfailed firms in 2012. Test sample comprises 39,688 firms, where 707 are failed firms and 38,981 are nonfailed firms in 2014. Accuracy = (True negative + True positive) / (True negative + True positive + False negative + False positive). True negative rate = 1 - Type 1 error rate. True positive rate = 1 - Type II error rate.

Table 9. Private firms. Univariate logistic regressions analysis for predicting bankruptcy, showing Beta coefficients and significance levels. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

	Model 1	Model 2	Model 3	Model 4	Model 5
ROA	13.404***	8.350***	8.262***		5.554
RE/TA	5.141***	6.452***	6.223***		7.956***
EQ/TL	0.050	-0.188***	-0.181***		0.873
WC/TA	0.496	-0.340	-0.271		0.010
ROTA	0.274**	0.279**	0.263*		0.354
CASH		9.710***	9.310***		7.005*
PROFIT		1.122***	1.015**		1.421**
INT/S		0.425*	0.467**		0.542
ΔSALES		0.157	0.129		0.145
DSRI				0.305	0.073
LEVI				-1.231	3.815
AQI				0.041	-0.020
SGAI				-0.614	-1.871**
DEPI				0.397	0.047
DDI				0.121	0.680
TATA				1.080	-1.226
SGI				1.599***	0.000
CvSALES				-3.660**	-1.196
GMI				-1.158	-0.578
C_VPRO				-0.004	0.081
EM-index			-0.170***	-0.288***	-0.144
Constant	-1.062***	-2.143***	-1.913***	1.566	-5.001
R^2 Nagelkerke	0.633	0.702	0.704	0.468	0.770
-2 Log likelihood	270.02	228.18	225.09	269.87	148.23
Train sample	(N obs = 364)	(N obs = 357)	(N obs = 357)	(N obs = 283)	(N obs = 283)
Confusion matrix	146 36	148 30	151 27	92 45	120 17

	27	155	23	156	22	157	24	122	13	133
Accuracy (%)	82.7%		85.2%		86.3%		75.6%		89.4%	
True negative rate (%)	80.2%		83.1%		84.8%		67.2%		87.6%	
True positive rate (%)	85.2%		87.2%		87.7%		83.6%		91.1%	
Test sample	(N obs = 10,507)		(N obs = 9,830)		(N obs = 9,830)		(N obs = 6,976)		(N obs = 6,976)	
Confusion matrix	206	63	201	58	210	49	105	46	124	27
	2,039	8,199	2,036	7,535	1,908	7,663	1,300	5,525	1,111	5,714
Accuracy (%)	80.0%		78.7%		80.1%		80.7%		83.7%	
True negative rate (%)	76.6%		77.6%		81.1%		69.5%		82.1%	
True positive rate (%)	80.1%		78.7%		80.1%		81.0%		83.7%	
F_β-score	99.22%		99.22%		99.35%		99.16%		99.51%	
Area under ROC curve (AUC)	0.800		0.801		0.813		0.776		0.860	

Confusion matrix

True negative	*Type I error*
Type II error	*True positive*

Train sample comprises 364 public firms, where 182 are failed firms and 182 are nonfailed firms in 2012. Test sample comprises 10,507 firms, where 269 are failed firms and 10,238 are nonfailed firms in 2014. Accuracy = (True negative + True positive) / (True negative + True positive + False negative + False positive). True negative rate = 1 - Type 1 error rate. True positive rate = 1 - Type II error rate. F_β-score = harmonic average combining both Type I and II errors. β equals 1/35 for F_β-score. The AUC values come from a plot of true positive rates against false positive rates.

Table 10. Public firms. Logistic regression analysis for predicting bankruptcy, showing Beta coefficients and significance levels. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**

ROA	4.102***	1.069	0.703		2.570
RE/TA	2.466***	1.937***	1.919***		2.696**
EQ/TL	-0.028**	0.006	0.001		0.973
WC/TA	0.331	0.380	0.367		0.605
ROTA	-0.052	-0.151***	-0.151***		-0.072
CASH		8.496***	8.215***		7.747**
PROFIT		1.218***	1.073***		0.975**
INT/S		-0.174	-0.133		-1.396*
ΔSALES		-0.493***	-0.480***		0.250
DSRI				0.392***	0.174
LEVI				-0.297	2.362*
AQI				0.011	-0.074
SGAI				-0.011	-0.301
DEPI				0.118	-0.267
DDI				-0.325	-0.048
TATA				1.586**	0.632
SGI				0.732**	0.000
CvSALES				-3.231***	-2.352*
GMI				-1.120***	-1.651***
C_VPRO				0.043	0.098*
EM-index			-0.100**	-0.271***	-0.066
Constant	-0.268**	-0.990***	-0.776***	1.241	-1.293
R^2 Nagelkerke	0.299	0.441	0.449	0.355	0.617
-2 Log likelihood	880.70	723.34	716.82	384.05	272.68
Train sample	(N obs = 778)	(N obs = 735)	(N obs = 735)	(N obs = 358)	(N obs = 358)
Confusion matrix	277 112	261 98	265 94	137 54	153 38
	101 288	65 311	69 307	42 125	32 135
Accuracy (%)	72.6%	77.8%	77.8%	73.2%	80.4%
True negative rate (%)	71.2%	72.7%	73.8%	71.7%	80.1%
True positive rate (%)	74.0%	82.7%	81.6%	74.9%	80.8%

Test sample	(N obs = 39,688)		(N obs = 28,519)		(N obs = 28,519)		(N obs = 11,657)		(N obs = 11,657)	
Confusion matrix	470	237	359	231	357	233	112	56	125	43
	11,393	27,588	7,155	20,774	6,993	20,936	2,786	8,703	2,139	9,350
Accuracy (%)	70.7%		74.1%		74.7%		75.6%		81.3%	
True negative rate (%)	66.5%		60.8%		60.5%		66.7%		74.4%	
True positive rate (%)	70.8%		74.4%		75.0%		75.8%		81.4%	
F_β-score	99.12%		98.87%		98.87%		99.34%		99.52%	
Area under ROC curve (AUC)	0.725		0.734		0.746		0.765		0.837	

Confusion matrix

True negative	*Type I error*
Type II error	*True positive*

Train sample comprises 778 private firms, where 389 are failed firms and 389 are nonfailed firms in 2012. Test sample comprises 39,688 firms, where 707 are failed firms and 38,981 are nonfailed firms in 2014. Accuracy = (True negative + True positive) / (True negative + True positive + False negative + False positive). True negative rate = 1 - Type 1 error rate. True positive rate = 1 - Type II error rate. F_β-score = harmonic average combining both Type I and II errors. β equals 1/35 for F_β-score. The AUC values come from a plot of true positive rates against false positive rates.

Table 11. Private firms. Logistic regression analysis for predicting bankruptcy, showing Beta coefficients and significance levels. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

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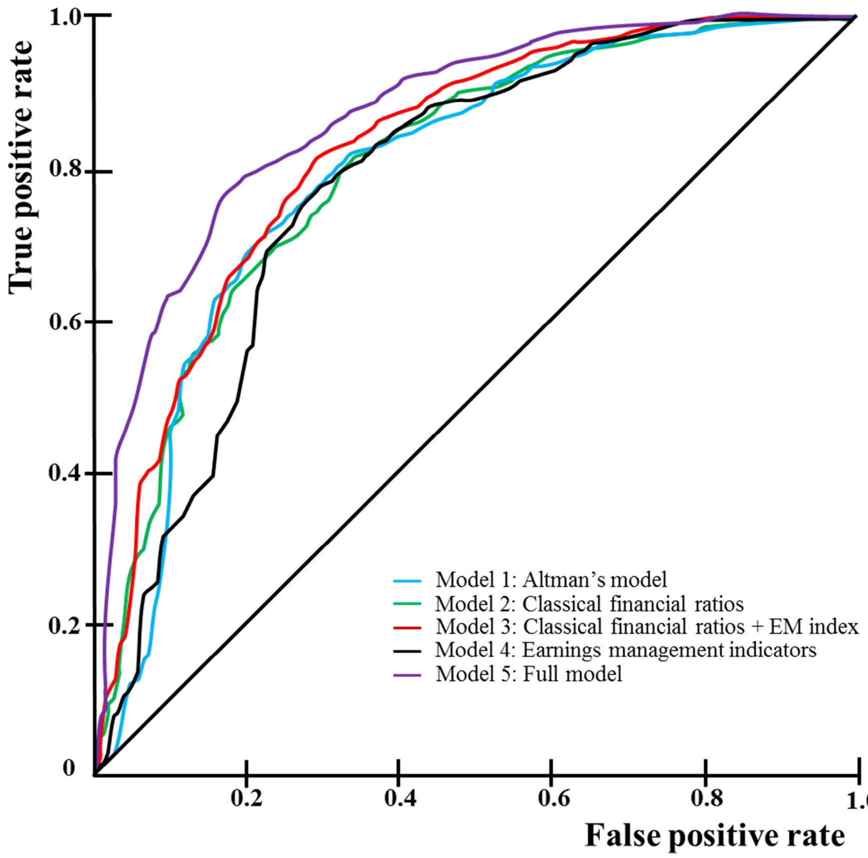

Figure 5. Public firms. Receiver operating characteristic (ROC) curve for the test sample.

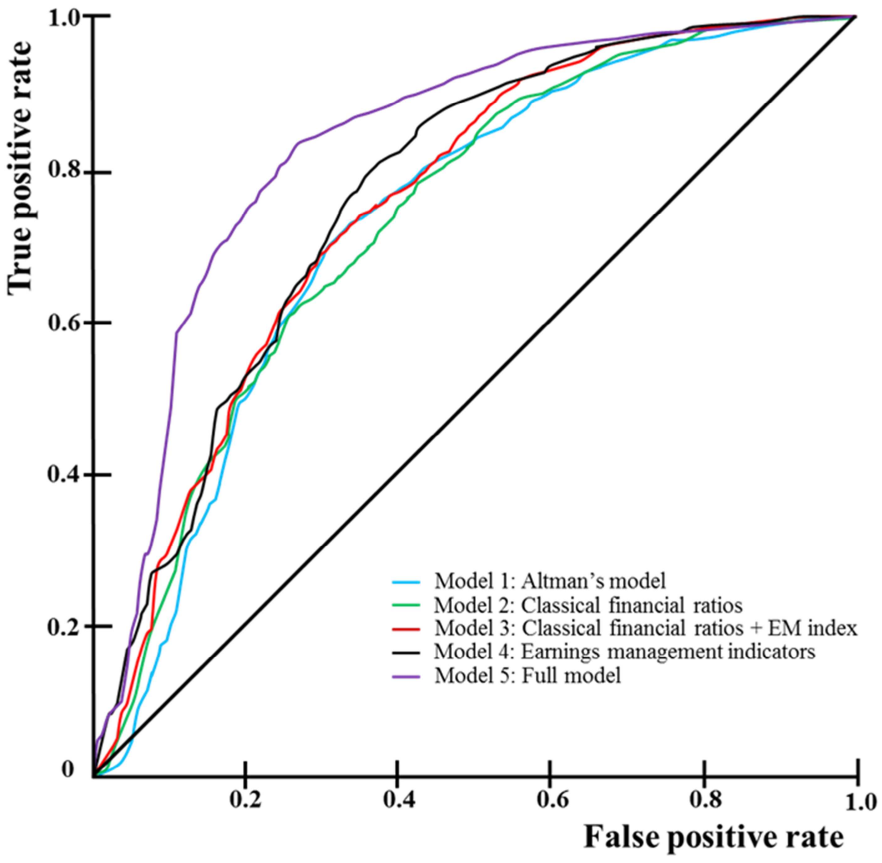

Figure 6. Private firms. Receiver operating characteristic (ROC) curve for the test sample.

Node	Rule	Forecasted category	Train		Test	
			Total cases N (%)	Correctly classified N (%)	Total cases N (%)	Correctly classified N (%)
	'All firms will be nonfailed'	Nonfailed	364 (100%)	182 (50%)	10,507 (100%)	10,234 (97.4%)
1	EM-index <-0.152	Nonfailed	109 (29.9%)	88 (80.7%)	4,697 (44.7%)	4,659 (99.2%)
4	EM-index <-0.152 AND PROFIT =1	Nonfailed	88 (24.2%)	80 (90.4%)	3,719 (35.4%)	3,701 (99.5%)
12	EM-index <-0.152 AND PROFIT =1 AND RE/TA>0.12	Nonfailed	65 (17.8%)	63 (97.1%)	2,963 (28.2%)	2,954 (99.7%)
8	-0.130<EM-index <3.670 AND RE/TA>0.196	Nonfailed	44 (12.1%)	37 (83.0%)	2,280 (21.7%)	2,262 (99.2%)
	'All firms will be failed'	Failed	364 (100%)	182 (50%)	10,507 (100%)	269 (2.6%)
3	EM-index >3.670	Failed	72 (19.8%)	53 (74.0%)	988 (9.4%)	71 (7.2%)
6	-0.152<EM-index <3.670 AND RE/TA<0.017	Failed	76 (20.9%)	62 (81.5%)	1,292 (12.3%)	90 (7.0%)
10	EM-index >3.670 AND PROFIT=0	Failed	57 (15.7%)	50 (86.9%)	588 (5.6%)	62 (10.5%)

Table 12. Public firms. Decision rules for the prediction of the failed/nonfailed status from the CHAID algorithm. Growing method: exhaustive CHAID. Train sample comprises 364 public firms, where 182 are failed firms and 182 are nonfailed firms in 2012. Test sample comprises 10,507 firms, where 269 are failed firms and 10,238 are nonfailed firms in 2014. For the train sample, the accuracy

equals 85.2%, true negative rate equals 81.9% and true positive rate equals 88.5%. For the test sample, the accuracy equals 79.0%, true negative rate equals 75.5% and true positive rate equals 79.1%.

Accuracy = (True negative + True positive) / (True negative + True positive + False negative + False positive). True negative rate = 1 - Type 1 error rate. True positive rate = 1 - Type II error rate.

Node	Rule	Forecasted category	Train		Test	
			Total cases N (%)	Correctly classified N (%)	Total cases N (%)	Correctly classified N (%)
	'All firms will be nonfailed'	Nonfailed	778 (100%)	389 (50%)	39,688 (100%)	38,981 (98.2%)
1	EM-index <-1.371	Nonfailed	155 (19.9%)	110 (71.0%)	11,218 (28.3%)	11,102 (99.0%)
5	EM-index <-1.371 AND PROFIT =1	Nonfailed	129 (16.6%)	101 (78.3%)	8,152 (20.5%)	8,076 (99.1%)
15	EM-index <-1.371 AND PROFIT =1 AND RE/TA>0.237	Nonfailed	67 (8.6%)	60 (89.6%)	5,462 (13.8%)	5,425 (99.3%)
9	-1.371<EM-index <2.349 AND RE/TA>0.237	Nonfailed	119 (15.3%)	101 (84.9%)	11,366 (28.6%)	11,278 (99.2%)
21	-1.371<EM-index <2.349 AND RE/TA>0.237 AND CASH>0.033	Nonfailed	67 (8.6%)	65 (97.0%)	6,392 (16.1%)	6,361 (99.5%)
	'All firms will be failed'	Failed	778 (100%)	389 (50%)	39,688 (100%)	707 (1.8%)
4	EM-index >4.576	Failed	77 (9.9%)	61 (79.0%)	1,038 (2.6%)	99 (9.5%)
12	EM-index >4.576 AND CASH<0.008	Failed	44 (5.7%)	42 (95.5%)	434 (1.1%)	65 (15.0%)
13	2.349<EM-index <4.576 AND PROFIT =0	Failed	94 (12.1%)	76 (80.9%)	1,956 (4.9%)	96 (4.9%)
10	2.349<EM-index <4.576 AND RE/TA<-0.058	Failed	51 (6.6%)	50 (98.0%)	469 (1.2%)	46 (9.8%)

Table 13. Private firms. Decision rules for the prediction of the failed/nonfailed status from the CHAID algorithm. Growing method: exhaustive CHAID. Train sample comprises 778 private firms, where 389 are failed firms and 389 are nonfailed firms in 2012. Test

sample comprises 39,688 firms, where 707 are failed firms and 38,981 are nonfailed firms in 2014. For the train sample, the accuracy equals 76.2%, true negative rate equals 72.0% and true positive rate equals 80.5%. For the test sample, the accuracy equals 70.3%, true negative rate equals 68.6% and true positive rate equals 70.3%.

Accuracy = (True negative + True positive) / (True negative + True positive + False negative + False positive). True negative rate = 1 - Type 1 error rate. True positive rate = 1 - Type II error rate.