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Research and Development Spending in Bankruptcy Prediction: Examining an Adjusted Ohlson O-score Model

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Abstract

This thesis investigates whether bankruptcy prediction applying the Ohlson O-score model can be enhanced by modifying accounting variables associated with research and development (R&D) spending. To examine this, we study the expected risk of bankruptcy and R&D intensity among listed firms in the United States from 1990 to 2019. Through statistical tests, we determine whether accounting-based bankruptcy prediction can be improved through an adjustment for conservative R&D accounting. The findings of our study indicate that R&D intensive firms are more likely to be classified with the highest expected risk of bankruptcy and that the prediction accuracy of the Ohlson O-score model is enhanced through adjusting for conservative R&D accounting.

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Keywords: Bankruptcy Prediction, Research and Development (R&D), Ohlson O-score Model, Generally Accepted Accounting Principles (GAAP), Conservative Accounting

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1 Introduction

Bankruptcy prediction is a framework that is often applied in operational decision-making practices and analysis presented in accounting and finance literature. During the prior decades, numerous accounting-based bankruptcy prediction models have been developed and among the more prominent researchers are Altman (1968) and Ohlson (1980), whose respective studies showed to have significant explanatory power in the prediction of bankruptcy. To this day accounting-based bankruptcy prediction models are still commonly used, but as our societies and business environments evolve, there may be a need for these models to adapt correspondingly (Grice and Dugan, 2001). The purpose of this thesis is to investigate the effect of modifying accounting variables associated with research and development (R&D) spending to enhance bankruptcy prediction. Principally, the study aims to address the research question:
Can bankruptcy prediction be improved by adjusting for conservative R&D accounting?
The quantitative study is conducted on listed firms in the United States (U.S.) during the period 1990-2019. We investigate an unbalanced panel data set of 11,257 unique firms, totaling a main sample of 141,545 firm-years.

The subject of bankruptcy prediction has always been contemporary and of interest to many parties including investors, lenders, and corporate managers. Models predicting bankruptcy are adopted and applied as a means of corporate governance in business contexts and research. Insolvency situations leading to bankruptcy filings present a real threat to many businesses. During 2018 in the U.S., 513 bankruptcy filings were made by public companies, and in 2019 bankruptcy filings exceeded 579 (S&P Global Market Intelligence, 2020). This illustrates the increasing importance of firm assessment and forecasting, and the need for bankruptcy prediction estimates to be reliable.

Many of the early bankruptcy prediction models that are currently used are based on accounting measures. Despite the wide usage, researchers are becoming increasingly aware of that these models may not provide reliable estimates due to changes in business environments. According to Grice and Dugan (2001) and later Franzen et al. (2006), the frequently used accounting-based models including Altman (1968) and Ohlson (1980) are shown to be sensitive to industry-specific classifications emerged in recent time. Therefore, in the interest of increasing bankruptcy prediction accuracy, it is crucial to understand the changes in business environments and alter models accordingly.

Global R&D spending has increased steadily in the latest decades, ranging from USD 555 billion in 1996 to USD 2,233 billion in 2018 (UNESCO Institute of Statistics, 2021). This increase is primarily due to the technical evolution that has changed and developed business environments in the last 20 to 30 years. As PwC reported in their 2018 global innovation study, “innovation today is a key driver of organic growth for all companies – regardless of sector or geography”. Following the growing investments in R&D activity and its uncertainties in economic profit, the accounting standards of R&D reporting have become a subject of discussion.

As illustrated by Lev and Gu (2016), a discussion amongst authors includes the concern that accounting for intangibles, including R&D investments, affects financial statements in that they no longer reflect the supporting factors of value in modern firms. The primary topics of the ongoing debate include the outcomes of capitalizing or expensing R&D spending conjointly with the theory of conservative accounting (Cazavan-Jeny et al., 2011). As suggested by Chan et al. (2001), the effect of fully expensing R&D spending can heavily distort financial measures and alter accounting ratios for R&D intensive firms. Consequently, R&D accounting standards particularly affect the accounting-based bankruptcy prediction models which may impact the forecasting ability of such models.

Jones (2011) shows that voluntary capitalization of intangibles, such as R&D spending, has a strong predicting power in a model forecasting financial distress. Expanding on this, Franzen et al. (2005) examine whether accounting measures used in bankruptcy prediction reflect conservative accounting rather than poor financial performance. In a later report Franzen et al. (2006) document that higher R&D spending increases the likelihood of misclassifying solvent firms and that adjusting for conservative accounting of R&D spending increases the number of correctly identified distressed firms.

Inspired by Franzen et al. (2006) and considering the evolution of business environments and, the purpose of this study is to investigate the effect of modifying accounting variables associated with R&D spending to enhance bankruptcy prediction. We test this by studying listed firms in the U.S. and examine whether adjustments for conservative R&D accounting enhance the bankruptcy prediction of the Ohlson O-score model (1980). First, we investigate whether R&D intensity, measured as R&D spending to total assets, is higher for firms classified with the highest expected risk of bankruptcy. Second, we study if adjusting for conservative R&D accounting increases the prediction accuracy of the model. Moreover, recognizing that it may be of interest to stakeholders to know the attributes of the firms that are potentially misclassified by the original O-score, we investigate whether other financial characteristics than R&D intensity are associated with the reclassification under the adjustment process.

The results of this study indicate that R&D intensive firms are more likely to be classified with the highest expected risk of bankruptcy and that R&D spending appears to be a driver of misclassification. Furthermore, our findings imply that the O-score's prediction can be improved by adjusting for conservative R&D accounting. Additionally, the results suggest that the reclassification of non-bankrupt firms is mainly driven by R&D intensity and not explicitly by other financial characteristics.

This study will add value to existing research by extending the period scope, investigating if accounting-based bankruptcy prediction accuracy has decreased as R&D activity continues to increase. By examining more recent U.S. bankruptcy data, we aim to contribute with enhancements to bankruptcy prediction that are more relevant for investors, lenders, and corporate managers in current business environments. Furthermore, we aspire to contribute to research by testing the assumption made by Franzen et al. (2006) stating that firms classified with the highest expected risk of bankruptcy under the original O-score have higher R&D intensity than other firms. This is conducted with the ambition of legitimizing the need for research within the relevant field and further strengthening the results presented by Franzen et al. (2006) and ourselves.

Additionally, we aim to contribute to existing research by applying further assessments of our adjusted model, testing whether other financial characteristics than R&D intensity are associated with the reclassification under the adjustment process. This will provide a more comprehensive overview of the adjustments and help identify the attributes of the firms that were originally classified with the highest expected risk of bankruptcy. The focus on financial characteristics will further showcase which accounting attributes correspond with the firms that are reclassified as a result of the adjustments. The novelty of our thesis thereby lies in the usage of current data and our method of testing and reviewing the results derived from such data.

This thesis is composed of seven sections, and the disposition is as follows. Section 2 reviews previous literature and theories deemed relevant for the study scope and the development of the hypotheses tested. In section 3, the methodology is presented and in section 4 the data and sample are selected. The empirical results and analysis are reported in section 5, followed by a discussion in section 6. Finally, section 7 concludes the thesis and presents suggestions for further research.

2 Theory and Literature Review

This section will provide an overview of the literature that has driven the preferment of our study and hypotheses. The literature described serves as a foundation of the three main themes that underlie our focus, namely the usage of accounting-based bankruptcy prediction models, conservative R&D accounting, and finally the prevalence of R&D altering bankruptcy prediction models. These key fields provide an overview of the current U.S. based accounting landscape and the advancement towards our hypotheses.

2.1 Bankruptcy Models

To perform the study in alignment with our purpose, a bankruptcy prediction model is selected. This thesis aims to illustrate the impact of conservative accounting policy of R&D spending on conclusions related to distress risk as regularly estimated by accounting ratios. Considering this, not all bankruptcy models are applicable. While we recognize the increasing use of market-based prediction models as suggested by Hillegeist et al. (2003) and Campbell et al. (2006), we limit the study scope to accounting-based models within the purpose of this thesis. Market-driven models such as Shumway's hazard rate model (2001) and Black-Scholes-Merton option-pricing model (1974) are not applicable as they capture the value of investing in R&D to a greater extent. Hence, an accounting adjustment would have little effect on the model's prediction and be of limited interest. Subsequently, an accounting-based bankruptcy prediction model will be applied. The research of Altman (1968) and Ohlson (1980) are prominent within the field and have shown to have significant explanatory power in the prediction of bankruptcy. Alternative accounting-based models such as Zmijewski (1984) and Springate (1978) are not preferred considering that they contain less relevant accounting-based variables compared to the models developed by Altman (1968) and Ohlson (1980). Based on the preceding reasoning, we will further explore the Altman Z-score and the Ohlson O-score.

2.1.1 The Altman Z-score

In 1968, Altman introduced the Z-score as a prediction model to evaluate the probability of bankruptcy filings within two years. The Altman Z-score is based on multiple discriminant analysis, a statistical technique classifying observations into a priori grouping conditional on the individual characteristics of the observation. In his research, Altman (1968) utilized accounting data from the income statement and balance sheets of public manufacturing firms. He collected a sample of 66 firms to establish a linear model of five parameters that best discriminates between companies in two mutually exclusive groups: bankrupt firms and non-bankrupt firms. The numeric Altman Z-score provides a linear scale where a score close to 0.018 implies a higher likelihood that the firm will file for bankruptcy. The equation of the Altman Z-score is specified below.

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5 \quad (1)$$

$$\begin{aligned} Z &= overall\ index \\ X_1 &= working\ capital\ /\ total\ assets \\ X_2 &= retained\ earnings\ /\ total\ assets \\ X_3 &= earnings\ before\ interest\ and\ taxes\ /\ total\ assets \\ X_4 &= market\ value\ of\ equity\ /\ book\ value\ of\ total\ debt \\ X_5 &= sales\ /\ total\ assets \end{aligned}$$

Altman (1968) reported an accuracy of 72 percent of bankrupt firms within two years, with a type II error of 6 percent and a decreasing prediction value within the following years.

2.1.2 The Ohlson O-score

In 1980, a new accounting-based bankruptcy prediction model was introduced, the Ohlson O-score. The model raised questions of the relevance of the previous Z-score developed by Altman (1968), and quickly gained attention. Unlike the Altman Z-score, the O-score is constructed through a logit approach consistent of nine explanatory variables including financial ratios and dummies. The score can be interchanged for a probit model, which provides an adaptable view of bankruptcy risk. Instead of simply categorizing expected bankruptcy by a numeric threshold, the model states that the firms with the highest O-scores suffer the greatest expected probability of bankruptcy. The parameters of the O-score are presented below.

$$\begin{aligned} O = {} & -1.32 - 0.407 * SIZE + 6.03 * TLTA - 1.43 * WCTA + 0.0757 * CLCA - 1.72 * \\ & OENEG - 2.37 * NITA - 1.83 * FOTL + 2.285 * INTWO - 0.521 * CHIN \end{aligned} \quad (2)$$

$$\begin{aligned} O &= overall\ index \\ SIZE &= log\ (total\ assets\ /\ GNP\ price\text{-}level\ index) \\ TLTA &= total\ liabilities\ /\ total\ assets \\ WCTA &= working\ capital\ /\ total\ assets \\ CLCA &= current\ liabilities\ /\ current\ assets \\ OENEG &= dummy\ equal\ to\ 1\ if\ total\ liabilities\ exceed\ total\ assets \\ NITA &= net\ income\ /\ total\ assets \\ FOTL &= funds\ of\ operations\ /\ total\ liabilities \\ INTWO &= dummy\ equal\ to\ 1\ if\ net\ income\ was\ negative\ in\ the\ past\ two\ years \\ CHIN &= change\ in\ net\ income\ for\ the\ most\ recent\ period \end{aligned}$$

Ohlson's study was intended to extend the scope tested by previous bankruptcy predictions, a goal illustrated in the increase of sample size. In the period of 1970-1976, 105 failing and 2,058 non-failing companies were observed, all of which were listed industrial firms. Ohlson conferred three different models, (1) the estimation of bankruptcy probability in one year, (2) the estimation of bankruptcy probability in two years given no bankruptcy in the first year, and (3) the estimation of bankruptcy probability within two years. The three models provided different prediction accuracy, and in the prediction of bankruptcy within two years, Ohlson achieved an estimation sample accuracy of 93 percent (Ohlson, 1980).

2.1.3 Motivation of Model

Today, many researchers still apply the Altman Z-score when predicting bankruptcy, nonetheless, the model is subject to heavy criticism. A primary argument submitted by Ohlson (1980) conveys that the logit O-score model has a timing advantage to the Altman Z-score since it better utilizes whether a firm has filed for bankruptcy prior to, or after, the release of the financial reports. This proves beneficial when considering individual firms and firms within contrasting industry scopes. Moreover, it is argued that the multiple discriminant analysis in the Altman Z-score further depends on the assumption of an equal probability of group membership based on sample proportions (Jones, 1987). The requirement of a normally distributed predictor contradicts the use of a dummy variable of bankrupt and non-bankrupt firms, limitations which severely restrict the use of Altman's model (Ohlson, 1980).

Furthermore, in their research Wu et al. (2010) find that the Ohlson O-score (1980) performs superiorly when comparing the Altman model (1968) and the Ohlson model. The paper analyzes a sample of U.S. listed firms consistent of 887 bankrupt and 49,724 non-bankrupt firms and reports an accuracy in the Altman Z-score model of 28.7% and the O-score model of 79.7% when predicting bankruptcy within one year (Wu et al., 2010). Considering the arguments made, this thesis will henceforth apply the Ohlson O-score as a bankruptcy prediction measure, following Griffin and Lemmon (2002) and Franzen et al. (2006). The decision to apply the Ohlson model does not imply that this is a better predictor of bankruptcy than other models, simply that it is more applicable for the aim and extension of this study. It is important to note that no model is entirely accurate, and our ambition thereby primarily lies in the enhanced accuracy of the existing O-score model.

2.1.4 Bankruptcy Codes

In the U.S., cases of bankruptcy are filed under different chapters in the United States Bankruptcy Code. In their studies, both Altman (1968) and Ohlson (1980) applied Chapter X as the definition for bankruptcy. Chapter X was used to determine whether a company merited reorganization or liquidation. However, in 1978, Chapter X was reshaped through the

Bankruptcy Reform Act and primarily incorporated into the modern Chapter 11 (previously known as Chapter XI), the code generally provided for reorganization (United States Courts, 2015). As Chapter 11 is not identical to Chapter X, this thesis includes one additional code to represent the model's prediction as accurately as possible. Consequently, following Franzen et al. (2006), we include the liquidation chapter, Chapter 7, which also reflects segments of previous Chapter X. By applying both Chapter 7 and Chapter 11, we aim to replicate Chapter X to the best of our abilities but acknowledge the potential limitation due to this alteration.

Continuing, we identify a potential problem with so-called strategic bankruptcies that are more prevalent under the current pro-debtor regime of Chapter 11 according to Delaney (1992), Moulton and Thomas (1993), and James (2016). We suggest that if firms are more likely to file strategic bankruptcies without undergoing financial distress, this would, all else equal, affect the Ohlson O-score towards misclassifying bankrupt firms as firms with a lower expected risk of bankruptcy. To our knowledge, previous papers have not adjusted for this phenomenon and we proceed by raising the issue at play without altering the Ohlson model.

Moreover, a limited number of firms file for bankruptcy on multiple occasions. It is important to highlight the difference in financial reporting post-bankruptcy and its potential effect on the O-score's bankruptcy prediction. Under the current regime Chapter 11, firms are more likely to survive than under the previously applied Chapter X. When emerging from bankruptcy under Chapter 11, a firm is qualified for fresh start reporting, whereby balance sheet items are adjusted to fair value to denote a new beginning. Fresh start reporting includes the potential forgiveness of debt, adjustments of assets, termination of burdensome contracts, and separately, related tax effects (United States Courts, 2021). If firms file for bankruptcy on several occasions, we should expect an increase in bankrupt firms misclassified with a low expected risk of bankruptcy. However, due to the limited number of multiple filings and our primary concern with the overall identification of bankruptcy, we will not exclude such firms following Franzen et al. (2005).

2.2 R&D Accounting

This study investigates the effect of R&D spending on bankruptcy prediction, and we thereby proceed by describing R&D accounting. Fundamentally, R&D investments are the costs that a firm incurs for efforts intended to develop, design, or improve a product, service, or process. These costs can be expensed or capitalized. From an economic perspective there are different perceptions of how R&D spending should be classified. However, the following description does not aim to convey an opinion of which accounting approach is superior. The intent of the following descriptions is to address the accounting differences of capitalizing versus expensing and to assess how annual reporting is altered by the two approaches.

The method of expensing R&D spending affects the firm's income statement but does not affect the balance sheet. The total expense lowers the net income for the specific year in which the spending occurred and lowers the taxable income for that year. This approach is distinctly different from R&D capitalization where the spending is categorized as an investment and thereby affects both the income statement and the balance sheet. On the income statement the net income is decreased by the amortization of the R&D spending, which is calculated as the annual decrease in the investment value. This decreases the taxable income for that specific year and decreases the firm's taxable income for as many years as the investment depreciates. The R&D spending is also reflected on the balance sheet under intangible assets represented by the total value of the investment decreased by the accumulated amortization.

According to the Congressional Research Service (2020), there is an upward trend in R&D activity. In the late 20th century, the U.S. became a global leader in R&D spending, and measured in current dollars, business funding of R&D spending has grown nearly every year since the 1950's. Between 2000 and 2018 alone, business R&D spending grew by a compound annual growth rate of 4.4%. Considering the role that R&D plays in the U.S., the primary accounting standard used, United States Generally Accepted Accounting Principles (USGAAP), is further investigated.

USGAAP is a set of principles that encompass the legal standards and procedures of business and corporate accounting in the U.S. Issued by the Financial Accounting Standards Board (FASB), USGAAP is the foundation for American accounting methods that all U.S. listed firms are required to follow. The principles are not required for non-publicly traded companies, but since USGAAP is viewed favorably by lenders and creditors, most firms follow the guidelines. Under USGAAP, companies are obligated to expense all R&D investments according to ASC 730 in the same fiscal year when incurred. This follows the principle of conservative accounting, where all probable losses are recorded and gains are only registered when fully realized. The mandatory expensing of R&D spending implies greater volatility in profits or losses than capitalization, and creates difficulties in measuring individual firm's rates of return on assets and investments.

The international equivalent to USGAAP is referred to as International Financial Reporting Standards (IFRS), which is issued by the International Accounting Standards Board (IASB). IFRS is followed by more than 120 countries, including those in the European Union.

Under IFRS, research spending is expensed the same fiscal year when incurred while development costs are capitalized if certain conditions are met. The investments are capitalized and depreciated over multiple periods if they are proved to be commercially viable, i.e., expected to generate revenue. Many of the IFRS' criteria are contingent on subjective judgment, creating a risk of excessive optimism from companies' management of how commercially viable new investments are. This leaves the trade-off for companies uncertain and contrasting, which causes inconsistencies in different firms' financial statements. Regardless of the potential benefits or drawbacks of IFRS, USGAAP is the primary interest considering our sample of U.S. listed firms.

2.3 Previous Research

The growth in R&D activity has increased the interest in the effect that reporting of intangibles has on financial statements. As presented by Cazavan-Jeny et al. (2011), the debate surrounds the theory of conservative accounting and the outcomes of capitalizing or expensing R&D spending. This notion is contextualized by Chan et al. (2001) who illustrates how expensing R&D spending following USGAAP ultimately results in lower reported incomes and net assets relative to less conservative standards such as IFRS. They argue that the current U.S. accounting standards significantly affect firms with high R&D spending, portraying them with lower performance (Chan et al. 2001).

Additionally, through capitalizing R&D investments, Lev and Sougiannis (1996) find a significant intertemporal association between firms' R&D capital and subsequent stock returns. This suggests that there is either systematic mispricing of the shares of R&D intensive firms or compensation for a market risk factor associated with R&D spending (Lev and Sougiannis, 1996). In later research, Lev and Gu (2016) and Lev and Srivastava (2019) argue that the growing R&D investments have major effects on firms' financial data leading to an increasing mismeasurement of book values and value creation.

Several authors investigate the theory that variables used in accounting-based bankruptcy prediction models are sensitive to reporting standards and practices. In Australia, Bodle et al. (2016) documented an advantage in bankruptcy prediction through the change from Australian GAAP (AGAAP) to IFRS in 2005 by measuring the effects of intangibles. The findings suggest that adopting IFRS improves bankruptcy prediction through Altman's model (1968), primarily by enhancing the quality of information contained in financial statements. Bodle et al. (2016) adjust from fully capitalizing R&D under AGAAP to a combination of capitalizing and expensing R&D under IFRS and demonstrates how the more conservative IFRS improves the quality of the reports necessary for bankruptcy prediction.

The results documented by Bodle et al. (2016) challenge the view presented by Beaver et al. (2012) who discredits the belief that more conservative treatment of intangibles results in more informative financial statements. Beaver et al. (2012) illustrate that intangibles have a systematic effect on bankruptcy prediction, and similar to Beaver et al., Jones (2011) finds that voluntary capitalization of intangibles has a strong discriminating and predictive power in bankruptcy prediction.

Continuing, Bai and Tian (2020) investigate the effect of R&D spending and the insufficiency of the traditional accounting-based bankruptcy prediction models. Their research aims to improve bankruptcy prediction and they find that the variables R&D intensity and R&D effectiveness act as determinants of bankruptcy probability (Bai and Tian, 2020). Finally, Franzen et al. (2005) showcase the effect that conservative accounting has on the accuracy of accounting measures in bankruptcy prediction models. Through further research, Franzen et al. (2006) report that higher R&D spending increases the likelihood of misclassifying non-bankrupt firms, a phenomenon that can be partially counteracted through an adjustment for conservative R&D accounting.

2.4 Hypotheses

The hypotheses emanate from the formerly mentioned literature to determine the effect of modifying Ohlson's accounting-based bankruptcy prediction model in consideration to conservative R&D accounting. To ensure that no unnecessary changes are made to the Ohlson model, the relationship between R&D intensity, measured as R&D to total assets, and O-score classification is investigated. The aim is to examine if the O-score model proves to be unreliable in the classification of higher R&D intensive firms, specifically categorizing R&D intensive firms that do not file for bankruptcy within two years as *bankruptcy imminent*.

The classification of bankruptcy imminent refers to a firm having the highest expected risk of bankruptcy within two years. It is defined as having an O-score in the 80th percentile, i.e., quintile 5, further described in section 3.1. Considering this, the purpose of our first hypothesis is to establish whether firms with higher R&D intensity have a higher expected risk of being classified as bankruptcy imminent. These firms are investigated to determine whether the R&D intensive firms have a higher representation in the O-score quintile 5 compared to the lower O-score quintiles. This is essential to establish the relationship between R&D intensity and O-scores, and thereby the foundation for our study.

H1. R&D intensity is higher for firms in the bankruptcy imminent classification than for other firms.

We continue by investigating if the potential deficiency of the Ohlson model's classification of R&D intensive firms can be counteracted by adjusting for conservative R&D accounting. We anticipate that the expensing of R&D spending is one potential reason behind misclassification of non-bankrupt R&D intensive firms, and that this specific misclassification should decrease if R&D is capitalized. Considering this, we want to uncover if the Ohlson model's prediction of R&D intensive firms can be improved by adjusting for conservative R&D accounting. Additionally, we want to explore whether an adjusted O-score is preferred when predicting bankruptcy imminency amongst all firms.

H2. Adjusting for conservative R&D accounting increases the prediction accuracy of the bankruptcy imminent classification.

3 Methodology

This section provides a detailed explanation of the construction of the study, and the exercised technique derived from the Ohlson O-score model. The construction of the original O-score model and our adjusted O-score model are presented. We describe the process of testing our hypotheses and the statistical tests performed. These include a two-sample t-test, a two-sample Mann-Whitney test, a descriptive Accuracy Ratio, and McNemar's chi-square test. Thereupon, a logit regression is conducted to further investigate the financial characteristics of the firms in the original O-score quintile 5 that are reclassified as a result of the model adjustments.

3.1 O-score Construction

The variables fundamental to the O-score are constructed. Following the Ohlson model (found in section 2.1.2, equation 2) the variables consist of log of total assets ($SIZE$), total liabilities to total assets ($TLTA$), current liabilities to current assets ($CLCA$), working capital to total assets ($WCTA$), dummy equal to 1 if total liabilities exceed total assets ($OENEG$), net income to total assets ($NITA$), funds of operations to total liabilities ($FOTL$), dummy equal to 1 if consecutive net losses ($INTWO$), and change in net income ($CHIN$). Due to changes in reporting under USGAAP, we are unable to replicate Ohlson's (1980) version of $FOTL$, the funds of operations divided by total liabilities. Instead, following Franzen et al. (2006) and Hillegeist et al. (2003), an approximation of pre-tax income plus depreciation divided by total liabilities is applied. Moreover, consistent with Franzen et al (2006), no consideration is taken for GNP price-level index when computing the variable $SIZE$. The O-score variable definitions and detailed explanations can be found in Appendix 2.

We compute the O-score (equation 2) for each observation in the sample. Considering the probit function of the Ohlson model, a firm with a higher O-score is classified with a higher expected risk of bankruptcy. Therefore, we sort all the observations' O-scores from the smallest to the largest for each year in the sample period and divide them into five O-score dependent quintiles, denoted as Q. Quintile 1 consists of the 20% lowest O-scores, 20-40% represents quintile 2, 40-60% are quintile 3, 60-80% denotes quintile 4, and the final 80-100% is included in quintile 5, for each year in the sample period. The observations with O-scores in quintile 5 (Q5) have the highest expected risk of filing for bankruptcy and are defined as *bankruptcy imminent* in this thesis. Based on the quintiles we split the sample into two groups following the definition provided by Franzen et al. (2006): Q5 with higher expected risk of bankruptcy and quintile 1-4 (Q1-4) with lower expected risk of bankruptcy.

Before dividing the observations into quintiles, all O-scores are winsorized and replaced at the 2nd and 98th percentile to remove the effect of extreme values and outliers. Subsequently, we generate the R&D intensity variable, defined as R&D spending to total assets. All observations with positive R&D spending are divided into quintiles with the highest R&D intensity in the highest quintile for each year, following the same methodology as for the O-score. The firms included in R&D quintile 5 (R&D Q5) are referred to as *R&D intensive*.

3.1.1 Two-sample T-test and Mann-Whitney Test

After constructing the O-score and R&D intensity quintiles, we test our initial hypothesis, stating that R&D intensity is higher for firms in the bankruptcy imminent classification than for other firms. This is conducted through a two-sample t-test that examines whether the difference in mean R&D intensity between O-score Q5 and Q1-4 is statistically significant for our main sample. The underlying assumptions for the test are variable independence, random sampling, equal variances, and normal distribution in the population (Woolridge, 2012). However, we find that the R&D intensity variable shows a negatively skewed distribution (Figure 3.i, Appendix 3), rejecting the validation criteria of normal distribution. Consequently, we generate the natural logarithmic value of R&D intensity leading to a normal distribution variable shown in Figure 3.ii found in Appendix 3. Hence, the two-sample t-test is performed with the logarithmic value of R&D intensity instead and we interpret our results with caution due to this adjustment. Additionally, we complement the test with a non-parametric two-sample Mann-Whitney test on R&D intensity. The non-parametric test is used to identify the differences in variable medians in a two-sided test on unmatched data, and hence adjusts for any extreme outliers (Woolridge, 2012).

3.2 O-score Adjustment Process

We anticipate that adjusting for conservative R&D accounting can reduce the potential misclassification of R&D intensive firms under the original O-score and increase the prediction accuracy of the bankruptcy imminent classification. We thereby continue with an adjustment process, where certain modifications need to be made and assumptions considered. Initially, contingent on Franzen et al. (2006), we adjust for the conservative accounting by treating R&D spending as an intangible asset that is both capitalized on the firm's balance sheet and amortized over an assumed utility of five years. Adjusting from fully expensing R&D spending to capitalizing requires an alteration to the variables affected in the O-score model. Net income and total assets are first adjusted to $Adj. Net\ Income$ and $Adj. Total\ Assets$, as specified below.

$$Adj. Net\ Income = NI + RD_{it} - 0.2 * (RD_{it-1} + RD_{it-2} + RD_{it-3} + RD_{it-4} + RD_{it-5}) \tag{3}$$

$$Adj. Total\ Assets = TA + RD_{it} + 0.8 * RD_{it-1} + 0.6 * RD_{it-2} + 0.4 * RD_{it-3} + 0.2 * RD_{it-4} \tag{4}$$

Subsequently, the adjustment process produces tax effects, of which we make two assumptions. First, the assumption that firms choose to expense R&D spending for tax purposes is made. Since R&D capitalization is completed for financial reporting purposes and not tax reporting purposes, this results in the recognition of a deferred tax liability (DTL) defined as R&D capital multiplied by tax. We thereby assume that firms take advantage of the current tax savings available. Second, we assume that the firms with negative net income experience no tax effects. In general, tax effects lower income measures and increase liabilities, and if we disregard this second assumption and presume tax effects where non-existent, this would leave our adjusted model bias in favor of identifying more firms as bankrupt. Accordingly, we assume that there are no tax effects for firms with negative net income. The two outlined assumptions lead to a new adjustment of total liabilities, $After\text{-}tax\ (AT)\ Adj. TL$, as well as a further adjustment of net income, now $After\text{-}tax\ (AT)\ Adj. Net\ Income$. The following equations apply when net income is positive.

$$AT\ Adj. Net\ Income = NI + (RD_{it} - RD\ Amortization) * (1 - t) \quad (5)$$
$$RD\ Amortization = 0.2 * (RD_{it-1} + RD_{it-2} + RD_{it-3} + RD_{it-4} + RD_{it-5})$$

$$Adj. Total\ Assets = TA + RD\ Capital \quad (6)$$
$$RD\ Capital = RD_{it} + 0.8 * RD_{it-1} + 0.6 * RD_{it-2} + 0.4 * RD_{it-3} + 0.2 * RD_{it-4}$$

$$AT\ Adj. TL = TL + Deferred\ Tax\ Liability\ (DTL) \quad (7)$$
$$DTL = RD\ Capital * t$$

The appropriate annual statutory tax rate is defined as t, 34% in 1990-1992, 35% in 1993-2017, and 21% in 2018-2019 (Tax Policy Center, 2021). These adjusted accounting measures are combined into the adjusted Ohlson O-score model as presented below.

$$\begin{aligned} After\text{-}tax\ AO = & -1.32 - 0.407 * A\_SIZE + 6.03 * AT\_A\_TLTA - 1.43 * A\_WCTA \\ & + 0.0757 * CLCA - 1.72 * AT\_A\_OENEG - 2.37 * AT\_A\_NITA - 1.83 \\ & * AT\_A\_FOTL + 2.285 * AT\_A\_INTWO - 0.521 * AT\_A\_CHIN \end{aligned} \quad (8)$$

The new adjusted O-score metrics are thereby log of adjusted total assets (A_SIZE), after-tax adjusted total liabilities to adjusted total assets (AT_A_TLTA), adjusted working capital to adjusted total assets (A_WCTA), current liabilities to current assets ($CLCA$), after-tax adjusted dummy equal to 1 if after-tax adjusted total liabilities exceed adjusted total assets (AT_A_OENEG), after-tax adjusted net income to adjusted total assets (AT_A_NITA), adjusted funds from operations to after-tax adjusted total liabilities (AT_A_FOTL), after-tax adjusted dummy equal to 1 if consecutive net losses (AT_A_INTWO), and after-tax adjusted change in net income (AT_A_CHIN). Variable definitions and detailed explanations can be found in Appendix 2. The adjusted O-score is winsorized and replaced at the 2nd and 98th percentile to remove the effect of extreme values and outliers. Based on the preceding reasoning of the original O-score, we divide the adjusted O-score into quintiles for each year in the sample period, denoted as AQ. The adjusted O-score is divided into two groups: quintile 5 (AQ5) with higher expected risk of bankruptcy and quintile 1-4 (AQ1-4) with lower expected risk of bankruptcy.

With the formation of the adjusted O-score, the original O-score will henceforth be referred to as the unadjusted O-score model. We continue by testing our second hypothesis and thereby the prediction accuracy of the two models. Initially, we establish the Accuracy Ratio (AR) for the unadjusted and the adjusted O-score model to provide a single summary statistic of accuracy for both Type I and Type II errors. However, since the AR is entirely descriptive, we also incorporate a McNemar's chi-square test to further investigate the predictive ability of the two models. Furthermore, to ensure that our results are not driven by the tax assumptions previously made, all tests are completed with the pre-tax adjusted O-score model as defined in equation 2.i (Appendix 2). Descriptions of the pre-tax adjusted variables applied can also be found in Appendix 2.

3.2.1 The Accuracy Ratio

In 2000, Moody's Investors Service developed the cumulative accuracy profile (CAP) and its summary statistics of Type I and Type II errors, the AR. To calculate the AR of the unadjusted and adjusted O-score models, each O-score is divided into equally sized percentiles. The AR measures the discriminatory power of models and is defined as the ratio of the area above and under the plotted CAP, versus an ideal discriminating model. The cumulative sum of the percentage of firms filing for bankruptcy within two years in each percentile is calculated and plotted as the CAP, shown in Appendix 4. The ideal CAP line represents the perfect O-score model, meaning that the first percentiles would consist only of bankrupt firms. If, on the other hand, the O-score showed no predictive information, the bankrupt firms would be evenly distributed among the percentiles, resulting in a straight line called the random CAP. The curved line in Appendix 4 embodies a constructed model with some predictive power, i.e., the actual CAP, and the AR is the ratio of A over $(A+B)$. In a successful model, the AR ratio can take values between zero and one, where an AR closer to one implies a stronger predictive power and hence, a better model. The AR is shown below.

$$AR = \frac{2\int_0^1 y(x)dx - 1}{1-f} \tag{9}$$

The CAP curve for a population of x is defined as $y(x)$ and f denotes the fractions of firm-years that file for bankruptcy over the total number of firm-years.

3.2.2 McNemar's Chi-square Test

To test if there is marginal homogeneity between the unadjusted and the adjusted O-score models' prediction of bankruptcy amongst firms, McNemar's chi-square test for goodness-offit is performed. McNemar's test is applied to a $2x2$ contingency table which displays the frequency of observations correctly and incorrectly identified by the two models (Kavzoglu, 2017). The prediction is defined as *correct* when the model classifies firms that filed for bankruptcy within two years into Q5 or non-bankrupt firms into Q1-4, and *incorrect* when the model fails to do so. Subsequently, the contingency table as shown below is constructed with the prediction frequency of the unadjusted and adjusted model.

Two-way contingency table

	Adj. O-score predicts correctly	Adj. O-score predicts incorrectly
O-score predicts correctly	n_{cc}	n_{cf}
O-score predicts incorrectly	n_{fc}	n_{ff}

We test the null hypothesis $H_0: p_{cf} = p_{fc}$, where p_{ij} denotes probability. p_{cf} is defined as the probability of n_{cf} and illustrates the cases where the adjusted O-score predicts bankruptcy incorrectly and the unadjusted O-score predicts bankruptcy correctly. p_{fc} denotes the probability of n_{fc} and exhibits the cases where the adjusted O-score predicts bankruptcy correctly and the unadjusted O-score predicts bankruptcy incorrectly. If the null hypothesis is rejected at a statistically significant level, it would discard equal predictive accuracy of the unadjusted and adjusted O-score model. The formula is expressed below.

$$\frac{(n_{cf} - n_{fc})^2}{n_{cf} + n_{fc}} \sim \chi^2 \tag{10}$$

3.3 Logit Regression of Escaped Firms

With the aim of contributing to research within the field, we perform a logit regression. The intent is to investigate the financial characteristics of firms that are reclassified from unadjusted O-score quintile 5 to a lower adjusted quintile under the adjustment process. This is driven by two ambitions. First, we assume that it may be of interest to stakeholders to identify the financial attributes, other than R&D intensity, of those firms that are potentially misclassified by the original O-score. Second, we want to examine if our adjustments are primarily driven by R&D intensity or if there are other financial characteristics that should be considered. The logit regression is applied considering that it is a predictive non-linear model with a binary dependent variable and that assumptions regarding linearity, normal distribution, heteroskedasticity, and equal variances are not required (Woolridge, 2012). Among the firms who were originally classified into O-score Q5, we distinguish between observations that *stayed*, i.e., were classified into quintile 5 by both the unadjusted and the adjusted O-score, and those that *escaped*, i.e., were classified into quintile 5 by the unadjusted O-score but reclassified into lower quintiles by the adjusted O-score. The distinction is implemented through a statistical logit model as shown below.

$$\begin{aligned} P(Escaped_{it} | \, x) \\ &= L(\beta_0 + \beta_1 R\&D_{it} + \beta_2 Other\ Intangibles_{it} + \beta_3 Goodwill_{it} \\ &+ \beta_4 CAPEX_{it} + \beta_5 Sales_{it} + \beta_6 Dividend_{it} + \beta_7 Cash_{it} + \beta_8 ROE_{it} \\ &+ \alpha_t + \varepsilon_{it}) \end{aligned} \tag{11}$$

$Escaped$ is the dependent binary variable denoting 0 if the observation stayed and 1 if the observation escaped. L implies that it is a logit model. The variables $R\&D$, $Other\ Intangibles$, $Goodwill$, $CAPEX$, $Sales$, $Dividend$, and $Cash$ are all defined through their intensity, i.e., divided by total assets. *ROE* is the return on equity. Inspired by Lev and Srivastava (2019), we find these variables to be of particular interest to include in the regression. Further explanations and definitions of the financial characteristic variables can be found in Appendix 5. We control for year fixed effects by including year dummies α to reduce any differences in reclassification activity between the years and to mitigate the heterogeneity of omitted variable bias. Standard errors are clustered at firm level. The subscripts i indicates the firm, t the year, and ε is the error term. Moreover, to check for multicollinearity between the independent variables, a correlation matrix is presented. However, as the logit regression is not the main focus of this thesis, no VIF–analysis is conducted. All independent variables are winsorized and replaced at the 1st and 99th percentile to remove the effect of extreme outliers.

4 Empirical Data

4.1 Data Collection

The study is conducted through the domain of quantitative research with data on U.S. listed firms. The geographical scope is chosen on the grounds that both the study of Ohlson (1980) and Franzen et al. (2006) were based in the U.S. and considering that the country assembles a large data set. Moreover, the U.S. geographical scope is preferred due to their coherent R&D accounting practices following USGAAP and considering that other countries' bankruptcy legislation and practices may not be perfectly translated into the model.

The company scope extends to all U.S. listed firms. However, following Ohlson (1980) and Franzen et al. (2006), companies in financial services are excluded based on their different company structures and higher leverage. Financial services include banks, insurance companies, brokers, dealers, real estate, and other financial services. The periodical scope for the study lies between the years 1990 and 2019. These years are selected firstly due to the large increase in R&D spending in the last 30 years, and secondly because of the lack of sufficient data in the year 2020 and the years prior to 1990.

Conforming to Franzen et al. (2006), firm specific data on U.S. listed firms is obtained using the database Compustat. This data includes both bankrupt and non-bankrupt companies over the study period 1988-2019. The years 1988 and 1989 are included to provide a two-year time lag for the firms that filed for bankruptcy in 1990. U.S. listed firms' relevant accounting data is collected from Compustat under the prerequisite that they have a sufficient Committee on Uniform Securities Identification Procedures (CUSIP) number, considering that only these can be matched with the bankruptcy data in question.

In the interest of collecting ample bankruptcy data, the two databases UCLA-LoPucki Bankruptcy Research Database (UCLA) and Federal Judicial Center (FJC) are used to gather data on how many and which companies filed for bankruptcy during the period 1990-2019. Given that the Ohlson O-score is based on bankruptcy filing under what is today most closely resembling Chapter 7 and Chapter 11 in the U.S., filing under these chapters is the primary definition of bankruptcy adopted in this study. UCLA provides data on all U.S. firms with total assets exceeding USD 100 million that filed for bankruptcy under Chapter 7 and Chapter 11. These are collected together with additional bankruptcy data from FJC. All duplicate observations are removed.

4.2 Sample Selection

When the relevant data is collected, we integrate the three separate datasets into one unbalanced panel data set. The CUSIPs are used as the identifiers, and the initial sample consists of 29,265 unique firms, totaling to 312,501 firm-years. Presented in Table 1 we first remove all firm-years with insufficient data in the variables that form the O-score. After this, we exclude firm-years with inaccurate negative values in current liabilities, depreciation and amortization, total assets, and current assets, as they do not correspond correctly with associated financial statements. Next, following the delimitation in the UCLA bankruptcy dataset excluding firms with lower total assets, we choose to remove firms in the sample under the same criteria. Hence, only firms with total assets exceeding USD 100 million in at least one year during the sample period are selected. Furthermore, all observations that did not have adequate financial data to form an O-score were withdrawn from the sample. In total, the sample is reduced to 11,257 unique firms, totaling 141,545 firm-years. Moreover, Compustat firms that did not report R&D spending are allocated a R&D expense of zero, which is confirmed through firms' financial statements.

Table 1: Sample Selection

Reduction	**Firm-years**
Total firm-years of all U.S. listed firms from 1998-2019 with CUSIPs	312,501
with missing data	-99,954
with inaccurate negative values	-920
with total assets below USD 100 million	-70,006
with missing O-scores	-76
Main sample	**141,545**
With bankruptcy filing within two years	*1,989*

Of the main sample, 61,337 firm-years are included in the R&D quintiles (R&D Q) considering these observations have positive R&D spending. Furthermore, the logit regression described in section 3.3 analyzes the firms who were originally classified into O-score Q5, totaling 28,299 firm-years. Of these, 1,204 firm-years did not have adequate financial data for the variables used to form the desired logit regression. Hence, the subsample used in the regression consists of 27,095 firm-years. Table 2 reports the final number of observations and bankruptcy filings across the sample period 1988-2019. In total 971 firms filed for bankruptcy under the sample period and 1,989 firm-years filed for bankruptcy within two years.

Table 2: Sample description and bankruptcy filings over time

Year	Firms	Bankruptcy filings	Percent bankruptcy filings (%)	Bankruptcy filings within two years (FBT)
1988	3,302	-	-	5
1989	3,360	-	-	49
1990	3,486	23	0.660	68
1991	3,685	32	0.868	56
1992	4,017	30	0.747	45
1993	4,247	19	0.447	38
1994	4,522	14	0.310	36
1995	5,072	17	0.335	39
1996	5,262	17	0.323	43
1997	5,250	19	0.362	59
1998	5,554	27	0.486	99
1999	5,520	37	0.670	141
2000	5,322	64	1.203	143
2001	5,054	81	1.603	121
2002	4,975	75	1.508	86
2003	4,901	51	1.040	57
2004	4,832	33	0.683	41
2005	4,767	24	0.503	34
2006	4,590	12	0.261	48
2007	4,449	16	0.360	99
2008	4,397	37	0.841	74
2009	4,316	80	1.854	65
2010	4,233	24	0.567	47
2011	4,225	24	0.568	46
2012	4,261	24	0.563	36
2013	4,256	23	0.540	39
2014	4,174	18	0.431	63
2015	4,055	25	0.617	67
2016	3,975	46	1.157	58
2017	3,937	32	0.813	50
2018	3,874	22	0.568	80
2019	3,675	25	0.680	57
Total	**141,545**	**971**	**0.719**	**1,989**

Note: FBT denotes bankruptcy filing within two years.

5 Empirical Results and Analysis

In this section we present the descriptive statistics of the unadjusted and adjusted Ohlson model and showcase how the adjustment process affects the O-score classifications. Results are conveyed with foundation in our hypotheses and the analysis is presented. Moreover, we analyze the financial characteristics of companies who were originally classified into O-score Q5 through a logit regression to gain a deeper understanding of the effects of our adjustments.

5.1 O-score Results

5.1.1 O-score Descriptive Statistics

Table 3 reports the mean values of the O-score components and R&D intensity for our sample across the years 1988-2019. The table illustrates that the overall mean R&D intensity increases over time, from 0.024 in 1988 to 0.062 in 2019. Furthermore, we can distinguish a declining change in $NITA$, reporting lower mean values in 2016 to 2019. The mean value of $INTWO$ after year 2000 shows a slight increase, indicating that firms are reporting lower and more consecutive losses in later years. Consistent with previous research presented by Franzen et al. (2006), the increase in $SIZE$ illustrates a rising trend of firm size measured by log of total assets in the listed U.S. firm sample. We can also note distinctive differences in mean statistics for $WCTA$, $CLCA$, and $NITA$ the year 2007, potentially reflecting the financial crisis.

Table 3: Mean statistics of O-score variables and R&D intensity over time

Year	O-score	SIZE	TLTA	WCTA	CLCA	OENEG	NITA	FOTL	INTWO	CHIN	RDTA
1988	-1.203	5.593	0.586	0.204	0.854	0.037	0.024	0.236	0.000	0.593	0.024
1989	-0.810	5.619	0.625	0.171	1.178	0.051	0.036	0.268	0.000	0.006	0.026
1990	-0.618	5.564	0.621	0.169	1.019	0.065	-0.008	0.210	0.105	-0.004	0.030
1991	-0.621	5.490	0.624	0.173	0.997	0.065	-0.035	0.173	0.120	-0.017	0.030
1992	-0.754	5.451	0.611	0.168	1.157	0.059	0.038	0.188	0.128	0.075	0.030
1993	-0.869	5.501	0.630	0.171	1.075	0.049	-0.009	0.181	0.138	0.090	0.032
1994	-0.915	5.538	0.663	0.131	1.007	0.050	-0.019	0.208	0.133	0.140	0.047
1995	-0.771	5.471	0.617	0.169	2.136	0.055	-0.029	0.203	0.104	0.065	0.049
1996	-0.917	5.623	0.579	0.203	1.256	0.051	-0.011	0.282	0.101	0.057	0.044
1997	-0.846	5.742	0.590	0.196	1.333	0.054	-0.046	0.297	0.138	0.017	0.047
1998	-0.304	5.674	0.624	0.177	1.031	0.075	-0.080	0.621	0.137	-0.075	0.069
1999	-0.499	5.929	0.651	0.149	1.140	0.070	-0.180	-0.010	0.153	0.000	0.054
2000	-0.496	6.133	0.611	0.159	1.103	0.069	-0.089	-0.115	0.225	-0.035	0.042
2001	-0.061	6.130	0.814	-0.051	1.497	0.082	-0.189	-0.266	0.232	-0.135	0.050
2002	-0.269	6.122	0.620	0.159	1.029	0.086	-0.153	-0.112	0.253	0.027	0.054
2003	-0.833	6.193	0.617	0.166	0.986	0.073	-0.054	0.035	0.279	0.164	0.049
2004	-1.074	6.303	0.587	0.186	1.015	0.068	-0.054	0.021	0.245	0.135	0.047
2005	-1.087	6.350	0.579	0.187	1.265	0.065	-0.052	0.149	0.191	0.051	0.049
2006	-1.275	6.501	0.569	0.198	0.969	0.059	-0.007	0.182	0.177	0.078	0.047
2007	-1.262	6.621	2.769	-2.009	3.124	0.053	-29.252	0.167	0.180	0.027	0.051
2008	-0.665	6.600	0.659	0.127	0.949	0.073	-0.119	0.069	0.166	-0.139	0.075
2009	-1.071	6.622	0.736	0.048	4.526	0.073	-0.054	0.889	0.187	0.043	0.054
2010	-1.446	6.741	0.653	0.109	0.867	0.063	0.039	0.228	0.220	0.168	0.048
2011	-1.230	6.789	0.711	0.053	0.970	0.063	-0.136	0.096	0.176	0.018	0.059
2012	-0.985	6.800	0.796	-0.022	1.486	0.069	-0.060	0.078	0.159	-0.041	0.086
2013	-0.998	6.873	0.725	0.051	0.987	0.066	-0.053	0.033	0.188	-0.008	0.068
2014	-0.918	6.983	0.785	-0.006	1.126	0.063	-0.066	0.014	0.218	-0.024	0.060
2015	-0.625	7.015	1.457	-0.669	1.900	0.077	0.283	-0.107	0.228	-0.077	0.062
2016	-0.557	7.003	1.147	-0.355	1.524	0.083	-0.250	0.210	0.231	-0.015	0.083
2017	-0.735	7.085	0.823	-0.043	1.468	0.077	-0.173	0.294	0.261	0.048	0.082
2018	-0.813	7.166	1.058	-0.284	1.603	0.069	-0.142	-0.081	0.255	0.016	0.070
2019	-0.725	7.318	1.543	-0.759	1.939	0.069	-0.202	0.002	0.257	-0.055	0.062
Mean	**-0.808**	**6.249**	**0.792**	**-0.010**	**1.388**	**0.065**	**-0.980**	**0.143**	**0.177**	**0.033**	**0.053**

Note: Variable definitions and descriptions can be found in Appendix 2.

In Table 4, we demonstrate how the mean of O-score variables and R&D intensity vary across O-score quintiles. Q5 includes the firms with the highest O-scores and thereby the highest expected risk of bankruptcy. As documented by Franzen et al. (2006), smaller firms run a higher risk of declaring bankruptcy, and as anticipated, the firms in Q5 have a smaller $SIZE$ than the firms in the other quintiles. Continuing, we showcase how all the mean values of the model's components in Q5 are in alignment with what is expected for bankruptcy imminent firms. These firms have higher $TLTA$, smaller $WCTA$, lower $NITA$, and have a higher likelihood of consecutive losses ($INTWO$) and total liabilities that exceed total assets ($OENEG$). Furthermore, consistent with statistical descriptives provided by Franzen et al. (2006), firms in O-score Q5 have the highest mean ratio of R&D intensity of 0.149.

Table 4: Mean statistics of O-score variables and R&D intensity by quintile

O-score Q	O-score	SIZE	TLTA	WCTA	CLCA	OENEG	NITA	FOTL	INTWO	CHIN	RDTA
1	-4.509	6.356	0.273	0.371	0.415	0.000	0.152	1.432	0.061	0.258	0.040
2	-2.266	6.927	0.463	0.222	0.635	0.001	0.054	0.248	0.087	0.170	0.026
3	-1.110	6.899	0.578	0.157	0.786	0.008	0.027	0.120	0.107	0.070	0.021
4	0.115	6.281	0.679	0.140	0.866	0.056	-0.014	-0.007	0.199	-0.042	0.026
5	3.732	4.780	1.965	-0.942	4.240	0.261	-5.120	-1.076	0.430	-0.290	0.149
Mean	**-0.808**	**6.249**	**0.792**	**-0.010**	**1.388**	**0.065**	**-0.980**	**0.143**	**0.177**	**0.033**	**0.053**

Note: Quintile 1, 2, 3, 4, 5 represent the sample at a 0-20 percent, 20-40 percent, 40-60 percent, 60-80 percent, and 80-100 percent level, respectively. Variable definitions and descriptions can be found in Appendix 2.

Figure 1 plots the mean values of R&D intensity by O-score quintile over time. The figure suggests that mean R&D intensity in Q5 is higher compared to all other quintiles. Q5 ranges from 0.05 in 1988 to 0.2 in 2019 and illustrates an increase in R&D activity over time. Moreover, Q1-4 have similar levels of mean R&D intensity across all years, and the figure shows no signs of distinct increase in R&D intensity.

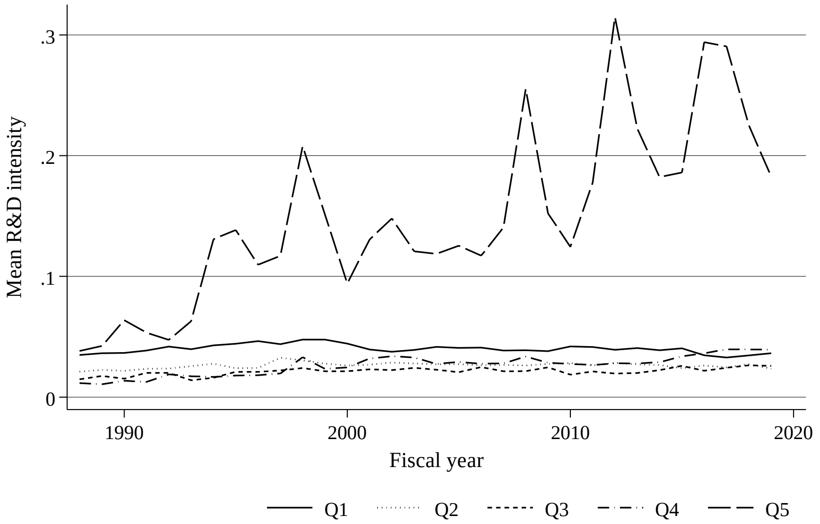

Figure 1: Mean R&D intensity by O-score quintile over time

Note: Quintile 1, 2, 3, 4, 5 represent the sample at a 0-20 percent, 20-40 percent, 40-60 percent, 60-80 percent, and 80-100 percent level, respectively. This figure includes the main sample of 141,545 firm-years.

Figure 2 reports classification errors among firms classified as bankruptcy imminent by R&D intensity quintile. For the firms with positive R&D spending in Q5, the percentage of non-bankrupt firms ranking with different R&D intensity are plotted for each year. The figure shows that the R&D Q5 has a higher percentage of non-bankrupt firms classified with higher expected risk of bankruptcy than all other quintiles. The range of R&D Q5 falls between approximately 30-60% misclassification, and R&D Q1-4 falls between approximately 5-25% misclassification.

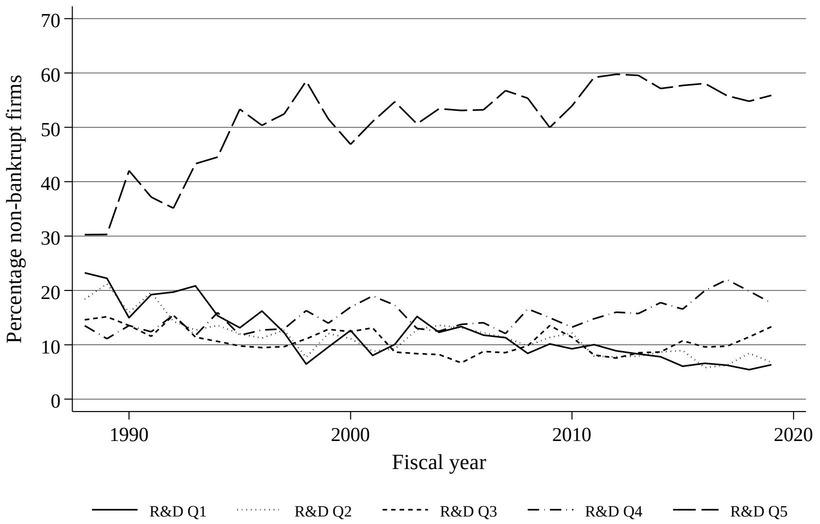

Figure 2: Percentage non-bankrupt firms in O-score Q5 by R&D quintile over time

Note: This figure presents the percentage of misclassified firms in the bankruptcy imminent quintile, by R&D intensity quintile. Quintile 1, 2, 3, 4, 5 represent the R&D positive sample at a 0-20 percent, 20-40 percent, 40-60 percent, 60-80 percent, and 80-100 percent level, respectively. The R&D intensity quintiles include firms with positive R&D spending totaling to 13,112 firm-years in Q5.

5.1.2 O-score Analysis

The Ohlson model identifies nine accounting measures used to predict bankruptcy, and their development over time is showcased in Table 3. Despite the U.S.' period of economic advancements and growth, the statistics in Table 3 do not appear to indicate a desired development of accounting indicators of bankruptcy. Four of the O-score components include income, which are expected to be affected by the USGAAP requirement of expensing R&D spending to full extent. Furthermore, the other five O-score variables are also likely to be affected by an increased R&D intensity considering that they are balance sheet measures.

We continue by exploring if the R&D intensity is in fact higher for firms with the highest expected risk of bankruptcy, and if the Ohlson model provides lower predictive ability of bankruptcy as R&D activity increases. As illustrated in Table 4 the mean R&D intensity in Q5 is higher than the mean R&D intensity in all the other quintiles combined. This supports our initial hypothesis, stating that R&D intensity is higher for the bankruptcy imminent classification. As reported in Table 5, the difference between Q5 and Q1-4 is shown to be statistically significant through both a two-sample t-test and a non-parametric Mann-Whitney test.

Table 5: Test of R&D intensity difference between O-score Q1-4 and Q5

O-score variables	**Mean log R&D intensity**	**Standard error**	**Mean R&D intensity**
Quintiles 1-4	-3.425	0.007	0.029
Quintile 5	-2.172	0.014	0.149
Difference	-1.254		
Observations	141,545		
t-statistic	-86.395***		
Mann-Whitney z-statistic	-42.119***		

Note: This table presents the results from a two-sided two-sample t-test and a non-parametric Mann-Whitney test of the difference in mean logarithmic and median R&D intensity between two groups: quintiles 1-4 and quintile 5. The significance sign refers to a two-sided test. ***p<0.01, **p<0.05, *p<0.1.

We continue our investigation by exploring the firms classified in O-score Q5 that did not file for bankruptcy within two years. We theorize that the increase of mean R&D intensity over time, shown in Table 3, is linked to a greater proportion of misclassification of non-bankrupt R&D intensive firms as bankruptcy imminent. Figure 1 and Figure 2 support this conjecture and indicate that among the misclassified non-bankrupt firms in O-score Q5, the R&D intensive firms represent a higher proportion than the other non-bankrupt firms. However, as no statistical test is conducted, we can only suggest and not confirm this based on the descriptive figures.

Considering the relationship between R&D intensity and the misclassification of non-bankrupt firms as bankruptcy imminent, we further investigate the effect of adjusting the Ohlson model for conservative R&D accounting. We hypothesize that by adjusting the O-score components for the full expensing of R&D spending we will improve the prediction accuracy of the bankruptcy imminent classification.

5.2 Adjusted O-score Results

5.2.1 Adjusted O-score Descriptive Statistics

Table 6 reports the mean values of the adjusted O-score components and R&D intensity across the adjusted O-score quintiles. The descriptives of the adjusted O-score variables are qualitatively similar to those of the unadjusted, which are presented in Table 4. The firms in AQ5 are the smallest in $SIZE$, have the highest $TLTA$, the lowest $WCTA$, the highest $CLCA$, the lowest $NITA$, and have a higher frequency of total liabilities exceeding total assets ($OENEG$) and of consecutive losses ($INTWO$). These statistics are in line with what is expected from bankruptcy imminent firms according to the model. It is worth noting that mean spread of R&D intensity across the quintiles decreases jointly with the adjustments. The spread in the unadjusted model totaled between 0.021 and 0.149 (reported in Table 4), and in the adjusted between 0.037 and 0.090 (reported in Table 6).

Table 6: Mean statistics of O-score variables and R&D intensity by adjusted quintiles

Adj. O-score AQ	Adj. O-score	SIZE	TLTA	WCTA	CLCA	OENEG	NITA	FOTL	INTWO	CHIN	RDTA
1	4.566	6.399	0.273	0.345	0.399	0.000	0.145	1.439	0.063	0.246	0.051
2	-2.444	6.854	0.440	0.222	0.595	0.000	0.050	0.297	0.108	0.154	0.041
3	-1.309	6.840	0.550	0.157	0.746	0.005	0.024	0.156	0.129	0.073	0.037
4	-0.184	6.367	0.649	0.124	0.852	0.038	-0.010	0.055	0.189	-0.022	0.044
5	2.413	5.228	1.400	-0.462	4.351	0.237	-0.366	-0.398	0.359	-0.271	0.090
Mean	**-1.219**	**6.337**	**0.662**	**0.077**	**1.388**	**0.056**	**-0.031**	**0.310**	**0.170**	**0.036**	**0.053**

Note: Quintile 1, 2, 3, 4, 5 represent the sample at a 0-20 percent, 20-40 percent, 40-60 percent, 60-80 percent, and 80-100 percent level, respectively. Variable definitions and descriptions can be found in Appendix 2.

Table 6.i found in Appendix 6, shows the amount of R&D intensive firms in the unadjusted and adjusted O-score quintiles. According to the table, the distribution of R&D intensive in the unadjusted model is skewed towards the highest quintile, with more than 50% of the firm-years

in Q5. Comparatively, we find that the amount of R&D intensive firms in the adjusted model is more evenly distributed between the different quintiles. Furthermore, the table suggests that there are 3,691 less R&D intensive firm-years in the adjusted O-score AQ5 than in the unadjusted. This is dependent on the finding that 53.43% (3,693) of R&D intensive firm-years that were originally in the O-score Q5 are reclassified into lower adjusted O-score quintiles, and that only 0.03% (2) of R&D intensive firm-years are reclassified from lower O-score quintiles into the adjusted O-score AQ5.

In Figure 3 we present mean levels of R&D intensity across the adjusted O-score quintiles and compare these to the unadjusted O-score quintiles originally presented in Figure 1. The comparison suggests that the adjustments result in lower mean R&D intensity among the AQ5 firms, but a higher mean value amongst the other adjusted O-score quintiles. This is consistent with the redistribution of R&D intensive firms into the lower quintiles shown in Table 6.i (Appendix 6) and implies that the adjusted O-score is less influenced by firms' R&D intensity.

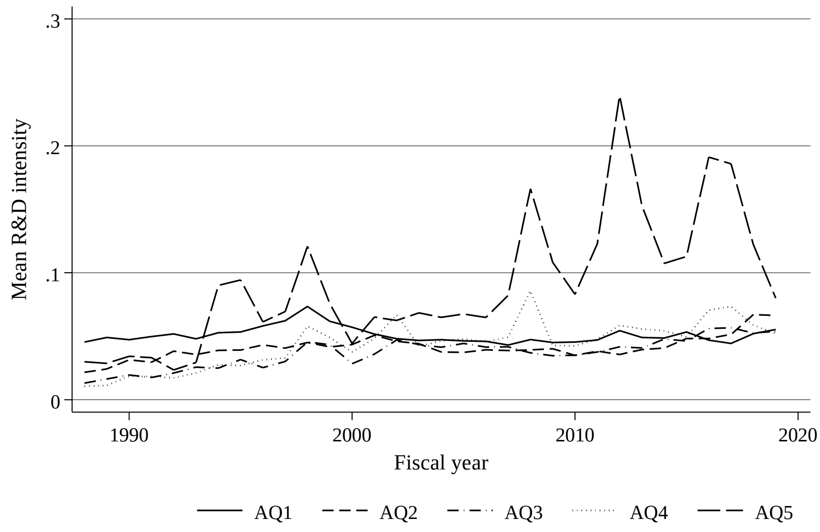

Figure 3: Mean R&D intensity by adjusted O-score quintile over time

Note: Quintile 1, 2, 3, 4, 5 represent the sample at a 0-20 percent, 20-40 percent, 40-60 percent, 60-80 percent, and 80-100 percent level, respectively. This figure includes the full sample of 141,545 firm-years.

Figure 4 shows the percent of non-bankrupt firms misclassified as bankruptcy imminent under the adjusted O-score model by R&D intensity quintile. The figure is directly comparative to the previously presented Figure 2 and suggests that the disparity between the percent of firms in quintile 5 with higher versus lower R&D intensity has reduced as a result of the adjustment process. The percent of firms classified as bankruptcy imminent that do not declare bankruptcy within two years is still the highest for firms with high R&D intensity. The R&D Q5 range of misclassification has thereby decreased from approximately 30-60%, as shown in Figure 2, to approximately 20-45%.

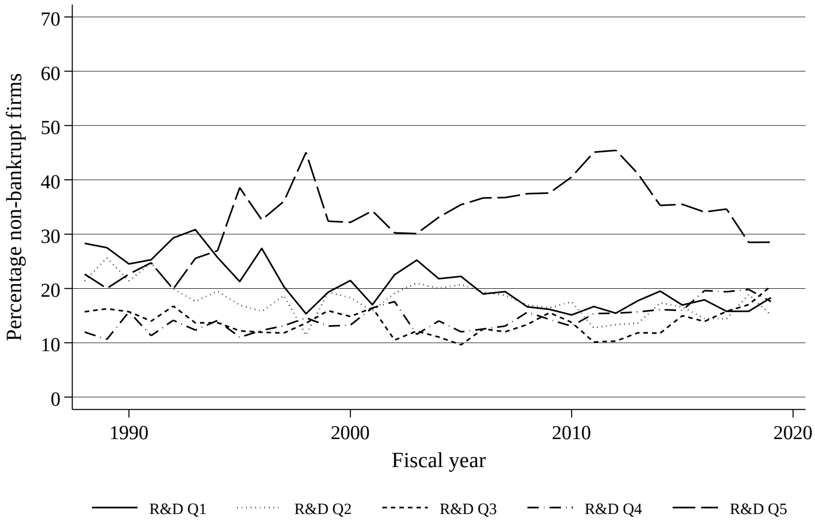

Figure 4: Percentage non-bankrupt firms in adjusted O-score AQ5 by R&D quintiles over time

Note: This figure presents the percentage of misclassified firms in the adjusted bankruptcy imminent quintile, by R&D intensity quintile. Quintile 1, 2, 3, 4, 5 represent the R&D positive sample at a 0-20 percent, 20-40 percent, 40-60 percent, 60-80 percent, and 80-100 percent level, respectively. The R&D intensity quintiles include firms with positive R&D spending with a total of 13,112 firm-years in AQ5.

In Figure 5 we present the differences in the number of bankruptcies in the Q5 classification versus the AQ5 classification, occurring within two years. The figure illustrates that the number of correctly identified bankruptcies made by the adjusted model is the same or higher for all years except 1990 and 1991 compared to the unadjusted model.

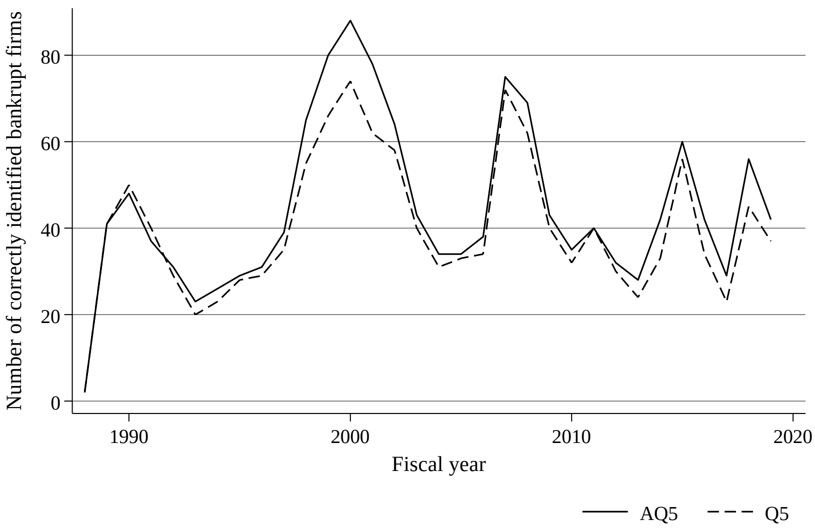

Figure 5: Correctly identified bankrupt firms in the unadjusted and adjusted quintile 5 over time

Note: This figure includes the firm-years of the main sample with the highest unadjusted and adjusted O-scores at the 80-100 percent level. This amounts to 28,299 firm-years in Q5 and AQ5, respectively.

Table 7 shows the amount of correctly identified bankruptcy filings in the Q5 classification and the AQ5 classification. It is reported that the unadjusted O-score correctly classifies 1,278 firms as bankruptcy imminent, whilst the adjusted O-score correctly classifies 1,424 firms as bankruptcy imminent. This entails that out of the 1,989 firm-years that went bankrupt within two years, 64.25% are captured under the unadjusted model, and 71.59% are captured under the adjusted model. This represents a 11.42% improvement in bankruptcy identification due to the adjustments over the sample period.

Table 7: Bankruptcy filings within two years by unadjusted and adjusted O-score quintiles

Quintile (Q / AQ)	**O-score FBT**	**Adj. O-score FBT**
1	38	37
2	75	63
3	140	115
4	458	350
5	1,278	1,424
Total	**1,989**	**1,989**
% correct	*64.25*	*71.59*

Note: FBT denotes bankruptcy filing within two years. Quintile 1, 2, 3, 4, 5 represent the sample at a 0-20 percent, 20-40 percent, 40-60 percent, 60-80 percent, and 80-100 percent level, respectively. The final row presents the percent correctly identified bankruptcies in quintile 5.

Table 8 reports the ARs for the unadjusted and adjusted O-score models for each year in the sample period. The adjusted O-score model shows a higher mean AR of 0.837 compared to the unadjusted of 0.809, and the AR for the adjusted model is higher for all years.

Table 8: Accuracy Ratio of unadjusted and adjusted O-score model over time

Year	O-score AR	Adj. O-score AR	Difference
1988	0.735	0.747	0.012
1989	0.877	0.887	0.010
1990	0.853	0.864	0.011
1991	0.813	0.820	0.007
1992	0.819	0.837	0.018
1993	0.807	0.826	0.019
1994	0.811	0.831	0.020
1995	0.827	0.846	0.019
1996	0.794	0.816	0.022
1997	0.795	0.819	0.024
1998	0.777	0.811	0.034
1999	0.749	0.781	0.032
2000	0.771	0.802	0.031
2001	0.775	0.813	0.038
2002	0.816	0.848	0.032
2003	0.809	0.835	0.026
2004	0.836	0.862	0.026
2005	0.913	0.938	0.025
2006	0.826	0.853	0.027
2007	0.835	0.857	0.022
2008	0.887	0.920	0.033
2009	0.743	0.763	0.020
2010	0.813	0.822	0.009
2011	0.870	0.892	0.022
2012	0.856	0.882	0.026
2013	0.811	0.847	0.036
2014	0.779	0.819	0.040
2015	0.873	0.913	0.040
2016	0.773	0.816	0.043
2017	0.708	0.755	0.047
2018	0.753	0.816	0.063
2019	0.786	0.838	0.052
Mean	**0.809**	**0.837**	**0.028**

Note: The description of the Accuracy Ratio can be found in section 3.2.1.

5.2.2 Adjusted O-score Analysis

Building on our previous hypothesis, an ambition behind the O-score adjustment process is to potentially reduce classification errors caused by conservative R&D accounting. As reported in Table 4 and Table 6, the mean R&D intensity in quintile 5 decreases due to the adjustments. Furthermore, as illustrated in Figure 3 and Figure 4, the adjustment process further appears to decrease the proportion of non-bankrupt R&D intensive firms misclassified into quintile 5.

In alignment with our second hypothesis, Table 7 suggests that more bankruptcy filings are in fact identified by the adjusted O-score model and indicates that the prediction accuracy of the bankruptcy imminent classification may increase through the adjustment process. Table 7 shows less bankruptcy filings in AQ1-4, further indicating an improvement in the model. It should be noted that this is partially due to the reduced misclassification in quintile 5 indicating that as R&D intensive firm-years move down to lower quintiles, the bankruptcy imminent classification captures more firms that file for bankruptcy within two years. In addition to this, Table 8 illustrates the relative improvements in our model's predictive ability resulting from our adjustments, where the higher mean AR of the adjusted O-score model implies a stronger predictive ability of bankruptcy within two years in the complete sample period. To test whether these suggestions are statistically significant we proceed by presenting the results of McNemar's test.

Table 9 shows the contingency table and outcome of McNemar's test reporting a frequency of n_{cf} equal to 131 and n_{fc} equal to 6,052. The test results in a chi-square value of approximately 5,670 with a p-value of 0.000. Hence, the difference in accuracy between the models is statistically significant, and the hypothesis of equal predictive accuracy of the unadjusted and adjusted O-score model is rejected. This further supports our second hypothesis and suggests that the adjusted model produces a more accurate ranking and potentially a better estimation model for bankruptcy.

Table 9: Test of bankruptcy prediction accuracy in the unadjusted and adjusted O-score model

	Adj. O-score predicts correctly	Adj. O-score predicts incorrectly	**Total**
O-score predicts correctly	107,304	131	**107,435**
O-score predicts incorrectly	6,052	28,058	**34,110**
Total	**113,356**	**28,189**	**141,545**
	McNemar's chi2(1) = 5,670.10***	Prob > chi2 = 0.000	

Note: The McNemar's test is defined in section 3.2.2. This table includes the main sample of 141,545 firm-years. ***p<0.01, **p<0.05, *p<0.1.

5.2.3 Tax Assumptions

To ensure that the improvement in the adjusted O-score classification is not solely due to our assumptions of tax effects, we perform our tests without tax assumptions. In Appendix 7, we present the number of correctly identified firms by our pre-tax adjusted model. The results indicate that without tax assumptions, the pre-tax adjusted model performs at a similar level as the adjusted model, indicating that bankruptcy prediction is in fact improved. Furthermore, we confirm that all statistical tests hold for the pre-tax adaptation of the adjusted Ohlson model. In untabulated results we find that both the t-test and Mann-Whitney test are significant at a p-value of 0.000, with values of -13.825 and 36.058, respectively. Furthermore, the pre-tax adjusted model shows a stronger predictive accuracy with a mean AR of 0.838, compared to the unadjusted O-score mean AR of 0.809. Finally, the McNemar's chi-square test results in a statistically significant value of approximately 6,404, with a p-value of 0.000.

5.3 Financial Characteristics of Escaped Firms

Table 6.ii in Appendix 6 presents the correlation matrix of the variables used in the logit regression, defined in section 3.3. According to Habshah et al. (2010), a correlation coefficient of the absolute value of 0.7 or above indicates strong multicollinearity. Thereby, no initial signs of multicollinearity are detected. However, as we cannot reject any dependence amongst the variables, we continue to analyze the results of the logit regression with caution.

Table 10 presents the estimates generated by the logit regression of the financial characteristics that correspond to the firms that stayed and the firms that escaped. The firms that *stayed* are defined as those that were classified into quintile 5 by the unadjusted and adjusted O-score, and the firms that *escaped* are defined as those that were classified into quintile 5 by the unadjusted O-score but reclassified into lower quintiles by the adjusted O-score. The financial characteristics variables $R\&D$, $Other\ Intangibles$, $Goodwill$, $CAPEX$, $Sales$, $Dividend$, and $Cash$ are found to significantly distinguish between the firms that stayed and the firms that escaped. Following our adjustments, the coefficient for $R\&D$ is naturally positive, and firms with higher R&D intensity are thereby more likely to be reclassified. In addition, $Cash$ is also positive at a significant level, and therefore provides another financial characteristic significantly differing between the group that escaped from the group that stayed. However, this result is to be expected as cash intensity is positively correlated with R&D intensity, with a value of 0.466 shown in Table 6.ii.

Moreover, all other intensity variables' coefficients, including the coefficient for $Goodwill$ and $Other\ Intangibles$, are statistically significantly negative, and implies that companies with higher intangible assets are more likely to stay in quintile 5 and not be reclassified. Finally, ROE did not significantly show correspondence between the firms that stayed and the firms that escaped. These results indicate that R&D intensity, and thereby cash intensity, are the primary drivers for reclassification, suggesting that the other financial characteristics tested may not be associated with the reclassification under the adjustment process. Furthermore, this suggests that the change in model accuracy recognized through the adjustments seem to be mainly driven by R&D intensity, and not by characteristics that are unaccounted for. This may be of interest to stakeholders since it implies that none of the other financial characteristics are particularly associated with misclassification under the original O-score.

Table 10: Differences in financial characteristics between the groups that stayed and escaped following the adjustment process

Variables	**Coefficient**	**Clustered St. Error**
R&D	2.307***	0.147
Other Intangibles	-1.891***	0.254
Goodwill	-1.451***	0.256
CAPEX	-6.202***	0.443
Sales	-0.878***	0.051
Dividend Payments	-3.058***	0.543
Cash	1.361***	0.104
ROE	-0.004	0.006
Constant	-2.174***	0.235
Observations	27,095	
Observations with value 1	4,523	
Year Fixed Effects	Yes	
Pseudo R Squared	0.266	
Log Likelihood Ratio	-8,963***	

Note: This table presents the results for the logit regression with year fixed effects, defined in section 3.3. The regression displays differences in financial characteristics between the firms that stayed and the firms that escaped, defined in Appendix 1. All variables except ROE are defined through their intensity i.e., divided by total assets. All definitions can be found in Appendix 5. Standard errors are clustered at firm level. ***p<0.01, **p<0.05, *p<0.1.

6 Discussion

In this section we discuss the implications of the key findings of our study and determine whether these are consistent with those of prior literature. Principally, the thesis identifies a relationship between R&D intensity and Ohlson O-scores where firms with higher R&D intensity seem to have a higher expected risk of bankruptcy. We find the original Ohlson O-score model to be potentially unreliable in the classification of R&D intensive firms and observe that this classification error seems to increase over time. Considering the importance of reliable bankruptcy estimates, we hypothesize the potential improvement of the Ohlson model. Through an adjustment process for conservative R&D accounting under USGAAP, we find that our adjusted Ohlson O-score model appears to provide a higher precision of bankruptcy prediction.

The findings demonstrated in this study are consistent with the results presented by Franzen et al. (2006) and contribute, among other things, to literature by extending the period scope. This further illustrates how the accuracy of accounting-based bankruptcy prediction potentially reduces as R&D activity increases. Furthermore, we perform a statistical test showing how R&D intensity is significantly higher for firms with the highest expected risk of bankruptcy according to the Ohlson model. This is an aspect that Franzen et al. (2006) primarily assume, and our study helps enhance the outcome of their research by strengthening the foundation of their study. Additionally, we contribute to existing research by further investigating whether other financial characteristics than R&D intensity are associated with the reclassification under the adjustment process. Our results thereby justify the adjustments made by us and Franzen et al. (2006), as R&D intensity and cash intensity seem to be the primary financial characteristics of firms reclassified under the adjustment process.

Continuing, we draw a comparison between our study and prior literature. Affirming the conclusions drawn by Chan et al. (2001), our results indicate that for R&D intensive firms, a higher expected risk of bankruptcy appears to be a product of accounting conservatism rather than an indication of low performance associated with bankruptcy. Furthermore, the findings presented by Beaver et al. (2012), illustrating that intangibles have a systematic effect on bankruptcy prediction, are somewhat coherent with our findings suggesting that the predictive power of accounting-based models is lower for firms with a higher degree of R&D intensity.

Despite alignment with previously mentioned authors, Bodle et al. (2016) showcase somewhat contradicting results to our findings. They report that the superior adjustments of bankruptcy prediction include partial capitalization and partial expensing of R&D spending, embodied in IFRS. These results are not in direct conflict with our findings but highlight that financial information used for bankruptcy prediction improves with restrictive limitations of capitalizing intangibles. Their results thereby indicate that partial capitalization would potentially improve the adjusted O-score model accuracy additionally, as partial expensing and capitalization may more accurately capture the underlying value of a firm.

Furthermore, divergent from the discoveries made by Jones (2011), this study makes no judgments whether the voluntary capitalization of R&D has any predictive power in bankruptcy prediction models. However, the results of our study partially support Jones (2011) showcasing that conservative R&D accounting appears to affect firm bankruptcy prediction to a greater extent than less conservative policies. We emphasize that we do not commend any opinions or changes regarding less conservative accounting standards generally but acknowledge the effects of conservative R&D accounting when predicting bankruptcy.

7 Conclusion

To conclude, the conducted study investigates whether bankruptcy prediction can be improved by adjusting for conservative R&D accounting. We find that an adjustment process of R&D conservatism appears to decrease misclassification of non-bankrupt R&D intensive firms as those with the highest expected risk of bankruptcy. Moreover, the findings indicate that our adjusted O-score model increases the prediction accuracy of all firms. Our data thereby illustrates the potential improvement of the Ohlson model, suggesting that investors, lenders, and corporate managers should conceivably apply caution when using the original Ohlson O-score in current business environments. In addition, we modestly suggest the application of our adjusted Ohlson O-score model as a complement to bankruptcy prediction for R&D intensive firms.

In address to the research question of whether bankruptcy prediction can be improved by adjusting for conservative R&D accounting, the results indicate that this is the case. However, the relevance of the results concluded from this thesis is restrained by the limitation of increased staleness in parameters in accounting-based models, as previously presented by Grice and Dugan (2001). A potential effect on the reliability of the results would thereby be the staleness of the model variables, leading to a trend of reduced accurate forecasting independent of the effect of accounting standards. A staleness in the parameters would imply an increasing misclassification for both bankrupt and non-bankrupt firms, Type I and Type II errors, for the Ohlson model. In consideration of stale parameters, we could potentially have increased the applicability of our results by applying models of higher accuracy including market-based variables, as argued by Hillegeist et al. (2003). However, this would have counteracted the purpose of this thesis to shed light on the effects of conservative R&D accounting on accounting-based bankruptcy prediction models.

Furthermore, a removal of observations is performed through our sample selection. Due to insufficient bankruptcy data, firms whose total assets do not exceed USD 100 million are excluded. Consequently, we acknowledge that the generalizability of our conclusions is limited to larger firms and we leave an opportunity for further research to examine our hypotheses with data on smaller firms. This would help strengthen the conclusions drawn from this thesis and potentially provide further explanations in areas in which this study is lacking. Furthermore, it would be useful to understand and investigate at which level the findings of bankruptcy prediction studies, including our study, affect stakeholders' decision-making in environments applying conservative R&D accounting. Future studies could fruitfully explore this issue by investigating the impact of adjustments and new bankruptcy prediction models on business environments where bankruptcy presents an issue.

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Appendix

Appendix 1: Definitions

Bankruptcy Imminent: Firms with the highest Ohlson O-scores, which in accordance to the model have the highest expected risk of filing for bankruptcy within two years. Firm-years classified as bankruptcy imminent are found in the 5th quintile, i.e., the 80th percentile.

Main Sample: The main sample is referring to our complete sample of 141,545 firm-years, including 1,989 observations with bankruptcy filings within two years.

R&D Intensity: Defined as R&D spending divided by total assets.

Firm-years: The definition for the observations used in the panel data set.

Stayed: Firms that were classified into unadjusted quintile 5 and adjusted quintile 5.

Escaped: Firms that were classified into unadjusted quintile 5 and classified into lower adjusted quintiles, quintile 1-4.

Appendix 2: O-score variable definitions

Variable	Definition	Source
O-score	*(USD million)*	*Compustat Annual Data Item*
SIZE	The natural logarithm of total assets	6
TLTA	Total liabilities divided by total assets	6, 181
WCTA	Working capital defined as current assets subtracted by current liabilities, divided by total assets	4, 5, 6
CLCA	Current liabilities divided by current assets	4, 5
OENEG	Dummy variable set equal to 1 if the firm has negative book value of equity (if total liabilities exceed total assets) and 0 otherwise	6, 181
NITA	Net income divided by total assets	6, 172
FOTL	Funds of operations defined as pre-tax income plus depreciation divided by total liabilities	14, 170, 181
INTWO	Dummy variable set equal to 1 if the firm has negative net income in the two prior years and 0 otherwise	172
CHIN	Change in net income defined as $\frac{NI_t - NI_{t-1}}{\lvert NI_t \rvert + \lvert NI_{t-1} \rvert}$	172

Pre-tax Adjusted O-score		
A_SIZE	The natural logarithm of adjusted total assets	6
A_TLTA	Total liabilities divided by adjusted total assets	6, 181
A_WCTA	Working capital defined as current assets subtracted by current liabilities, divided by adjusted total assets	4, 5, 6
CLCA	Current liabilities divided by current assets	4, 5
A_OENEG	Dummy variable set equal to 1 if the firm has negative book value of equity (if total liabilities exceed adjusted total assets) and 0 otherwise	6, 181
A_NITA	Adjusted net income divided by adjusted total assets	6, 172
A_FOTL	Funds of operations defined as adjusted pre-tax income plus depreciation divided by total liabilities	14, 170, 181
A_INTWO	Dummy variable set equal to 1 if the firm has negative adjusted net income in the two prior years and 0 otherwise	172
A_CHIN	Change in adjusted net income defined as $\frac{Adj.NI_t - Adj.NI_{t-1}}{\lvert Adj.NI_t \rvert + \lvert Adj.NI_{t-1} \rvert}$	172
After-tax Adjusted O-score		
A_SIZE	The natural logarithm of adjusted total assets	6
AT_A_TLTA	After-tax adjusted total liabilities divided by adjusted total assets	6, 181
A_WCTA	Working capital defined as current assets subtracted by current liabilities, divided by adjusted total assets	4, 5, 6
CLCA	Current liabilities divided by current assets	4, 5
AT_A_OENEG	Dummy variable set equal to 1 if the firm has negative book value of equity (if after-tax adjusted total liabilities exceed adjusted total assets) and 0 otherwise	6, 181
AT_A_NITA	After-tax adjusted net income divided by adjusted total assets	6, 172
AT_A_FOTL	Funds of operations defined as adjusted pre-tax income plus depreciation divided by after-tax adjusted total liabilities	14, 170, 181
AT_A_INTWO	Dummy variable set equal to 1 if the firm has negative after-tax adjusted net income in the two prior years and 0 otherwise	172
AT_A_CHIN	Change in after-tax adjusted net income defined as $\frac{AT.Adj.NI_t - AT.Adj.NI_{t-1}}{\lvert AT.Adj.NI_t \rvert + \lvert AT.Adj.NI_{t-1} \rvert}$	172

$$\begin{aligned} Pre\text{-}tax\ AO = {} & -1.32 - 0.407 * A\_SIZE + 6.03 * A\_TLTA - 1.43 * A\_WCTA \\ & + 0.0757 * CLCA - 1.72 * A\_OENEG - 2.37 * A\_NITA - 1.83 \\ & * A\_FOTL + 2.285 * A\_INTWO - 0.521 * A\_CHIN \end{aligned} \tag{2.i}$$

Appendix 3: The natural logarithm of R&D intensity

Figure 3.i

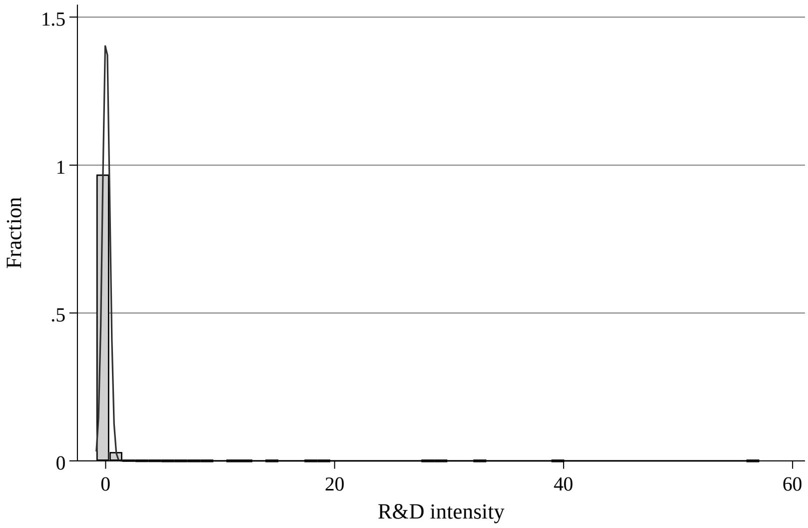
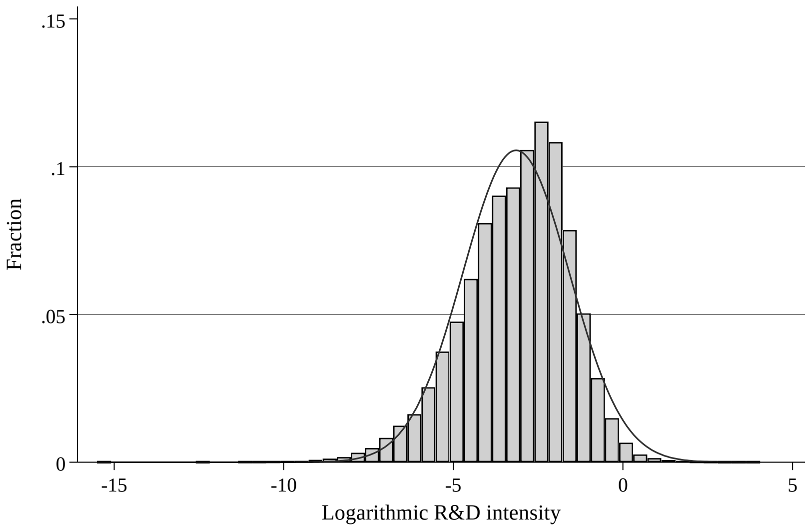
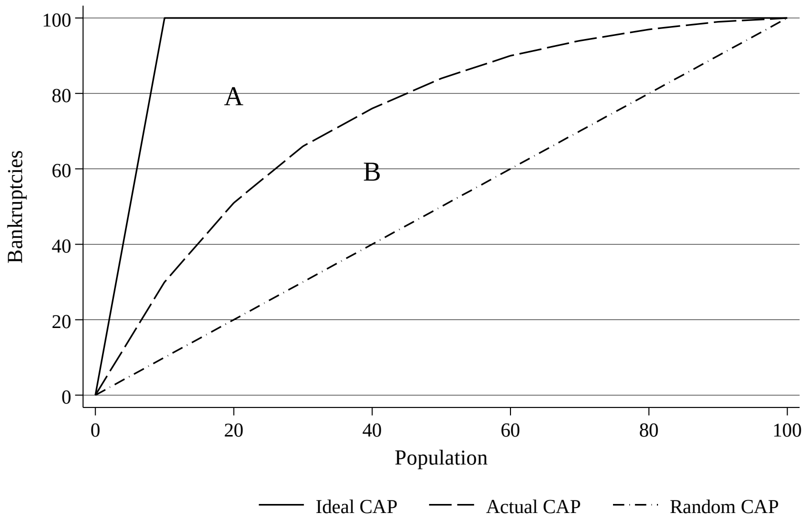


Figure 3.ii



Note: The following figures presents the difference between the R&D intensity variable and the logarithmic R&D intensity variable. The histograms are based on the main sample of 141,545 firm-years.

Appendix 4: The Accuracy Ratio CAP-line



Appendix 5: Logit regression variable definition

Variable	Definition	Source
Logit regression	*(USD millions)*	*Compustat Annual Data Item*
Escaped	Dummy variable equal to 1 if the firm-year escaped from the classification of the unadjusted O-score quintile 5 to a lower adjusted O-score quintile (1-4), 0 otherwise	*n.a.*
R&D	R&D spending divided by total assets	6, 46
Other Intangibles	Other intangibles, defined as intangibles excluding goodwill, divided by total assets	6, 352
Goodwill	Goodwill divided by total assets	6, 204
CAPEX	Capital expenditures divided by total assets	6, 128
Sales	Sales divided by total assets	6, 12
Dividend	Dividend payments divided by total assets	6, 21
Cash	Cash divided by total assets	6, 162
ROE	Return on equity defined as net income divided by equity	144, 172
α	Year dummies to control for year fixed effects, induces a dummy variable equal to 1 for each year 1988-2019, and 0 otherwise	*n.a.*

Appendix 6: Additional descriptive statistics

Table 6.i: R&D intensive firms by unadjusted and adjusted O-score quintile

Quintile (Q / AQ)	R&D Q5 in O-score	R&D Q5 in Adj. O-score	Difference
1	1,717	2,472	755
2	1,030	2,136	1,106
3	1,022	2,075	1,053
4	1,574	2,351	777
5	6,912	3,221	-3,691
Total	**12,255**	**12,255**	**-**

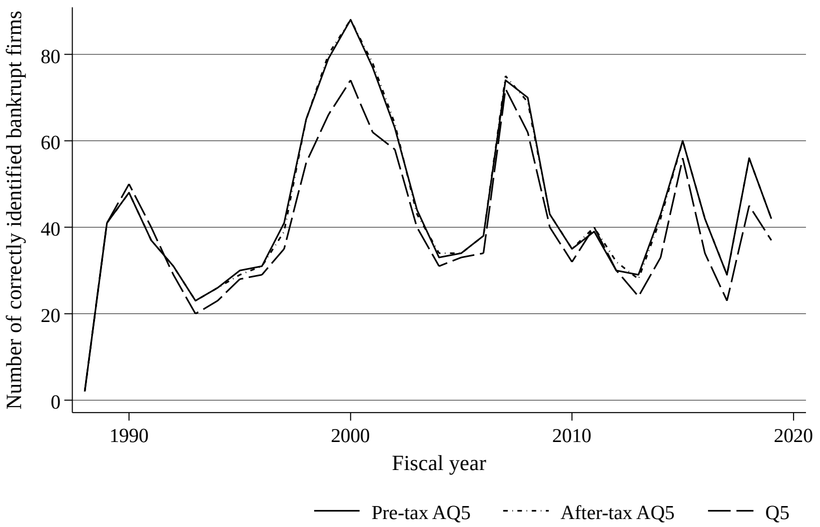
Note: Quintile 1, 2, 3, 4, 5 represent the sample at a 0-20 percent, 20-40 percent, 40-60 percent, 60-80 percent, and 80-100 percent level, respectively. The total firm-years of 12,255 represent the observations classified into R&D intensity quintile 5.

Table 6.ii: Correlation matrix of differences in financial characteristics

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) R&D Intensity	1.000							
(2) Other Intangibles Intensity	-0.094*	1.000						
(3) Goodwill Intensity	-0.168*	0.141*	1.000					
(4) CAPEX Intensity	-0.050*	-0.116*	-0.148*	1.000				
(5) Sales Intensity	-0.212*	-0.066*	0.055*	-0.025*	1.000			
(6) Dividend Payments Intensity	0.032*	0.015	0.000	0.013	0.035*	1.000		
(7) Cash Intensity	0.466*	-0.148*	-0.225*	-0.123*	-0.293*	0.043*	1.000	
(8) Return on Equity	-0.047*	-0.005	0.014	0.005	0.041*	0.004	-0.051*	1.000

Note: This table presents the correlation between the variables used in the logit regression described in section 3.3 and displayed in Table 10. The variable definitions can be found in Appendix 5. *p<0.01.

Appendix 7: Correctly identified bankrupt firms in the pre-tax adjusted quintile 5



Note: This figure presents the number of correctly identified bankrupt firms in the unadjusted, pre-tax adjusted and after-tax adjusted quintile 5 over time. The firm-years of the main sample with the highest O-scores at the 80-100 percent level are included. This amounts to 28,299 firm-years in Q5, pre-tax AQ5, and after-tax AQ5, respectively.