

Foretelling or foresight? Accounting-based bankruptcy prediction models and earnings quality in the case of Polish listed companies

Barbara Grabińska, Konrad Grabiński

ABSTRACT

Objective: The article aims to examine the relationship between bankruptcy risk and earnings quality in designing accounting-based bankruptcy prediction models. The models classify companies (firm-year observations) into two groups with high or low (no) bankruptcy risk. We investigated the difference in earnings quality between those two groups.

Research Design & Methods: We used quantitative research methods, such as descriptive statistics, correlation analysis (Pearson's and Spearman's rank correlation), and Welch ANOVA. The study sample consisted of firm-year observations of companies listed in the Warsaw Stock Exchange for 17 years (2007-2023) ranging from 5 004 up to 5 688 firm-year observations. We employed five accounting-based bankruptcy prediction models specific to the Polish context and two metrics of earnings quality: accrual and real earnings management. We estimated the proxy of accrual earnings management using the modified Jones model and real earnings management with the Roychowdhury model. We estimated the bankruptcy risk using five prediction models and then analyzed as a continuous (in correlation analysis) and dichotomous variable (Welch ANOVA).

Findings: The research results demonstrate that companies classified by company failure models as high bankruptcy risk are associated with lower earnings quality. The results of the Welch ANOVA analysis are consistent across all combinations of accounting-based prediction models and earnings quality proxies used in the study research. The findings imply that a high bankruptcy risk is associated with managers engaging in more intensive accrual and real earnings management. The results suggest managers are more inclined to influence reporting numbers and operational activities to achieve desired goals.

Implications & Recommendations: Scholars should consider diminishing the quality of earnings associated with higher bankruptcy risk in designing and developing future accounting-based bankruptcy prediction models. Financial statement users like investors, financial analysts, financial auditors, and other stakeholders should also consider earnings quality. The study provides an avenue for future research by calling for research across earnings quality and bankruptcy prediction models.

Contribution & Value Added: The study contributes to a better understanding of the relationship between accounting-based bankruptcy prediction models and how they estimate bankruptcy risk and earnings quality. As far as we know, earnings quality has not been considered a factor in the design of models for bankruptcy prediction.

Article type: research article

Keywords: bankruptcy prediction; accounting-based prediction models; earnings quality; accrual earnings management; real earnings management; bankruptcy risk

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INTRODUCTION

Accounting provides a variety of tools useful to the entity's management. One set of tools refers to so-called company failure models or models for bankruptcy prediction or financial health prediction models (FHPM). These models aim to assess the bankruptcy risk. However, they also indicate the company's financial health or condition (Bolek & Gniadkowska-Szymańska, 2022; Olszewska & Turek, 2018). We may trace the beginnings of this approach to the 30-es of the twentieth century when the global financial crisis took a severe toll, causing the bankruptcy of numerous companies, unemployment, and other social problems. Since then, many practitioners and scholars have praised FHPMs for their wide range of usability, decision-making process, and relative ease of application. The first models, like that developed by Fitzpatrick (1932), Merwin (1942), Tamari (1966) and Beaver (1966), employed univariate ratio analysis. The breakthrough was an Altman model (Altman, 1968) based on multiple discriminant analysis. In 1977, Altman *et al.* improved the prior model by introducing a measure of earnings stability (Altman *et al.*, 1977). Next came models developed by scholars like Springate, Zmijewski and Ohlson. The academic world and practitioners soon realised that the models' effectiveness is specific not only to the industry but also to the country (Prusak, 2018). Therefore, the field developed a variety of models considering country-specific settings. For example, at least several models have reasonable predictive power in Poland.

A subset of FHPMs built on accounting numbers reported in financial statements is referred to as accounting-based prediction models (ABPMs). We chose to use ABPMs due to their wide acceptance in economic practice in Poland. These models are typical in that they are based mainly on data generated by accounting and presented in financial statements. Therefore, the quality of the model's results depends on the quality of the reported financial statements. The paper's novelty is in investigating the relationship between bankruptcy risk (financial health) and earnings quality. We theorised that the quality of the earnings may influence the predictive power of the ABPMs. Therefore, future models should consider earnings quality when interpreting ABPMs' results.

We hypothesised that the group of firm-year observations characterised by the high risk of bankruptcy displays lower earnings quality than those with lower or no bankruptcy risk. The study employs two earnings quality concepts: accruals earnings management (AEM) and real earnings management (REM). To estimate AEM, one must use the modified Jones model and REM with the Roychowdhury model. The research design applies five popular ABPMs in Poland to determine bankruptcy risk. We employed correlation analysis and Welch ANOVA to test the main hypothesis.

Our sample consisted of companies listed on the Warsaw Stock Exchange that have been in operation for 17 years (2007-2023). The sample size ranges from 5 004 (when we considered the REM variable) up to 5 688 firm-year observations (in the case of the AEM variable). We chose Poland as the research sample due to the following reasons: a relatively large number of ABPMs in place and used by practitioners (*i.e.*, accountants, financial auditors, analysts), a large number of companies listed in the stock exchange (from 351 companies in 2007 up to 410 in 2023 in the main market) and finally Poland is one of the fastest developing countries in Europe in the last 30 years. Poland is a post-communist economy, one of the Central and Eastern European (CEE) countries and as an EU member since 2004, it was upgraded in 2018 to the status of a developed market by FTSE Russell. Therefore, Poland is an example of a success story, at least from the economic perspective. This type of research would probably be very difficult or impossible to conduct in any other CEE country.

Our findings suggest that managers of companies with a high risk of bankruptcy tend to engage in accrual and real earnings management. Consequently, those companies' earnings quality is significantly lower than those with lower or no bankruptcy risk. The results may be important for the development of future ABPMs as well as for financial statement users like financial analysts or financial auditors. The improvements in ABPMs' accuracy may prevent bankruptcies and stabilise economic development. Thus far, stakeholders do not fully recognise the significance of earnings quality in the decision-making process. Likewise, scholars avoid this issue while investigating bankruptcy prediction models.

The remainder of the article is structured as follows. Section 1 will provide a literature review and hypothesis development. It will begin with the concept of financial health and accounting-based bankruptcy models and end with a theoretical framework and metrics of earnings quality. Section 2 develops the research design, methodology, and sample characteristics. Section 3 will present results and discussion. The last section will conclude the most important results of empirical research.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

The first part of the literature review will address the issue of financial health and accounting-based bankruptcy models. The concept of financial health is not well-developed in the literature. Usually, it is taken as an axiomatic concept referring to an entity's finances, *i.e.*, expenses, savings, debt, investments, etc. For this study, we defined financial health as the entity's ability to survive in the competitive market, generate sustainable profit, pay its liabilities on time, and be sufficiently liquid and solvent. More specifically, it is an ability to generate enough profit to meet necessary expenses. A deeper understanding of financial health refers to the nature and quality of the capital and the way it is managed and can reproduce itself. We should understand capital from a multi-context perspective, such as financial, economic, social, intellectual, human, and many more. Financial information reported in financial statements and visible at the financial ratios level is a proxy (estimate) of some key capital characteristics, like growth and productivity. The important aspect of this concept is the opposite – an unhealthy entity – declining, decaying, and nodding to its fall. Financial health is of utmost interest to company stakeholders in the decision-making process. Most notably, a worse financial condition implies a bankruptcy risk.

The evolution of bankruptcy models is long and dates back to 1930s, when univariate models used individual financial ratios to signal financial distress. Thirty years later, in his seminal study, Altman (1968) applied multivariate statistical methods to formulate the Z-score model, which happened to be a pivotal moment in history. Developing bankruptcy prediction models leads to applying logistic regression (Ohlson, 1980), discriminant analysis, and AI techniques, including neural networks and machine learning (Hekanaho *et al.*, 1998; Zięba *et al.*, 2016). Wilson and Sharda (1994) provide empirical evidence suggesting that bankruptcy models based on neural networks had an accuracy of 96% compared to 91% of traditional MDA models. In recent decades, they have brought new developments based on deep learning models (Jones *et al.*, 2017).

Prusak (2018) provides an extensive research review into bankruptcy models with a special emphasis on CEE countries. He distinguishes at least several approaches like rough set theory, cash management methods, catastrophe theory, multicriteria decision aid methodology, case-based reasoning, data envelopment analysis, multidimensional scaling, concepts based on the entropy theory, pattern recognition method, the self-organizing map method, bankruptcy trajectories and opinions of auditors relating to the going-concern assumption.

Various methods are used to predict bankruptcy. Korol (2010) distinguishes three main groups: statistical, theoretical, and computational intelligence. The first statistical group encompasses MDPs, logit and probit models, and decision trees. The crucial area of statistical methods is the optimal selection of financial indices from the perspective of predictive power. The final product of the process is a single output metric describing financial health or bankruptcy risk, depending on the decision's purpose.

The important issue is the source of information that populates the model. From this perspective, the most popular are accounting-based models, where data are extracted from financial statements and financial ratios. Market-based models use stock market information, mainly stock prices. The next evolutionary step is the hybrid model class, which combines various methodologies and data sources. They integrate accounting-based and market-based information (Li & Faff, 2019).

Market-based models display advantages in using current market information (*i.e.*, Merton's model) reflecting real-time investors' expectations. For the same reason, they are deemed to incorporate market expectations for future cash flows, which are assumed to be reflected in stock prices. The strength is also a weakness, as they are exposed to stock-market fluctuations. Therefore, they implicitly assume market efficiency, which is not always true. As a result, Li and Faff (2019) recommend relying more on market-based rather than accounting-based information during the financial crisis.

Scholars praise accounting-based bankruptcy models for numerous advantages. The most important is the ease of application and the ability to reduce the wide variety of financial ratios to a single metric. The former addresses the issue of data availability – access to the financial statement and populating the model with the reported numbers. For these reasons, accounting-based models are widely used in accounting practice by managers, investors, creditors, financial auditors, or accountants. They often reveal specific problems that need to be addressed in financial management. The simplicity of the models makes them easy to understand and apply. Lastly, their predictive power is usually acceptable for decision-making compared to other methods.

On the other hand, scholars criticise the accounting-based models for ignoring key information related to the entity's competitiveness, market position, growth opportunities, managerial experience, macroeconomic factors, etc. They use historical data, which may be outdated during a crisis or rapidly changing market conditions. Therefore, their effectiveness is not constant over time. Another limitation is industry and country specificity. They require a linear assumption between the Z-Score parameter and the financial health, which is a significant limitation. Finally, interpreting the so-called 'grey zone' is one of the methods' imperfections (Pilch, 2021).

Many studies show that the failure process can take many years, in extreme cases, up to eight years (Ooghe & Prijcker, 2008). It is considered a systematic process with some predictive ability over time. Regarding financial variables, the predictive ability is high for a one-year horizon. However, it disappears quickly after that (Du Jardin, 2015). For this reason, using non-financial variables is important (Altman *et al.*, 2016). However, the application is limited when it comes to cross-country study. The main challenge is to improve prediction models by improving the accuracy and extending the horizon period (Altman *et al.*, 2010). Our study contributes to this line of research by providing insight into the impact of earnings quality on the prediction models. We conjecture that earnings quality is an important parameter influencing ABPMs' accuracy and prediction power.

Reisz and Perlich (2007) argue that standard accounting-based prediction models in short horizons (one or two years before bankruptcy) are superior to market-based models in accuracy. There is a plethora of prediction models in place. However, there is no widely accepted theoretical foundation for selecting financial ratios used in the model (Balcaen & Ooghe, 2006), even though some theories are applied (*i.e.*, cash-flow theory or option pricing). Consequently, the selection process of models' variables is sample and country-specific and difficult to generalise. Bellovary *et al.* (2007) provide an extensive literature review covering 150 studies from 1965 to 2004. They documented the application of more than 750 financial ratios and models using up to 57 variables. However, the number of variables is not correlated with the model's accuracy. Simple models, especially accounting-based, are considered superior to more complicated ones (Balcaen & Ooghe, 2006), mostly due to the problem of multicollinearity.

In the Polish context, the development of bankruptcy models started relatively late, in the early 1990s. The political and institutional change from central planning to a market-based economy played a crucial role. The first Polish models were adaptations of foreign models, mainly Altman's Z-score. In the mid-90s, scholars started to use more refined models based on multidimensional discriminant analysis (MDA) with more reference to the specificity of the Polish economy. Later on, academics incorporated macroeconomic indicators and specific firm-level characteristics. The attention switched to sector-specific models, adjusting to different business environments (Prusak, 2019). Currently, the most frequently used models predominantly rely on financial indicators. However, newly developed models incorporate additional information like economic cycle indicators (*e.g.*, economic growth, labour market status, inflation) or non-financial indicators like market value ratios (Pawełek *et al.*, 2020). Zvarikova *et al.* (2017) conclude that in Poland, over 60 models have been developed since the beginning of 90es. The most popular are models of Mączyńska, Pogodzińska and Sojak, Hadasik, Wierzba, Hołda and Prusak, Gajdka and Stos, Maślanka and 'Poznanski model.' There are predominantly accounting-based models which use information reported in financial statements. It translates to ease of application and popularity among practitioners while assuring an acceptable predictability level.

The second part of the literature review addresses the research design's theoretical framework and earnings quality metrics. Earnings quality is a cornerstone in accounting theory and empirical research. We may trace the concept's origins can to the 1930s in Graham and Dodd's book *Security*

Analysis (Graham & Dodd, 1934). However, in 1960s, there was a breakthrough in the field. The seminal works of Ball and Brown (1968) and Beaver (1968) revolutionised the landscape of accounting research. Their contributions based on the assumption that accounting information is useful when it influences investors' behaviour. Investors react to financial statements by changing share prices on the stock market or trade volume. Many years later, Lev defined earnings quality as the power of correlation between the accounting income reported in financial statements and the stock market returns (Lev, 1989). However, in the literature, there is no widely accepted definition of earnings quality (Nelson & Skinner, 2013). Consequently, there are at least a dozen proxies for earnings quality, and only the most important ones are persistence, predictability, smoothing, value relevance, or accruals (earnings management).

Dechow *et al.* (2010) provide a wider perspective on earnings quality, stressing that high-quality earnings provide more information on attributes and context for making specific decisions by specific users. The quality is determined firstly by the intrinsic economic fundamentals of the entity and secondly by the quality of the accounting system, *i.e.*, the reliability of accounting numbers. The latter depends on managerial discretion, professional judgment, audit quality, and accounting regulations. The challenge for accounting research is to separate the first – innate factor from the second one. However, scholars widely accept the importance of earnings quality but they do not always appreciate its usefulness in decision-making. This is probably due to the measurement problem and the variety of metrics. We conjecture that using ABPMs for measuring health conditions may be affected by earnings quality, and the results may be biased due to lower low-quality earnings.

Francis *et al.* (2006) classify earnings quality metrics into accounting-based and market-based categories. The former includes earnings persistence, earnings predictability, accruals, and earnings smoothness. It is based on information reported in financial statements and estimated using regression. The latter refers to value relevance or timeliness. They estimate using stock market parameters like share prices, market returns, trading volume, and accounting data. Each of these metrics captures different attributes of earnings quality.

Earnings management is one of the most widely used proxies for earnings quality. It intends to capture intentional management activity aimed at limiting earnings fluctuations over time with the opportunity provided by accrual accounting. Empirical research provides evidence suggesting that accrual accounting produces more useful reported numbers than cash accounting. Generally, it leads to the conclusion that accrual-based earnings are more informative and better depict underlying economic performance.

Earnings management (EM) is often described as a managerial intentional influence on key reported financial items. Healy and Wahlen (1999) define EM as the modification of reported accounting profits made by managers or insiders to misinform stakeholders or achieve goals embedded in managerial contracts. The essence of accounting, like professional judgment or accounting estimates, allows for adopting subjective treatment and shaping reporting numbers. Schipper (1989) provides three possible ways of EM perception. She denotes the 'white' layer of earnings management. The discretion embedded in financial reporting allows management to signal the true financial situation of the reporting entity. The opposite 'black' version of EM depicts managerial behaviour as misleading, allowing managers to obtain unjustified benefits at the expense of shareholders and other stakeholders. The last 'grey' perspective implies signalling true information and obtaining higher benefits from managerial contracts.

Earnings management operates in two distinctive dimensions: accrual and real. Accrual earnings management (AEM) arises from innate (fundamental) economic performance and the quality of financial reporting. Analysts divide total accruals into normal and abnormal accruals, using the latter as a proxy for accrual earnings management. There are two interpretational layers. The first one adopts the view that the higher the absolute value of abnormal accruals, the lower the quality of financial reporting (*i.e.*, the quality of accounting profit). The second one distinguishes between income-increasing and income-decreasing earnings management. The measurement of earnings management is evolving, and there are at least several important models, *e.g.*, Healy (1985), Jones (1991), and the modified Jones model as proposed by Dechow *et al.* (1995) or Dechow and Dichev (2002).

Roychowdhury (2006) defines real earnings management (REM) as a departure from the normal course of action. Consequently, the structure and timing of transactions are modified, resulting in achieving financial goals as management desires. He provides the following examples: increasing sales by a more aggressive sales policy (*i.e.*, lower prices, longer payment terms), increasing the production volume above the market demand, which allows allocating fixed costs over the higher number of products or reducing advertisement or R&D costs. Therefore, real earnings management manifests itself by increasing production costs and decreasing administrative, advertising, and R&D expenses.

Earnings volatility is another aspect of earnings quality. From the stock market perspective, companies presenting less volatile earnings are rewarded with lower capital costs. For this reason, managers are motivated to smooth the earnings, even at the cost of long-term shareholder value (Graham *et al.*, 2005). Smoothed earnings allow for the maintenance of market valuation, credit rating position, and company's and manager's reputation. Reporting volatile earnings is detrimental to the company (*i.e.*, higher cost of capital, lower market capitalization) and the manager. Tucker and Zarowin (2006) conclude that only companies with good fundamentals and growth opportunities have the luxury of earnings management.

We conjectured that financial problems are an important factor affecting earnings quality. Managers tend to maintain the appearance of a stable financial situation either by influencing reported earnings or by structuring and timing transactions. Therefore, we hypothesised:

H1: High bankruptcy-risk companies are accompanied by more intensive accrual earnings management.

H2: High bankruptcy-risk companies are accompanied by more intensive real earnings management.

To test the hypotheses, we used correlation analysis and Welch ANOVA, which we will present in the following sections.

RESEARCH METHODOLOGY

We conjectured that financial problems are an important factor affecting earnings quality. Managers tend to maintain the appearance of a stable financial situation either by influencing reported earnings or by structuring and timing transactions. Therefore, we hypothesised that companies characterised by a high risk of bankruptcy display lower earnings quality than those with lower or no bankruptcy risk. From this perspective, controlling earnings quality also constitutes an important factor to consider in developing future ABPMs. We tested the hypothesis by investigating the co-occurrence of lower earnings quality with the high risk of bankruptcy. We intended to investigate the correlation relationship and not the causation. We used correlation analysis and Welch ANOVA.

We selected five popular accounting-based bankruptcy prediction models in Poland, for which the interpretation threshold was exactly zero (Table 1). It means the Z-score values below zero suggest high bankruptcy risk and above zero otherwise. One of the most praised was the Mączyńska model, which scholars often use to gauge the financial health of companies (Prusak, 2019). The model adapts O. Jacobs's model to the Polish economic environment. However, the other models are also popular and are often used in practice. For each model, we calculated the Z-score based on the financial statements of companies listed on the Warsaw Stock Exchange.

We used two metrics of earnings quality: accrual earnings management (AEM) and real earnings management (REM). We proxied AEM by the modified Jones model (Dechow *et al.*, 1995). We started by calculating total accruals ($TAC_{i,t}$) to determine the difference between the profit (net income) and cash flows from operations. Then, we determined discretionary accruals ($DA_{i,t}$) for company i in year t as the difference between total accruals and the non-discretionary accruals ($NDA_{i,t}$). We estimated the cross-sectional model for every firm-year observation in the sample with reference to the group of 10 similar observations chosen from the same year, industry, and most similar size (proxied as total assets). Overall, we regressed a group of 11 firm-year observations using the modified Jones model as follows:

Table 1. Description of accounting-based bankruptcy prediction models (variables codes in brackets)

Mączyńska model (Z_MACZ)		
$Z_MACZ = 1.5 \cdot X1 + 0.08 \cdot X2 + 10.0 \cdot X3 + 5.0 \cdot X4 + 0.3 \cdot X5 + 0.1 \cdot X6$		
X1 = (gross profit + depreciation) / liabilities X2 = assets/liabilities and provisions for liabilities X3 = gross profit/assets X4 = gross profit/sales revenue X5 = inventories/sales revenue X6 = sales revenue/assets	very good financial condition, no risk of bankruptcy	$Z > 2$
	good financial condition, no risk of bankruptcy	$1 < Z < 2$
	worse financial condition, no risk of bankruptcy	$0 < Z < 1$
	risk of bankruptcy	$Z < 0$
Mączyńska and Zawadzki model (Z_MA_ZA)		
$Z_MAC_ZAW = 9.498 \cdot X1 + 3.566 \cdot X2 + 2.903 \cdot X3 + 0.452 \cdot X4 - 1.498$		
X1 = EBIT / assets X2 = equity/assets X3 = (net income + depreciation & amortization) / liabilities X4 = current assets / current liabilities	no risk of bankruptcy	$Z > 0$
	high risk of bankruptcy	$Z < 0$
Wierzbą model (Z_WIERZ)		
$Z_WIERZ = 3.26 \cdot X1 + 2.16 \cdot X2 + 0.3 \cdot X3 + 0.69 \cdot X4$		
X1 = (EBIT – depreciation&amortization) / assets X2 = (EBIT – depreciation&amortization) / sales revenues X3 = current assets/liabilities X4 = working capital/assets	no risk of bankruptcy	$Z > 0$
	high risk of bankruptcy	$Z < 0$
Hadasik model (Z_HAD)		
$Z_HAD = 0.365425 \cdot X1 - 0.765526 \cdot X2 - 2.40435 \cdot X3 + 1.59079 \cdot X4 + 0.00230258 \cdot X5 + 0.0127826 \cdot X6 + 2.36261$		
X1 = current assets / current liabilities X2 = (current assets – stock) / current liabilities X3 = liabilities/assets X4 = working capital/assets X5 = receivables x 365 / sales revenue X6 = stock x 365 / sales revenue	no risk of bankruptcy	$Z > 0$
	risk of bankruptcy	$Z < 0$
The Poznan model (Z_POZN)		
$Z_POZN = 3.652 \cdot X1 + 1.588 \cdot X2 + 4.288 \cdot X3 + 6.719 \cdot X4 - 2.368$		
X1 = net income/assets X2 = (current assets – stock) / current liabilities X3 = (equity + non-current liabilities) / assets X4 = gross profit/sales revenues	no risk of bankruptcy	$Z > 0$
	risk of bankruptcy	$Z < 0$

Source: own study based on literature review (Hamrol *et al.*, 2004; Mączyńska *et al.*, 2018; Pilch, 2021; Wierzbą, 2000).

$$\frac{TAC_{i,t}}{A_{i,t-1}} = \beta_{1,j} \left(\frac{1}{A_{i,t-1}} \right) + \beta_{2,j} \left(\frac{REV_{i,t} - \Delta REC_{i,t}}{A_{i,t-1}} \right) + \beta_{3,j} \left(\frac{PPE_{i,t}}{A_{i,t-1}} \right) + \varepsilon_{i,t} \quad (1)$$

in which:

$TAC_{i,t}$ - total accruals determined as net income minus cash flows from operations for i-company in t-year;

$A_{i,t-1}$ - change in sales revenue for i-company in t-year;

$\Delta REV_{i,t}$ - change in receivables for i-company in t-year;

$\Delta REC_{i,t}$ - gross property, plant and equipment for i-company in t-year;

$PPE_{i,t}$ - gross property, plant and equipment for i-company in t-year.

Second, with the use of beta coefficients estimated from the above model, we estimated non-discretionary accruals ($NDA_{i,t}$) as follows:

$$NDA_{i,t} = \beta_{1,j} \left(\frac{1}{A_{i,t-1}} \right) + \beta_{2,j} \left(\frac{REV_{i,t} - \Delta REC_{i,t}}{A_{i,t-1}} \right) + \beta_{3,j} \left(\frac{PPE_{i,t}}{A_{i,t-1}} \right) + \varepsilon_{i,t} \quad (2)$$

Finally, we determine $AEM_{i,t}$ as the proxy for accrual earnings management by subtracting $NDA_{i,t}$ from $TAC_{i,t}$, which were residuals from the first model:

$$AEM_{i,t} = \left(\frac{TAC_{i,t}}{A_{i,t-1}} \right) - NDA_{i,t} \quad (3)$$

We also used our research design's second earnings quality metric, $REM_{i,t}$ – real earnings management. We used the Roychowdhury model (Roychowdhury, 2006) to determine abnormal cash flows from operations. We applied the same procedure for selecting the peer group for each firm-year observation. To determine the proxy for REM, we used the cross-sectional model for every firm-year observation as follows:

$$\frac{CFO_{i,t}}{A_{i,t-1}} = \beta_{1,j} \left(\frac{1}{A_{i,t-1}} \right) + \beta_{2,j} \left(\frac{REV_{i,t}}{A_{i,t-1}} \right) + \beta_{3,j} \left(\frac{\Delta REV_{i,t}}{A_{i,t-1}} \right) + \varepsilon_{i,t} \quad (4)$$

in which:

$CFO_{i,t}$ - cash flows from operations of i-company in t-year;

$REV_{i,t}$ - sales revenue for i-company in t-year;

Then, we used beta coefficients from the model to estimate non-discretionary cash flows from operations ($NFCO_{i,t}$) as follows:

$$NFCO_{i,t} = \beta_{0,j} + \beta_{1,j} \left(\frac{1}{A_{i,t-1}} \right) + \beta_{2,j} \left(\frac{REV_{i,t}}{A_{i,t-1}} \right) + \beta_{3,j} \left(\frac{\Delta REV_{i,t}}{A_{i,t-1}} \right) + \varepsilon_{i,t} \quad (5)$$

in which:

$CFO_{i,t}$ - cash flows from operations of i-company in t-year;

$REV_{i,t}$ - sales revenue for i-company in t-year;

Finally, we determined the proxy for real earnings management ($REM_{i,t}$) as the discretionary cash flows from operations as follows:

$$REM_{i,t} = \left(\frac{CFO_{i,t}}{A_{i,t-1}} \right) - NFCO_{i,t} \quad (6)$$

Based on the accounting-based bankruptcy prediction models and two proxies of earnings quality, the dataset contained seven key variables. Table 2 presents their descriptive statistics. We winsorised all variables at the top and bottom of one percentile to neutralise the impact of outliers. The sample covered 17 years (2007-2023) and, depending on the variable, contained from 5 004 (the REM variable) up to 5 688 firm-year observations (the AEM variable). We examined banks and financial institutions from the sample due to their financial reporting specificity.

Table 2. Descriptive statistics of variables accounting-based bankruptcy prediction models and accrual and real earnings management

Variable	Obs.	Mean	Median	Std. Dev.	Min	25%	75%	Max	Skewness
(1) AEM	5 688	0.190	-0.003	1.567	-3.023	-0.133	0.126	5.508	1.667
(2) REM	5 004	-0.048	-0.047	0.233	-4.780	-0.112	0.013	4.455	-0.784
(3) Z_MACZ	5 532	7.481	5.727	7.889	-15.463	3.887	8.991	53.110	2.581
(4) Z_MA_ZA	5 553	2.033	1.876	5.900	-25.991	0.620	3.451	30.604	0.063
(5) Z_WIERZ	5 117	0.005	0.575	3.839	-28.308	0.074	1.038	6.750	-5.350
(6) Z_HAD	5 193	2.548	1.710	4.401	-7.786	0.988	2.873	31.147	3.938
(7) Z_POZN	5 641	6.254	4.526	12.722	-33.149	2.755	7.015	98.55	4.345

Source: own study based on data extracted from the ORBIS database.

The means and medians of proxies for earnings quality, AEM, and REM were very close to zero value (Table 2). The skewness of the AEM variable was high and positive, while REM is moderate and negative. The variability, as measured by the standard deviation, was relatively high. In the case of ABPMs, the variability coefficients were lower but still higher than the mean values. The values of the Mączyńska model were the most symmetric, indicating low skewness, while the values of the other models were highly skewed. The median and means of the Z-score model were positive, indicating no bankruptcy risk in most firm-year observations.

RESULTS AND DISCUSSION

For each ABPM, we calculated the number of firm-year observations above and below zero to learn how each prediction model divides the sample between firm-year observations with high bankruptcy risk and the others (Table 3). The Table presents the 'optimism' of each ABPM model, suggesting that the Wierzbka model is the most conservative by suspecting almost 23% of the sample to be at high bankruptcy risk. Conversely, the Mączyńska model is the most liberal and suspects only 3%. The difference presented in Table 3 is a problem of type I and type II errors and the accuracy of ABPMs.

Table 3. Firm-year observations with high ($Z < 0$) and no bankruptcy risk ($Z > 0$)

Variable	Obs.	$Z < 0$	$Z > 0$	% of risk failure
(1) Z_MACZ	5 532	191	5 341	3.45%
(2) Z_MAC_ZAW	5 553	1 019	4 534	18.35%
(3) Z_WIERZ	5 117	1 160	3 957	22.67%
(4) Z_HAD	5 193	353	4 840	6.80%
(5) Z_POZN	5 641	360	5 281	6.38%

Source: own study based on data extracted from ORBIS database.

We used the correlation analysis to test the main hypotheses. We did not investigate the causality between the quality of reported earnings and the ABPMs' results. The question was whether the higher bankruptcy risk is accompanied by lower earnings quality. Table 4 presents the results of the first correlation analysis.

Table 4. Pairwise correlations: Pearson (lower triangle) and Spearman (upper triangle)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) AEM	1.000	-0.267***	-0.041	0.093***	0.122***	0.112***	0.050**
	–	(0.000)	(0.131)	(0.000)	(0.000)	(0.000)	(0.015)
(2) REM	-0.142***	1.000	0.263***	0.372***	0.258***	0.545***	0.188***
	(0.000)	–	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(3) Z_MACZ	-0.012	0.248***	1.000	0.436***	0.326***	0.022	0.545***
	(0.375)	(0.000)	–	(0.000)	(0.000)	(1.000)	(0.000)
(4) Z_WIERZ	0.023*	0.405***	0.389***	1.000	0.700*	0.214***	0.645***
	(0.084)	(0.000)	(0.000)	–	(0.000)	(0.000)	(0.000)
(5) Z_POZN	-0.012	0.306***	0.231***	0.516***	1.000	0.241***	0.372***
	(0.385)	(0.000)	(0.000)	(0.000)	–	(0.000)	(0.000)
(6) Z_HAD	0.046***	-0.149***	0.017	0.047***	-0.178***	1.000	0.037
	(0.001)	(0.000)	(0.229)	(0.001)	(0.000)	–	(0.251)
(7) Z_MA_ZA	0.030**	0.136***	0.654***	0.504***	0.223***	0.073***	1.000
	(0.023)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	–

Note: p-values in brackets and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$;

Source: own study based on data extracted from the ORBIS database.

Pearson correlation evaluates the linear relationship between two continuous variables, while the Spearman correlation evaluates the monotonic relationship, which means that two variables tend to change together, but not necessarily at a constant rate. In Table 4, correlation coefficients were of limited values. We recorded the highest values recorded between Z-scores of the Mączyńska-Zawadzki model and Wierzbka model (Spearman corr. coef. of 0.700 and Pearson of 0.516), and Mączyńska-Zawadzki model and Poznanski model (Spearman corr. coef. of 0.645 and Pearson corr. coef. of 0.504), and Mączyńska model and Poznanski model (Spearman corr. coef. of 0.545 and Pearson corr. coef. of 0.654). As we considered the correlation coefficients, they were of moderate values; however, in most cases, p-values were equal to zero, suggesting a strong significant relationship. All the correlation coefficients were positive. However, we found significant differences in how ABPMs perceive bankruptcy risks and financial conditions.

Table 5 presents content similar to Table 4, but with one difference. We use absolute values of AEM (absAEM) and REM (absREM). In this case, the correlation coefficients between the absAEM and the absREM with Z-scores values of ABPMs are even lower than in Table 4. However, in most cases, p-values were equal to zero, suggesting a strong significant relationship.

Table 5. Pairwise correlations: Pearson (lower triangle) and Spearman (upper triangle). Absolute values of AEM and REM

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) AbsAEM	1.000	0.478***	0.137***	-0.099***	-0.051**	-0.092***	0.053***
	–	(0.000)	(0.000)	(0.000)	(0.011)	(0.000)	(0.007)
(2) AbsREM	-0.142***	1.000	0.012	-0.126***	-0.032	-0.036	-0.002
	(0.000)	–	(1.000)	(0.000)	(0.297)	(0.349)	(1.000)
(3) Z_MACZ	0.134***	0.078***	1.000	0.436***	0.326***	0.022	0.545***
	(0.000)	(0.000)	–	(0.000)	(0.000)	(1.000)	(0.000)
(4) Z_WIERZ	-0.061***	-0.047**	0.389***	1.000	0.700*	0.214***	0.645***
	(0.000)	(0.001)	(0.000)	–	(0.000)	(0.000)	(0.000)
(5) Z_POZN	-0.125***	-0.202***	0.231***	0.516***	1.000	0.241***	0.372***
	(0.000)	(0.000)	(0.000)	(0.000)	–	(0.000)	(0.000)
(6) Z_HAD	0.062***	0.052***	0.017	0.047***	-0.178***	1.000	0.037
	(0.000)	(0.000)	(0.229)	(0.001)	(0.000)	–	(0.251)
(7) Z_MA_ZA	0.086***	0.032**	0.654***	0.504***	0.223***	0.073***	1.000
	(0.000)	(0.023)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: p-values in brackets and *** p<0.01, ** p<0.05, * p<0.1;

Source: own study based on data extracted from the ORBIS database.

To investigate the relationship between ABPMs and earnings quality, we recoded the Z-scores to a dichotomous variable in the following way:

- the value of one for firm-year observation, where the Z-score was below zero, implying a high bankruptcy risk,
- the zero value for firm-years observation, where the Z-score value was above or equal to zero, implying the no or low bankruptcy risk.

The recoding of variables allowed us to proceed with the ANOVA analysis to determine whether there are significant differences between the means. We constrained the analysis to the absolute values of AEM and REM for interpretation reasons. The intensity of earnings management is important and not a direction. High intensity (an absolute value of AEM or REM) implies low earnings quality and the opposite. The dataset is imbalanced – a small number of high bankruptcy risk firm-year observations compared to those of no risk of bankruptcy. This probably is one of the main reasons for unequal variances (heteroscedasticity) between groups (Table 3). Bartlett's test (p-value < 0.05) in the majority of cases (Z-scores and earnings quality) implies the problem of unequal variances between groups. Therefore, it is not advisable to use a regular one-way ANOVA. The results may not be reliable as they become more prone to Type I errors (false positive). We decided to use Welch's ANOVA, which is more robust to heteroscedasticity and differences in sample sizes across groups and helps to reduce Type I errors. It also uses a different method to calculate degrees of freedom. Overall, Welch ANOVA allows for obtaining more reliable results.

Table 6 presents the results of Welch ANOVA of the absAEM variable concerning two groups of firm-year observations: high risk and no/low risk of bankruptcy. The results of the F-stat suggested a high variability between group means compared to the variability within groups. The very low p-value implies statistically significant differences in the groups' means. The post-hoc Bonferroni test displayed a p-value of zero in all combinations, suggesting that observed differences in means of high risk of bankruptcy and no risk of bankruptcy are statistically significant, and it is highly unlikely to have occurred by chance. The firm-year observations with high bankruptcy risk came with lower quality of earnings (higher values of absAEM). The findings suggested that high bankruptcy risk was associated with managers engaging in discretionary earnings management techniques.

Table 7. Results of Welch ANOVA and Bonferroni test of absREM and a group of high-risk and no-risk firm-year observations

Variable absREM	Risk of bankruptcy	Mean	Std. Dev.	Freq.	F-stat	p-value	Bonferroni test
(1) Z_MACZ	0 (no)	0.108	0.166	4 726	39.716	0.000	0.305
	1 (yes)	0.413	0.602	155			p-value = 0.000
(2) Z_MA_ZA	0	0.099	0.156	1 013	87.452	0.000	0.106
	1	0.204	0.328	883			p-value = 0.000
(3) Z_WIERZ	0	0.093	0.12	3 504	59.535	0.000	0.081
	1	0.174	0.33	1 029			p-value = 0.000
(4) Z_HAD	0	0.105	0.165	4 278	22.982	0.000	0.108
	1	0.213	0.396	313			p-value = 0.000
(5) Z_POZN	0	0.109	0.172	4 659	38.418	0.000	0.158
	1	0.267	0.446	308			p-value = 0.000

Note: Z-scores < 0 are coded as one and zero otherwise.

Source: own study.

Table 7 presents the results of Welch ANOVA of the absREM variable with respect to the same two groups of firm-year observations as above. The high values of F-stat and very low p-values lead to the same conclusions as in the case of the absAEM variable. Therefore, it suggests that firm-year observations with a high risk of bankruptcy came with lower earnings quality. Since we investigated the correlation relationship, not the causation, we may conclude that higher bankruptcy risk causes lower earnings quality. However, without direct empirical evidence, we may only speculate that managers of companies with a high risk of bankruptcy engage in real earnings management techniques, *i.e.*, influence real business operations and related cash flows. The consequences may be even more harmful than accrual earnings management.

Our results corroborate Garcia-Lara *et al.*'s (2009) findings. Based on the UK firm-year observations covering 1998-2004, they concluded that accruals manipulation is more pronounced in *ex-post* bankrupt firms. Similarly, Campa and Camacho-Minano (2015), based on the sample of Spanish SMEs, provide empirical evidence suggesting upward earnings manipulation of bankrupt firms as compared to non-bankrupt firms. We provide another argument supporting the call of Séverin and Veganzones (2021) to use earnings management information to improve the bankruptcy prediction models. Their study was conducted on the French SMEs. Thus far, we do not know of any application of this concept in other countries or at the level of larger, publicly listed companies.

CONCLUSIONS

The study aimed to investigate the relationship between earnings quality and bankruptcy risk as estimated by accounting-based prediction models. We used a sample of Polish-listed companies due to the popularity of ABPMs in Poland among practitioners and scholars and the fact that the academic community developed at least several interesting models of sufficient accuracy. Therefore, applying a set of models designed for the specificity of the Polish economic context was possible. The simplicity of ABPMs' use makes them a useful tool in the hands of managers, accountants, financial auditors or investors. It is especially important in the case of emerging economies characterised by a lower level of institutional development. Poland exemplifies an economic success story as it was upgraded in 2018 to the status of a developed market and, simultaneously, a post-communist CEE country, an EU member. Many other CEE countries share a similar heritage, history, and institutional background. Therefore, scholars may generalise the results and apply them to the CEE countries and other emerging economies.

Based on the literature review, we posited two hypotheses. The first conjecture was that high-bankruptcy-risk companies were accompanied by more intensive accrual earnings management. The correlation analysis shows a weak but statistically significant correlation between bankruptcy risk and accrual

earnings management as proxied by AEM and absolute AEM values estimated with the modified Jones model. In the correlation analysis, we applied Pearson and Spearman rank correlations. Overall, 7 out of 10 combinations of AEM and ABPMs were statistically significant, and in the case of absAEM (absolute values of AEM) all were statistically significant. Further investigation involved the application of Welch ANOVA, which demonstrated that the group of firm-year observations classified as high bankruptcy risk was accompanied by a more intensive accrual earnings management compared to no or lower-risk bankruptcy risk firm-year observations. Therefore, it implies that a higher bankruptcy risk is assisted by managerial behaviour intended to influence reporting numbers. We can only speculate whether it is the white, grey, or black version of earnings management and whether the discretion embedded in financial reporting regulations is used by managers to signal the true financial problems or just the opposite – to cover them up. To sum up, empirical evidence supports the first hypothesis.

The second hypothesis conjectured that high-bankruptcy-risk companies are accompanied by more intensive real earnings management as estimated by the Roychowdhury model. The correlation analysis showed a weak or moderate correlation between REM and bankruptcy risk as measured by five ABPMs. However, in all cases, the correlation was statistically significant (as measured by Pearson and Spearman rank correlation). In the case of absREM, the results were similar in the case of the Pearson correlation coefficients, while the Spearman rank correlations showed statistical significance only in the case of the Wierzbka model. The Welch ANOVA analysis supported the conjecture that the group of firm-year observations classified as high bankruptcy risk was accompanied by a more intensive real earnings management. Therefore, it implied that a higher bankruptcy risk is assisted by managerial behaviour aimed at influencing operational activities and departing from the normal course of action to achieve desired goals. It involves changing business decisions and, consequently, the timing and amounts of the firm's cash flows. Thus, the study provides empirical evidence supporting the second hypothesis.

The higher risk of bankruptcy is associated with more intensive accrual and real earnings management, which translates into lower earnings quality. Therefore, the reliability and usefulness of reported numbers were diminished. Moreover, ABPMs are based on reported numbers, and the issue of earnings quality should be considered in the development of future bankruptcy prediction models. Finally, awareness of the relationship between earnings quality and bankruptcy risk may be important for financial statement users, investors, financial analysts, or financial auditors. From this perspective, a decline in earnings quality may be interpreted as a potential sign of increased bankruptcy risk.

From a policymaking perspective, academics should continue their efforts to develop financial ratios that effectively capture the broad concept of earnings quality, including measures of accrual-based and real earnings management. Professional accounting and auditing bodies should consider promoting those metrics to facilitate their widespread adoption. Furthermore, there is a clear need to educate investors, shareholders, and auditors on the significance and application of such measures. The study's limitations include the following: the research design used only five ABPMs and only two metrics of earnings quality (accrual and real earnings management) and it did not investigate the other aspects of earnings quality (*i.e.*, earnings predictability or earnings response coefficient). Moreover, the study investigated the relationship between key variables of interest without causation analysis. The study focused on the intensity of earnings management (accrual or real) without investigating income-increasing or income-decreasing techniques. This was a single-country study, thus generalizability may be impeded by differences in legal and regulatory frameworks, institutional backgrounds, *etc.* The study does not suggest how the concept of earnings quality may be implemented in designing new ABPMs. Those limitations constitute an avenue for future research.

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Authors

The contribution share of authors is equal and amounted to 50% for each of them.
BG & KG – conceptualization, literature writing, methodology, calculations, discussion.

Barbara Grabińska

Assistant Professor at the College of Economics and Finance, Krakow University of Economics, Department of Finance and Financial Policy. She received a PhD in economics from the Faculty of Finance, Krakow University of Economics. Her research interests include financing science and higher education, innovation policy, R&D, financial analysis and financial policy.

Correspondence to: Dr Barbara Grabińska, Krakow University of Economics, Department of Finance and Financial Policy, ul. Rakowicka 27, 31-510 Kraków, Poland; e-mail: grabinsb@uek.krakow.pl

ORCID  <https://orcid.org/0000-0003-4425-0530>

Konrad Grabiński (corresponding author)

Associate Professor at the College of Economics and Finance, Krakow University of Economics, Department of Financial Accounting. He received a PhD in economics from the Faculty of Finance, Krakow University of Economics and completed his habilitation (dr hab.) in economics and finance at the same university. His research interests include earnings quality, earnings management, financial reporting, accounting diversity and corporate finance.

Correspondence to: Dr hab. Konrad Grabiński, Prof. UEK, Krakow University of Economics, Department of Financial Accounting, ul. Rakowicka 27, 31-510 Kraków, Poland; e-mail: kg@uek.krakow.pl

ORCID  <https://orcid.org/0000-0002-1071-3317>

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Use of Artificial Intelligence

Our text is free of AI/GAI usage.

Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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