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Does recasted data improve the predictive accuracy of bankruptcy prediction models?

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May 23, 2017

Abstract This paper examines conventional bankruptcy prediction models under the thesis that such models perform better when applied to adjusted financial statement data, rather than to reported data. This hypothesis is tested by revisiting already existing bankruptcy models as well as developing two new models for predicting imminent corporate failures. The result of the study reveals that financial adjustments are not necessary for conventional bankruptcy prediction models, whereas such adjustments lead to improved predictive accuracy for our models. So even though the necessity of using recasted financials in other areas of finance is generally accepted, we find that this necessity is not as apparent within the field of bankruptcy prediction.

Seminar date:	29 May 2017
Course:	Degree Project: Accounting and Finance (BUSN79)
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Five key words:	Bankruptcy prediction model, reported financial data, adjusted financial data, off-balance sheet debt, bankruptcy prediction accuracy.
Purpose:	This paper examines if using recasted financial statements, instead of as reported financial statements, improve the accuracy of bankruptcy prediction models.
Methodology:	The purpose of this study will be tested by applying both as reported and recasted financial statement data on (1) already existing bankruptcy prediction models and (2) our own bankruptcy prediction model. We mainly use a conditional logistic regression analysis as the econometric methodology.
Theory:	The basis for this study is previous research that examines bankruptcy prediction models and financial statement adjustments.
Empirical foundation:	The study is based on secondary data collected from S&P Capital IQ and Thomson Reuters Datastream. The sample consists of 56 U.S. listed manufacturing and retail firms, of which 28 are classified as bankrupt and 28 as non-bankrupt.
Conclusions:	We find that financial adjustments are not necessary for the studied conventional bankruptcy prediction models: using reported data, the conventional models are more likely to successfully foresee imminent business failures as compared to adjusted data. So even though the necessity of using recasted financials in other areas of finance is generally accepted, we find that this necessity is not as apparent within the field of bankruptcy prediction. For recasted numbers, the coefficients derived in our model (Model II) should instead be applied, where an age factor is included.

We wish to extend our sincere gratitude to Niclas Andrén and Maria Gårdängen for their valuable inputs and continuous support throughout the past year.

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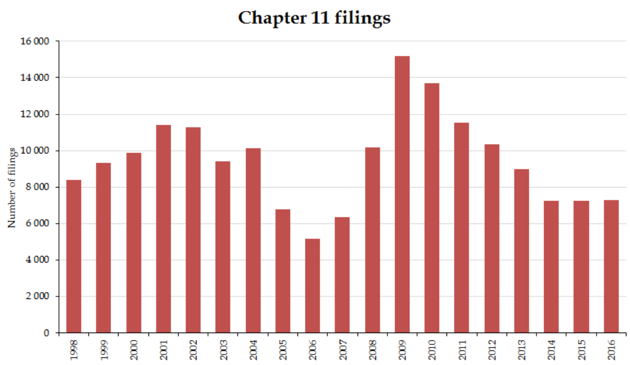
1. Introduction

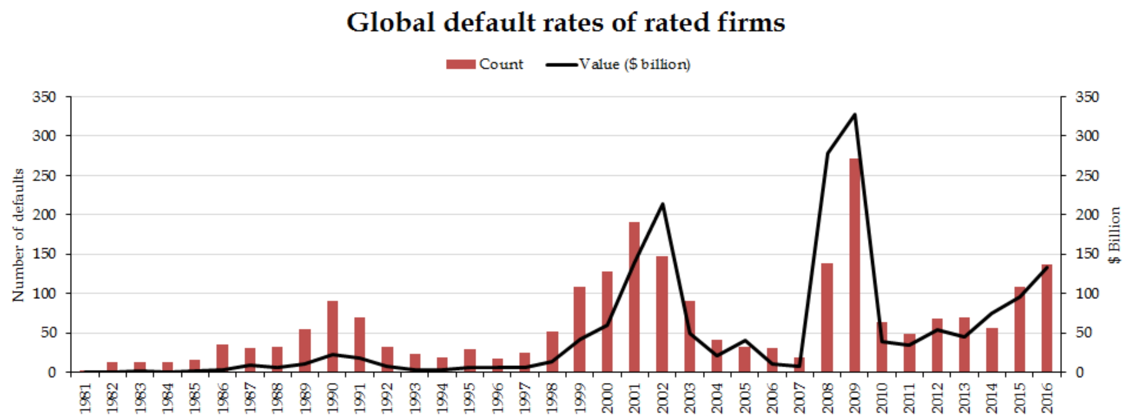
Since the breakout of the Great Financial Crisis (GFC) in 2008, most of the world has experienced extreme financial and economic turmoil. Consequently, leveraged loan defaults surpassed previous records and 2009 denoted the highest number of chapter 11 filings ever recorded. (Altman, 2010) Since then, the number of chapter 11 filings has decreased annually and is currently well below its 20-year average (see Figure 1). However, the pace of corporate defaults is yet again in a rising trend and during 2016 the default tally for rated corporate issuers reached its highest level since 2009 (Moody's, 2016b). Actually, the number of defaulting firms has increased by 157% over the last two years and the dollar volume has increased from $74.5 billion to $135 billion during the same period, as depicted in Figure 2. Simultaneously, the total amount of outstanding U.S. non-financial corporate debt has been on a steady rise since 2006, and in 2015 the sector surpassed $5,000 billion in accumulated debt, an unprecedented figure. This increase in debt has over the last year been accompanied by a corresponding rise in U.S. GDP which consequently has held the U.S private debt to GDP at a fairly constant level (see Figure 3).

Figure 1. 2009 denoted the largest number of chapter 11 filings ever recorded



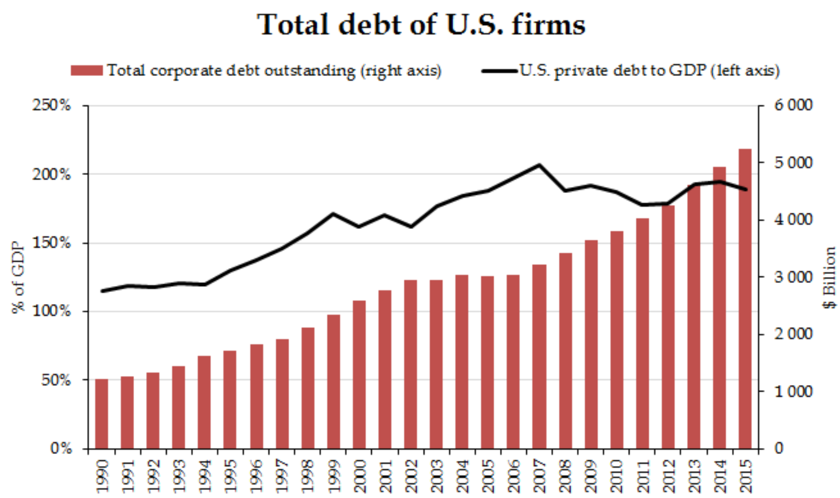
Source: Administrative Office of the United States Courts (2017)

Figure 2. Global default rates are on the rise



Source: Moody's Annual Default Study: Corporate Default and Recovery Rates, 1920-2016 (Moody's, 2016b)

Figure 3. U.S. firms holds unprecedented debt levels



Source: Bank of International Settlements (2017)

If the unprecedentedly high debt levels in the U.S. continues to rise and the trend in corporate bankruptcies continues to develop in the same manner, the necessity of bankruptcy modelling will likely become increasingly important for stakeholders such as debt holders and market participants. Whether or not this necessity materializes, the development has sparked our interest for bankruptcy prediction models and raises the question if existing models are fully applicable under current market conditions, since several of the conventional models are getting outdated.

Forecasting bankruptcies and business failures has been a thoroughly investigated topic for academics over the years.[1] To accurately predict and identify impending financial distress is of great importance to a wide set of actors, ranging from practitioners to academics and regulators (Altman & Narayanan (1997) and Shumway (2001)). As a result, several bankruptcy forecasting models have been developed to price corporate debt, monitor financial health and for hypothesis testing etc. (Shumway, 2001). Perhaps the most notable and famous model is the Z-score model developed by Edward Altman in 1968. The Z-score model combines financial statement and market value ratios to derive a so-called Z-score, which can be used to classify a certain non-financial firm into a distressed or non-distressed category. These ratios attempt to measure a firm's profitability, liquidity, leverage, solvency and earnings and cash flow coverage, factors which are said to prevail as the most significant indicators of corporate distress. (Altman & Hotchkiss, 2006) The original Z-score model has since its publication been criticized and revised by both Altman himself and other researchers such as Ohlson (1980), Zmijewski (1984), Begley et al. (1996), Shumway (2001)[2] and Hillegeist et al. (2004) (a review of previous publications relevant for this paper is presented in Section 2). To a large extent, the criticism of Altman's model has focused on the outdated data set on which the model was first developed. For example, Begley et al. (1996) argues that applying current data to Altman's model is likely to introduce measurement errors and biased results. Despite the obsolescence of the data used in the 1968 model, it is still widely used by accounting researchers as an indicator of financial distress (Begley, 1996). Another alleged faulty component of the original model that has attracted attention is that it is based on unadjusted accounting numbers (Business Insider, 2011).

[1] See for example Altman & Narayahan (1997), which lists 44 different international studies of bankruptcy prediction models.
[2] Shumway's criticism mainly centers around Altman's use of static models, which arguably fails to capture changes over time.

Financial statements are conventionally adjusted or "recasted" to better reflect the debt amount and financing cost of indebted companies, since relying on reported numbers often leads to an underestimation of the total debt burden (Batta et al., 2012). Indeed, credit rating agencies and other practitioners usually adjust accounting numbers to improve the analytical insights from assessing credit risk (e.g. Moody's, 2010). Thus, failing to incorporate off-balance sheet financing and adjusting for other relevant items in financial statements may very well lead to inaccurate credit risk assessments, underestimations of expected loan losses and erroneous credit risk-model inferences (Batta et al., 2012). Interestingly, many previous bankruptcy prediction studies take no, or few, such adjustments into account (e.g. Altman (1968), Begley et al. (1996), Shumway (2001) and Hillegeist et al. (2004)), revealing a discrepancy between the methodology used by e.g. above mentioned credit rating institutes and scholars within the field of bankruptcy prediction. Therefore, since the original Z-score model and subsequent bankruptcy prediction models are based on reported, unadjusted numbers rather than recasted numbers, the question arises whether bankruptcy models based on recasted numbers are more accurate in predicting bankruptcies.

Motivated by this debate, this paper examines if using recasted financial statements, instead of as reported financial statements, improve the accuracy of bankruptcy prediction models. This notion will be tested by applying both as reported and recasted financial statement data on (1) already existing bankruptcy prediction models and (2) our own bankruptcy prediction models.

As previously described, it is reasonable to expect recasted data to better reflect a firm's true indebtedness and consequently their repayment capacity. Therefore, we expect that using recasted numbers in credit models is superior to using as reported accounting numbers when predicting bankruptcies. Apart from incorporating adjusted numbers in various credit models, this paper contributes to prior research regarding credit risk assessment in several ways:

(1) Since few studies are conducted after the GFC of 2008, this paper offers insights into the predictability of bankruptcy models post GFC.

(2) Since modern data is applied, we offer insight into how the predictive accuracy of established bankruptcy models have been affected by the ever-changing business environment.

(3) As we revisit several conventional bankruptcy models, we can draw inferences on which model that is best suitable for predicting bankruptcies today.

(4) By recasting financial statements, we derive which adjustments that have the greatest impact when assessing bankruptcy risks.

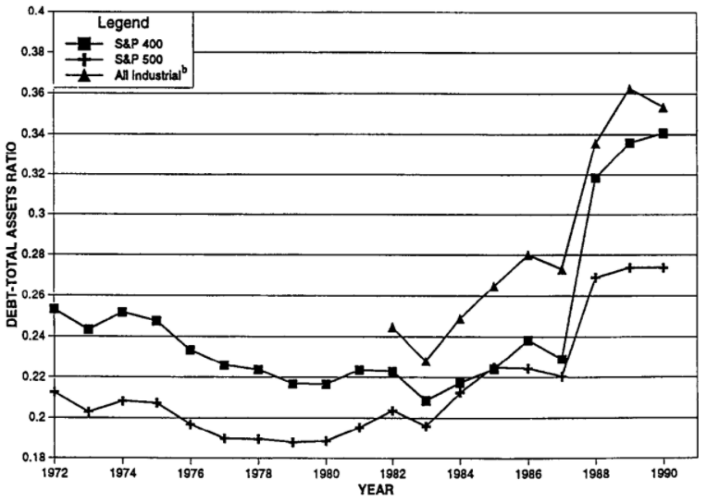
The next section contains background information on bankruptcy and distress prediction models, a brief literature review of the topic as well as an overview and discussion of the necessity of adjusting financial reports. Section 3 describes our data selection and provides descriptive statistics of our sample. Section 4 outline the methodology used in this paper and in Section 5, we present, analyze and discuss our results. Finally, in Section 6 we provide our concluding remarks and propose aspects relevant for future research.

2. Background and literature review

As described in the previous section, the identification of operating and financial difficulties has been a subject of interest for researchers and practitioners throughout the years. These types of firm-specific difficulties are alleged to be particularly convenient to detect by analyzing financial ratios. One of the pioneers in predicting business failures using financial ratios was Beaver (1967) who paved the way for multivariate attempts, which was later adopted by Altman (1968) and other researchers (Altman, 2000). For this paper, the main takeaway from studies based on Beaver's methodology is the potential of using financial ratios as predictors of financial distress and bankruptcy. Since Beaver's publication in 1967, there has been a fair share of contributions to the field of modelling and predicting corporate failures, where the more notable contributions are Altman (1968; 1977; 2000), Lev (1971), Deakin (1972), Blum (1974), Libby (1975), Altman, Haldeman and Narayanan (1977), Moyer (1977), Ohlson (1980), Zmijewski (1984), Begley et al. (1996), Shumway (2001) and Hillegeist et al. (2004). (Ohlson (1980) and Shumway (2001)) It is noteworthy that at the time of Beaver's publication in 1967, academics were questioning the widespread use by practitioners of ratio analysis as an analytical technique to assess corporate performance (Altman, 1968). In an attempt to assess the quality of financial ratios as an analytical technique Altman developed the Z-score model in 1968, which was meant to serve as an illustrative case of the possibility of using financial and economical ratios to predict firm bankruptcies. Altman referred to earlier studies within the field and argued that failing firms exhibit significantly different ratios than non-defaulting firms. (Altman, 1968) By performing a Multiple Discriminant Analysis (MDA) based on five financial ratios on a sample of 66 firms, Altman was able to predict bankruptcy correctly with 95% accuracy one year prior to failure (Altman, 1968). Even though the original Z-score model was developed almost 50 years ago, it still serves as a commonly used model to estimate default probabilities (Altman, 2000).

As mentioned in Section 1, criticism has been made on the Z-score model, perhaps most notably by Ohlson (1980), Begley et al. (1996) and Shumway (2001). Ohlson highlights some fairly well-known problems with the MDA approach and instead advocate the use of conditional logit analysis in bankruptcy prediction models (Ohlson, 1980). Ohlson is also critical to the limited amount of observations used in Altman's model and base his own study on data collected from 105 bankrupt firms and 2,058 non-bankrupt firms. Ultimately, Ohlson's model is able to correctly predict bankruptcies one and two years prior to failure with an accuracy of 96.1% and 95.5% respectively. Begley et al. (1996), on the other hand, highlights the problems that stems from applying the Z-score model on current data without considering the measurement errors and biases that current data likely introduces. Indeed, the Z-score model was estimated using data from the 1940s through the 1970s and the authors emphasizes several reasons for concern when applying the model on more recent data. One of the stated concerns was the rising acceptance of relatively high corporate debt levels that occurred in the 1980s. As leverage variables play an important role in Altman's model, they argue that *"a given level of debt in the 1980s may not be associated with the same likelihood of bankruptcy as it was in the pre-1980 time period"*. (Begley et al., 1996) This notion is derived by the sharp increase in the debt-to-total asset ratios for U.S. companies during the cited period and is illustrated in Figure 4. Another source of concern that Begley et al. (1996) points to is the change in bankruptcy laws that took place in the late 1970s, which allowed for greater strategic use of corporate bankruptcy. The study concludes that although the original Z-score model performed relatively well when it was developed, it does not perform as well in more recent time periods even when Altman's coefficients are re-estimated. (Begley et al., 1996)

Figure 4. Yearly debt-to-total assets ratios, 1972-1990



Source: Begley et al. (1996)

Shumway (2001) does not solely direct criticism to Altman's Z-score model but also question other bankruptcy models developed by e.g. Ohlson (1980), Zmijewski (1984) and Lau (1987), and states that these models are miss-specified. Shumway argues that these models ignore the fact that firms change over time, which results in bankruptcy probability approximations that are biased and inconsistent (Shumway, 2001). However, Altman responds to the critic of using static analysis and claims that the established method of basing bankruptcy models on financial statements one year prior to default yields the most accurate results (Altman & Hotchkiss, 2006). Nevertheless, Shumway developed a new bankruptcy model based on a hazard model approach which is said to resolve the problems of static models by explicitly accounting for the time dimension and allowing for time-varying covariates. Shumway thereby argue that hazard models are preferable to static models, such as the MDA approach, both empirically and theoretically. Shumway add firm age[3] as a variable of interest since a firm's bankruptcy risk changes over time and thereby is a function of the firm's latest financial data and its age. (Shumway, 2001) However, firm age is never found to be statistically significant in any of the hazard models that

[3] Defined as the number of calendar years the firm has been publicly listed.

Shumway estimate after controlling for other relevant firm characteristics. The study concludes that half of the variables used by Altman and Zmijevski are statistically unrelated to bankruptcy probabilities, which indicates that previously used accounting ratios are poor predictors in failure-forecasting contexts and Shumway point out that several market-driven variables that are strongly related to bankruptcy probabilities have been neglected. (Shumway, 2001) Another concern worth mentioning is highlighted by Hillegeist et al. (2004), who questions the effectiveness of probability of bankruptcy measures that are based on accounting data. As bankruptcy predictions are forward looking by nature and financial statements are designed to reflect past performance, it is argued that accounting numbers may not be particularly informative about the future status of a given firm. Also, as financial reports are constructed according to the going-concern principle, which assumes that the firm will not go bankrupt, the accuracy and reliability of bankruptcy estimates will be limited by design (Hillegeist et al., 2004). Additionally, the study states that the conservatism principle generally applied by reporting firms often cause downward-biased asset valuations since asset values are likely to be understated relative to their market values under this principle. Consequently, Hillegeist et al. (2004) outlay the possibility that accounting-based leverage ratios are generally overstated.
Apart from previously stated criticism, the Z-score model has also drawn other statistical objections throughout the years, such as using data from relatively small firms and using unadjusted numbers (Business Insider, 2011). Although Altman has revisited his original model several times, the original model developed in 1968 is, as already mentioned, still widely used by practitioners for estimating bankruptcy probabilities (Altman, 2000).

Since this study to a large extent will focus on the potential weakness of using unadjusted accounting numbers when predicting bankruptcies, the next section attempts to justify and emphasize the necessity for financial statement adjustments in bankruptcy forecasting models.

2.1 The necessity for financial statement adjustments

Financial statements are generally permeated by distortions which makes as-reported numbers less informative than recasted numbers. This indicates that distortions in financial statements are likely to skew the economic reality of firms, and that it is possible to better reflect the economic reality through recasting. (Batta et al., 2012) Indeed, credit rating agencies categorically adjusts financial statements to "[...] *improve analytical insight from the perspective of assessing credit risk and to improve the comparability of a company's financial statements with those of its peers* […]" (Moody's, 2016a). Standard and Poor's (2013) state that "[...] *analytical adjustments are made to better portray reality."* and that "[...] *it is useful to have some notion of the extent performance or assets are overstated or understated."* It is generally accepted that many of the distortions found in as-reported financial statements can be improved via recasting. Thus, practitioners, analysts and credit rating agencies generally adjust for the impact of e.g. off-balance sheet debt leases and hybrid securities. (Batta et al., 2012) A list of typical adjustments made by rating agencies and recommended by three leading textbooks (as reported by Batta et al, 2012) are listed in Appendix A. It can be seen from the list that the adjustments made by Moody's and Standard and Poor's are very similar to the adjustments recommended by these textbooks.

A commonly cited reason for using off-balance sheet debt is to achieve a lower reported debt amount on the balance sheet, which may be useful in pursuing a higher debt rating (Lim et al., 2003). Naturally, it is quite intuitive that including off-balance sheet debt increase the total debt amount held by a firm. For example, Kraft (2011) could conclude that the on-balance sheet debt underestimated the "true" economic debt for more than 96% of the sample observations consisting of 1,210 firms, and that accounting for off-balance sheet items increased the leverage ratio for the median firm by 14%. Despite the impact that off-balance sheet financing has on the total debt burden of a firm, market participants are not fooled: by investigating how bond yields are affected by the use of off-balance sheet financing, Lim et al. (2003) draw the conclusion that bond yields indeed reflect off-balance sheet obligations in the same manner as balance sheet debt. If market participant's take off-balance sheet financing into account, it raises the question of why conventional bankruptcy prediction models are typically based on unadjusted accounting numbers when assessing the financial health of firms.

As mentioned above, the original Altman Z-score model was based on unadjusted accounting numbers. Implicitly, this indicates that the original model was based on numbers that underestimated the indebtedness of the firm. For example, Batta et al. (2012) conclude that financial statement adjustments that aim to reflect the "true" indebtedness of a firm have an economically significant impact on credit pricing and loss forecasting. Recasted accounting numbers generally leads to higher leverage and worsened solvency for any given firm, which is likely to reflect higher bankruptcy probabilities (Moody's (2016a) and Batta et al. (2012)). This comes as no surprise since greater leverage is known to be associated with greater risk (Merton, 1974). It is worth to mention that credit loss prediction models based on recasted numbers are suggested to predict significantly higher credit losses than models based on as-reported numbers (Batta et al., 2012). Not only do models based on adjusted numbers predict higher credit losses, they are also better able to predict both credit ratings and yield spreads (Kraft, 2011).

When Altman et al. (1977) subsequently revisited Altman's original model, they recognized the theoretical advantages of using recasted data and the new model developed accounted for the recent changes in financial reporting standards and accounting practices that occurred at that time. The revisited model, the ZETA model, accounted for a number of accounting modifications such as capitalization of leases and R&D costs (Altman et al., 1977). The study found that the revisited model was consistently more accurate in identifying bankrupt firms two to five years prior to default (e.g. five years prior to default the ZETA model was 70% accurate whereas the original Z-score model's accuracy was 36%). The author's findings in 1977 further highlight the advantage of using recasted accounting numbers when dealing with bankruptcy prediction models.

The above discussion indicates that off-balance sheet debt should be regarded as on-balance sheet debt and we therefore argue that basing bankruptcy prediction models on unadjusted accounting numbers is both inconsistent and misleading. In the next section, we present our sample selection along with descriptive statistics of our data set.

3. Sample selection and data characteristics

The data consists of 28 firms that went bankrupt between 2012 and 2016.[4] The bankrupt firms have been matched to a sample of 28 non-bankrupt firms, yielding a total data set consisting of 56 firms. A complete list of the firms included in this study is presented in Appendix B, and descriptive characteristics of the sample and the industry is presented in Table 1. The non-bankrupt firms have been matched to the bankrupt firms by industry, year of bankruptcy and the total assets reported in the latest annual report prior to bankruptcy. The data is limited to U.S. listed firms where sufficient data was available.[5] In accordance with Altman's studies in 1968 and 1977, we have limited our data set to only include firms classified as manufacturing (Standard Industrial Classification (SIC) code 2000-3999) or retailing firms (SIC code 5200-5999). In the manufacturing group, firms classified as "Chemicals and allied products" (SIC code 2800) have been excluded since they are deemed to have characteristics that distinguish them significantly from the typical manufacturing firm.[6] Note that manufacturers make up a majority of the bankrupt firms, 71% (20 of 28 firms) and that 43% (12 of 28) of the bankruptcies occurred in 2016 whereas the remaining failures are evenly distributed over the period studied. Based on Figure 1 and Figure 2 (Section 1), our sample of bankrupt firms might seem surprisingly small. However, after considering the above predetermined criteria and adjusting for firms with insufficient data, this is the data set we obtain. Accounting data is derived from financial statements one to five years prior to bankruptcy for failing firms and their respective match. The financial statement data is mainly retrieved from S&P Capital IQ, and whenever necessary complemented by data obtained from Thomson Reuters Datastream. Although we do consider both databases to be trustworthy, they have some drawbacks. Reasonably, both software are "standardized", i.e. when it comes to summarizing data (SIC codes, financial statements etc.) this is done according to some predefined criteria. This results in a

[4] The period chosen is motivated by our ambition to use the most recent financial data possible.

[5] 15 firms were excluded from the initial sample due to lack of data.

[6] By assessing the defaulting firms classified as "Chemical companies", we concluded that they differed from the rest of the data set for several firm-specific reasons. For example, some firms developed pharmaceutical product candidates that were yet to be approved, meaning that those firms e.g. did not have any sales.

risk that the data is not completely accurate. However, since our study aim to be easily replicable, we accept this for the benefit of practical usage.

The mean and median asset size for the bankrupt firms are $861.5 million and $48.2 million respectively, whereas the mean and median asset size for the matches are $772.7 million and $68.6 million respectively. The large difference between the mean and median asset size is explained by outliers that skew the data distribution.[7] We have chosen not to exclude outliers in this study for two reasons: first, removing outliers from the already limited data set would potentially yield too few observations, thereby making inferences unpredictable. Secondly, removing outliers is arguably an artificial way to improve the characteristics of the data and consequently the characteristics of the model (Brooks, 2014). Indeed, many econometricians argue that each observation represents a useful piece of information and should thus not be excluded (ibid).

By comparing our sample with the asset size for all U.S. listed manufacturers and retailers, it is obvious that our sample consists of firms that are considerably smaller: the mean and median asset size for U.S. listed firms amount to $7,613.0 million and $607.0 million respectively. Firm age is defined as the number of calendar years the firm has been publicly listed. The bankrupt firm has on average been listed for 15 years when declaring bankruptcy whereas the matching firm is slightly older, 18 years.[8] This is in line with the age of all listed manufacturing and retail U.S. firms for our period, which on average had been listed for 16 years.

[7] Removing the top and bottom decile yields a mean asset size of $238.9 million.

[8] Firm age for matching firms is defined as the number of calendar years the firm has been publicly listed when the bankrupt firm to which they have been matched declares bankruptcy.

Table 1. Sample characteristics

	Bankrupt	Non-Bankrupt	Industry
Number of firms	28	28	
Type of firm			
Manufacturer	20	20	
Retail	8	8	
Average size (total assets)	$861.5 million	$772.7 million	$7,613.0 million
Median size (total assets)	$48.2 million	$68.6 million	$607.0 million
Average age	15.1 years	17.6 years	15.1 years
Median age	13.0 years	16.0 years	16.0 years

Year of bankruptcy	Number of firms
2016	12
2015	4
2014	4
2013	4
2012	4
Sum	**28**

4. Methodology

In this section, we first present the coefficients and predictive variables used in previous research. These coefficients and predictors will then serve as the foundation from which we will develop our own models. Throughout Section 4.2. we review the development of our predictive models. Lastly, we discuss necessary financial statement adjustments and the respective methods used to recast our data.

4.1. Coefficients and predictive variables

As presented in Section 2, there has been a fair share of contributions to the field of modelling and predicting firm bankruptcies, e.g. Altman (1968; 1977; 2000), Lev (1971), Deakin (1972), Blum (1974), Libby (1975), Altman, Haldeman and Narayanan (1977), Moyer (1977), Ohlson (1980), Zmijewski (1984), Begley et al. (1996), Shumway (2001) and Hillegeist et al. (2004). (Ohlson (1980) and Shumway (2001)) For the purpose of this study, we make use of previously developed predictive variables. Consistent with Ohlson (1980), we motivate this by its pure simplicity and our ambition to present an easily replicable study with practical usage.

For our study, we make use of the work of Altman (1968), Begley et al. (1996), Shumway (2001) and Hillegeist et al. (2004), which we hereafter will refer to as the "conventional models". The reason to include Altman's original Z-score model from 1968 is natural, since it arguably laid the foundation for later bankruptcy prediction models, such as the models of Begley et al. (1996), Shumway (2001) and Hillegeist et al. (2004). These models all include Altman's five original predictive variables (see Table 2), which motivates why we also make use of these predictors.

Table 2. Predictive variables used in earlier studies

Working Capital/Total Assets	WC/TA
Retained Earnings/Total Assets	RE/TA
Earnings Before Interest and Taxes/Total Assets	EBIT/TA
Market Capitalization/Total Liabilities	MC/TL
Sales/Total Assets	S/TA

Working Capital/Total Assets (WC/TA)

Working capital is calculated as current assets less current liabilities. The ratio can be interpreted as a measure of the firm's liquidity relative to its size. Altman (1968) states that of all the tested liquidity ratios, WC/TA had the highest predictability.

Retained Earnings/Total Assets (RE/TA)

This ratio, with cumulative profitability in the nominator, implicitly takes firm age into consideration. For example, a young firm will probably have a lower ratio compared to a more mature firm, since their cumulative profits have been accumulated during a shorter period. Therefore, it could be argued that the ratio is discriminating against young firms, since they naturally will have a higher chance of being classified as bankrupt. However, such classifications are reasonable since young firms have higher probabilities of failure compared to mature firms. (Altman, 1968)

Earnings Before Interest and Taxes/Total Assets (EBIT/TA)

This ratio can be interpreted as a measure of the productivity of a firm's assets and since the earnings power of the assets are highly important for survival, the ratio is well-suited for predicting bankruptcies. It should be noted that EBIT/TA had the greatest contribution to the total discriminating power of Altman's original model (Altman, 1968).

Market Capitalization/Total Book Value of Liabilities (MC/TL)

Market capitalization is calculated as the market value of the total number of outstanding shares. Total liabilities include both short-term debt and long-term debt. Since the market value of equity for firms that are close to bankruptcy generally is discounted by market participants, it is an important predictor to take into consideration (Shumway, 2001).

Sales/Total Assets (S/TA)

The so-called capital-turnover ratio is a measure of the capability of the firm's assets to generate revenues, i.e. the efficiency of assets. Altman (1968) rank this ratio as the second most important contributor to the predictability of his original model.

Begley et al. (1996), Shumway (2001) and Hillegeist et al. (2004) differentiates from Altman's original study as they estimate new coefficients for the predictive variables. The coefficients used by these researchers are presented below in Table 3. Note that Shumway has two sets of coefficients, which are derived from different time periods for his sample (1962-83 and 1962-92). Furthermore, in the study of Hillegeist et al. (2004), the coefficients have the opposite sign to those presented below in Table 3. Hillegeist's et al. (2004) reason for this is simply expositional, i.e. a probability of default that is increasing with an increased Z-score, as opposed to Altman's (1968) original study where the probability of bankruptcy is decreasing with an increased Z-score. In our study, we make use of all the coefficients presented in Table 3.

Table 3. Coefficients for predictive variables

Variable	**Altman**	**Begley et al.**	**Hillegeist et al.**	**Shumway 62-83'**	**Shumway 62-92'**
WC/TA	1.20	10.40	0.08	0.40	1.20
RE/TA	1.40	1.00	-0.04	2.80	0.60
EBIT/TA	3.30	10.60	0.10	11.10	10.00
MC/TL	0.60	0.30	0.22	0.01	0.05
S/TA	1.00	-0.17	-0.06	-0.35	-0.47

As Hillegeist et al. (2004) states, the relationship between the probability of default and accounting variables are not stable over time. Therefore, by using a set of coefficients that have been calculated over a period of 30 years, we can draw analytical inferences based on a more solid foundation.

4.2. Development of Model I and Model II

In this section, the development of our models is dissected by presenting our choice of econometrical method, the matching technique used, the regression equation derived and the discriminant value applied.

4.2.1. Choice of econometrical method

We use a conditional logistic regression analysis as the econometric methodology when developing our own models. In recent research regarding bankruptcy prediction models, logit analysis has been widely used, but the choice of econometric method has not always been obvious. Many previous studies have made use of a so called Multiple Discriminant Analysis (MDA). For those not familiar with the concept, Khalili and Makvandi (2013) explain it as "[...] *a multivariable method in which the phenomena are divided into distinct groups with different qualities*". MDA then attempts to recognize the difference between the groups, and predict the likelihood of a subject ending up in a specific group (Khalili & Makvandi, 2013). MDA has been around for a long time in a variety of disciplines and was first implemented during the 1930s. During these early years, the main field of usage was biological and behavioral science, but later on the methodology was found to be applicable in financial areas as well, such as for investment classifications and credit analysis. For example, Altman (1968) refers to Walter (1959) who utilized MDA for classifying high and low P/E-ratios and further refers to Smith (1965) who used MDA to classify investment categories. In his famous bankruptcy study in 1968, Altman based his prediction model on a MDA technique for categorizing firms as bankrupt and non-bankrupt. (Altman, 1968)

Even though the MDA approach has been popular for many years, it has received criticism. Ohlson (1980) states that the variance-covariance matrices of the predictive variables should be the same for the groups of bankrupt and non-bankrupt firms. Ohlson (1980) also argues that the interpretation of the output from MDA models is often weak, since such models basically are constructed as ordinal ranking devices.

Historically, various matching techniques have been used when conducting discriminate analysis. Conditional factors such as industry and size have often been used to match firms, but Ohlson claims that such criteria often are somewhat arbitrarily chosen (we return to the notion of matching in Section 4.2.2). The disadvantages of MDA can be solved by using conditional logit analysis, where no assumption has to be made regarding prior bankruptcy probabilities or the distribution of predictive variables. (Ohlson, 1980) In their study, Khalili and Makvandi (2013) conclude that MDA has high accuracy when predicting bankruptcy, but its overall performance was lower compared to that of the logit model. Since the conditional logit analysis has advantages compared to MDA, we choose to use logit analysis as the econometric methodology when developing our own bankruptcy prediction models.

4.2.2. Matching

We use matching in order to derive our two groups: bankrupt and non-bankrupt firms. The idea is to use matching as a basis for estimating the counterfactual outcome of one group of firms (bankrupt), by looking at the outcome of a subsample of similar firms from another group (non-bankrupt). The benefit of using matching for regression-based analysis is its potential for mitigating asymptotic biases related to endogeneity or self-selection, and for regression-based analysis it can therefore provide a useful robustness test. (Roberts & Whited, 2012) However, matching is unfortunately, and perhaps not surprisingly, a flawless method. To quote Smith and Todd (2005): "[...] *matching does not represent a "magic bullet" that solves the selection problem in every context.*" Matching, on a stand-alone basis, is not likely to solve problems related to endogeneity, since it relies on the capability of the practitioner to observe all outcome relevant determinants (Roberts & Whited, 2012).

There is no conventional rule of thumb for deciding the optimal (or best) number of matches, but using a single match yields estimates with the least biased results and the highest credibility. However, at the same time, a single match results in the least precise estimates (this setting represents the bias-variance tradeoff). (Roberts &

Whited, 2012) Roberts and Whited (2012) refers to Dehejia and Wahba (2002) who suggest different methods for matching, and one of the methods suggested is known as the "nearest-neighbor" match, where the closest match is derived from certain predefined criteria. Consistent with Altman (1968) we use industry, year of bankruptcy and asset size as the predefined criteria. Matching is done without replacements, meaning that no match has been used more than once. Even though matching with replacements can result in fewer biases, it could also result in lower precision (Roberts & Whited, 2012).

Like many methodologies, matching techniques may not be statistically perfect, but in our opinion matching consist the most suitable approach for this study. Also, since the method have been used in previous research (e.g. Altman in 1968), we feel comfortable going forward.

4.2.3. Regression equation

When attempting to predict defaults based on our sample of bankrupt and non-bankrupt firms, we want to extend on previous research by calculating our own coefficients for the mentioned predictive variables. We do so by making use of two models, which are labeled Model I and Model II. In Model I we derive our coefficients based on the same predictive variables that were tested by Altman (1968), Begley et al. (1996), Shumway (2001) and Hillegeist et al. (2004). In Model II, the predictors are complemented with an age factor, as measured by the logarithm of the years the firm has been publicly listed. Consistent with Shumway (2001), the inclusion of the firm's trading age is an attractive alternative measure of how long the firm has been a viable enterprise. Both models are estimated using a logistic regression analysis. As discussed in Section 4.2.1, we deem this method to be a more suitable approach compared to a Multiple Discriminant Analysis. In order to derive new coefficients, we make the dependent variable a dummy, where *1 = bankrupt* and *0 = non-bankrupt*.

The discriminant function for our two models is as follows:

Model I: $y = \alpha + \beta_1 \frac{\text{WC}}{\text{TA}} + \beta_2 \frac{\text{RE}}{\text{TA}} + \beta_3 \frac{\text{EBIT}}{\text{TA}} + \beta_4 \frac{\text{MC}}{\text{TL}} + \beta_5 \frac{\text{S}}{\text{TA}}$

Model II: $\text{y} = \alpha + \beta_1 \frac{\text{WC}}{\text{TA}} + \beta_2 \frac{\text{RE}}{\text{TA}} + \beta_3 \frac{\text{EBIT}}{\text{TA}} + \beta_4 \frac{\text{MC}}{\text{TL}} + \beta_5 \frac{\text{S}}{\text{TA}} + \beta_6 \text{LN(AGE)}$

where $\text{y} = (0 = \text{non-bankrupt firm} | 1 = \text{bankrupt firm})$

To clarify for later interpretation: when the sign of a coefficient is negative (positive) and the predictive variable is positive, the firm is more likely to be classified as non-bankrupt (bankrupt). One potential problem when estimating our logistic models are the limited data sample on which the models are based.[9] The reason for not extending the data set of matching firms is simply due to the limited time at our disposal. Preferably, we would include all the 1,838 matching firms which met our predefined criteria (instead of the 28 best matching firms), but given the extensive time needed for adjusting the financial statements of the non-bankrupt firms, it was simply not possible.

4.2.4. Choice of discriminant value

Altman (1968) finds that the most accurate critical value, the so called "cut-off score", is a Z-score of 2.675, which he argues is the critical value that best discriminates between failing firms and surviving firms (Altman, 1968). Although a cut-off score of 2.675 also appears in later studies, Altman (2000) later advocate a lower cut-off point of 1.81. However, when testing the power of the coefficients and the predictive variables on our data set, we conduct our tests with cut-off scores of 2.675 as it prevails as the most commonly used discriminant value in mentioned studies.

When estimating our own coefficients, using dummy variables, the cut-off score is set to 0.5. A cut-off score of 0.5 is reasonable since the sample is evenly distributed between bankrupt and non-bankrupt firms and this cut-off score is consistent with

[9] E.g. Ohlson (1980) included 2,058 matching firms and 105 bankrupt firms.

that of Ohlson (1980). It should be noted that Ohlson (1980) mention that there is no apparent reason for why 0.5 would be a good cut-off score since it implicitly assumes a symmetric loss function between the classification errors.

4.3. Financial statement adjustments

There are, to say the least, many different financial adjustments that could be made, and institutions (e.g. credit rating agencies and investment banks) and authors of leading textbooks suggest various adjustments. When deciding which financial adjustments to make, we have consulted the methodology used by Moody's and the work of Batta et al. (2012). Appendix A summarize an excerpt of what Batta et al. (2012) claim to be typical adjustments made by rating agencies and recommended by leading textbooks. Since Batta et al. (2012) find that adjusting for off-balance sheet leases and pension liabilities have both a statistically and economically significant impact on simulated credit losses, we have chosen to include adjustments for these items. However, Batta et al. (2012) conclude that capitalized interest and stock-based compensation are statistically or economically insignificant when simulating credit losses and therefore we have chosen to not adjust financial statements for these items. Further, we have chosen to adjust our data for hybrid securities and LIFO valuation reserves in accordance with e.g. Standard & Poor's (2013), Moody's (2016a) and Koller et al. (2015), whereas adjustments for securitization of receivables are omitted since tightening accounting policies have caused many companies to discontinue their receivables securitization programs (Koller et al., 2015). Both Moody's (2016a) and Koller et al. (2015) consider adjustments for non-recurring and non-operating items, and even though we agree that these adjustments are important, they are too comprehensive to implement in a way that would not mitigate the practical usage of our study. Therefore, we choose not to adjust for these items. As nonstandard adjustments and allocating restructuring charges to prior periods are not widely implemented (based on the table presented in Appendix A), we refrain ourselves from making such adjustments. Naturally, adjustments for unusual and non-recurring cash flow items are left out since there are no explicit cash-flow based variables in any of the models studied.

In the remainder of this section, we list and carefully explain the six adjustments made to the original financial statements included in our sample.

Capitalized operating lease debt

By recognizing the value of capitalized operating lease debt, we equally increase the asset and liability side of the balance sheet. There are many techniques for capitalizing leases and different methods are suggested by credit rating institutes (e.g. Moody's and Standard & Poor's), previous research articles (e.g. Altman (1977) and Batta el al. (2014)), as well as in literature (e.g. Koller et al. (2015)). Rating agencies such as Moody's typically apply a multiple-based valuation method, whereas finance literature generally suggest using a perpetuity-based method (Koller et al., 2015). In our study, we make use of the so-called perpetuity method suggested by Lim et al (2003), which they find to be the most suitable technique for calculating operating lease debt (see Appendix C for how calculations of operating lease debt are made using the perpetuity method). Like most perpetuity methods for calculating operating lease debt, a cost of secure debt component is necessary. We use the *Bank of America Merrill Lynch U.S. Corporate AA Effective Yield* as the indicator for cost of secure debt, where the effective yield is set to an annual basis (The Federal Reserve Bank of St. Louis, 2017). When deriving the capitalized operating lease debt on the balance sheet, adjustments need to be made on the income statement as well. We use the methodology suggested by Moody's (2016a), where the lease interest is removed from the operating income (EBIT) and is instead included in financial expenses.

Pension obligations

The amount of debt recognized on the balance sheet is the amount by which the defined pension benefit obligation (PBO) is underfunded. The adjustment is derived from the gross underfunded value (PBO less fair market value of plain assets). (Moody's, 2016) When the PBO is categorized as excess, it is recognized as an excess pension asset on the asset side of the balance sheet. On the income statement, only the service-related cost to the PBO is included in the operating income (EBIT) (Koller et al., 2015).

Operating cash

According to Koller et al. (2015), excess cash should not be included as an operating item, since excess cash is not necessary for core operations. However, firms do not disclose how much of their cash holdings that is excess. In a study conducted by Koller et al. (2015), they conclude that firms with the smallest cash balances had operating cash levels below 2 percent of sales, and therefore use this as a proxy for determining operating cash levels. This is just a proxy, and we believe that for our particular data set, this estimate might not be suitable. We argue that 2 percent is too low and that including all the reported cash as operating is a more suitable proxy for our sample. We base this argument on the notion that distressed firms are likely to make use of all their cash holding to avoid failure. Therefore, we set the reported cash level as operating and recognize no excess cash.

Current interest-bearing debt

This financial item is included in working capital, which is included in one of the predictive variables (WC/TA). To remove the effect of capital structure, we adjust for short-term interest-bearing debt simply by removing it from current liabilities.

LIFO (last-in-first-out) valuation reserve

This reserve is permitted for firms included in our study as they report under U.S. GAAP. As mentioned by Moody's (2016a), adjustments to the balance sheet should be made if the firm carries any LIFO inventory valuation reserve. This is done in order to state inventory at the most recent cost and to improve comparability among companies. The balance sheet is adjusted by increasing inventory and retained earnings by the amount of the LIFO inventory valuation reserve. The income statement is not adjusted.

Hybrid securities

These securities are generally not pure equity or pure debt as they often entail characteristics of both. Therefore, analysts generally assign weights to the debt and equity components based on the security's particular features. (Moody's, 2016a) For simplicity, we have standardized the treatment of hybrid securities and assigned an equal weight (fifty-fifty) for the debt and equity components. Thereby, in the case where the hybrid security is recognized as pure debt, we have reclassified half of the value as equity, and vice versa. On the income statement, we reclassify preferred dividends to interest expense and interest expense to preferred dividends in accordance with the equal weighting of the debt and equity component.

We recognize that adjustments pertained to the capitalization of operating lease debt and the recognition of pension obligations yield an adjusted financial expense through the implicit interest expense entailed in these items. Similarly, as finance-related items affecting the reported taxable result (other than pure interest expenses) are deemed to be non-operating and consequently excluded, the adjusted taxable result will change. In order to make our study easily replicable and useful in a practical manner, we have assumed an U.S. federal tax rate of 35% for our sample in accordance with current U.S. taxation rules (Internal Revenue Service, 2016). For companies with a negative (or zero) adjusted taxable result, a tax rate of zero percent is applied. The recasted taxable result affects net income and consequently the balance sheet through the adjustments to retained earnings (triggered by the adjustment in net income).

5. Results

In this section, we present and interpret the predictive accuracy of the conventional models as well as our own developed models, using as reported and recasted accounting numbers. For our recasted data, two different types of methodologies have been used, and the results are presented in section 5.2 and 5.3 respectively. In section 5.1 we outline and analyze the unadjusted and recasted financial data as well as the conventional predictive variables.

5.1. Basic descriptive results

Table 4, Panel A reports the mean and median variables for one period prior to bankruptcy for the bankrupt group, non-bankrupt group and our full sample respectively using reported financials. To test the individual discriminating ability of each variable, a F-test has been conducted. The F-test relates the difference between the mean values of each variable in the two groups (bankrupt and non-bankrupt) to the variability of the values of the variables within each group (Altman, 1968). The variables presented in Table 4 are based on the actual numbers reported in the financial statements one period prior to bankruptcy. As can be seen, all variables except S/TA are statistically significant at the 0.1% level. This indicates that all the variables except S/TA are significantly different between the groups. An interesting note is that Altman (1968) neither found S/TA to be statistically significant in his original study. Altman (1968) states that the reason for including it, even though not being statistically significant, is its unique relationship with the other predictors, which is why we also chose to include it. As expected, the variables WC/TA, RE/TA and EBIT/TA are all negative for the bankrupt group one period prior to bankruptcy (also consistent with the findings of Altman (1968)).

For working capital, it is reasonable to assume that short-term liabilities for distressed firms exceed current assets, resulting in a negative WC/TA-ratio. For example, distressed firms might generate insufficient cash flows to service trade payables, while at the same time having limited cash holdings. Furthermore, distressed firms are likely to display negative earnings, which in turn contribute to cumulative losses. Companies with low and especially negative earnings relative to assets (as measured by EBIT/TA) are more likely to fail since the ability to service debt is hampered, and consequently, companies that accumulate losses over time (as measured by RE/TA) are more likely to fail based on the same argument. Somewhat surprisingly, these variables are also negative for the non-bankrupt group (albeit not as negative as for the bankrupt group).

The MC/TL-ratio is higher for the non-bankrupt group, possibly indicating that this group is higher valued and/or less indebted than the bankrupt group. Consistent with Shumway (2001), we interpret this discrepancy between the groups as market participants discounting the default risk, resulting in a lower market value of equity for bankrupt firms. The S/TA-ratio is somewhat higher for the bankrupt group, indicating a slightly higher capital turnover for the failing firms than for the matching sample. We do not draw any major inferences based on this result since the difference between the groups are neglectable and insignificant.

A notable result is the extremely negative mean RE/TA-ratio for both groups. Looking instead at the median RE/TA-ratio, the ratio appears less extreme. In fact, looking solely at the mean of all the variables, this might be misleading as the data contain outliers, resulting in large standard deviations. In Section 3, we pointed out the necessity of including such observations. It should be noted that the standard deviations of the variables are consistently larger for the bankrupt firms, compared to the non-bankrupt firms (except for MC/TL).

In Table 4, Panel B the mean and median variables for U.S. listed manufacturers and retailers are presented for comparative purposes. It is apparent that the characteristics of our sample of bankrupt and non-bankrupt firms differs from the average manufacturer and retailer, where the most notable difference is seen in the RE/TA-ratio. The firms in our sample display substantially higher accumulated losses relative to total assets compared to the industry, but it is surprising that the ratio is on average negative for the two industries as well. The EBIT/TA-ratio reveals that the average manufacturer and retailer are more profitable than the firms included in our sample and the positive WC/TA-ratio indicate that they are more liquid than the average sample firm. For the MC/TL-ratio, the bankrupt group have more in common with the industry than the non-bankrupt group, and the non-bankrupt group is higher valued relative to total liabilities compared to the industry average. Lastly, the capital turnover ratio (S/TA) is higher for our sample of firms than that of the industries as a whole.

TABLE 4. Summary statistics and test of significance (as reported numbers)

Panel A.

	Bankrupt Group			Non-Bankrupt Group				Full Sample		
Variable[1]	Mean	Median	Std.dev	Mean	Median	Std.dev	F-ratio	Mean	Median	Std.dev
WC/TA	-2.74	0.01	8.57	-0.14	0.37	1.95	19.31*	-1.44	0.14	6.29
RE/TA	-15.09	-0.99	34.83	-6.09	-0.15	16.73	4.33*	-10.59	-0.63	27.45
EBIT/TA	-1.32	-0.31	4.35	-0.27	-0.002	1.13	14.75*	-0.80	-0.11	3.19
MC/TL	1.87	0.64	2.99	5.13	2.28	6.11	4.16*	3.50	1.33	5.04
S/TA	1.86	1.57	1.55	1.78	1.43	1.41	1.19	1.82	1.53	1.47

[1] WC = Working Capital
TA = Total Assets
RE = Retained Earnings
EBIT = Earnings Before Interest and Taxes
MC = Market Capitalization
TL = Total Liabilities
S = Sales

* Significant at the 0.1% level

F (0.001) = 3.44
F (0.01) = 2.51
F (0.05) = 1.90

Panel B.

Manufacturer and retail industry[1]		
Variable	Mean	Median
WC/TA	0.25	0.26
RE/TA	-1.25	0.10
EBIT/TA	0.01	0.07
MC/TL	1.65	1.11
S/TA	1.14	0.96

[1]*Source: S&P Capital IQ*

5.1.1. Annual change in the predictive variables

In Table 5, we present the development of the predictive variables over time, ranging from five periods to one period prior to bankruptcy. The variables are derived from reported accounting numbers and the results are not surprising: all the ratios (except S/TA) for the bankrupt firms deteriorate as the firm moves closer to bankruptcy. Quite intuitive, the largest change in the predictors occurs one period prior to bankruptcy, with the exception of EBIT/TA. The liquidity ratio (WC/TA) is fairly constant for the non-bankrupt firms, whereas consistently falling for the failing firms. Obviously, and not that surprising, the ratio differs between the groups. Extending our analysis, a possible explanation for the declining trend in WC/TA of the failing firms is an erosion of cash holdings in combination with the incapability of supporting trade payables. The consistent fall in the RE/TA-ratio reflects that the average bankrupt firm operates with losses over the years and that the accumulated losses eventually forces the firm into bankruptcy. For the non-bankrupt group, it is hard to observe any obvious trend in RE/TA. The profitability of bankrupt firms, as measured by EBIT/TA, is negative and fairly constant over the years, which partly explain the consistent fall in RE/TA.

Since both groups display negative profitability, it is possible that the industry as a whole (U.S. manufacturing and retail) experienced economic difficulties during the time period studied. As many observations are collected during the aftermath of the Great Financial Crisis (GFC) of 2008, it is not hard to imagine that several of the firms in our sample faced declining revenues accompanied by constant (and perhaps rising) costs. This reasoning can be further extended to the consistent fall in the MC/TL-ratio of both groups (although the effect is most clear for the bankrupt group). The GFC of 2008 might be an explanatory factor, since it arguably resulted in diminishing market values for the industries as a whole. A notable observation is that there is no clear trend in the S/TA-ratio for either group: the ratio appears to be fairly constant.

Whereas the failing firms experiences the largest change for all but one of the predictive variables in T_{-1}, the largest change for most of the variables of the matching group occurs in T_{-4}.[10] It is quite intuitive that the largest impairment of the predictors for the bankrupt group occurs in T_{-1}, since this is arguably the most distressed period for the group. The reason for the non-bankrupt firms displaying these results in T_{-4} is ambiguous, and we limit ourselves to not draw any further inferences of why that is.

For illustrative purposes, the development of the predictive variables of the bankrupt and the matching sample is depicted in Figure 5.

[10] T_{-n} is defined as the point of default, where n is the number of periods (fiscal years) prior to default.

Table 5. Mean variables and annual change (as reported numbers)

Bankrupt Group

	T_{-5}		T_{-4}		T_{-3}		T_{-2}		T_{-1}	
Variable	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]
WC/TA	-0.92	-	-0.69	0.23	-1.09	-0.40	-1.36	-0.27	-2.74	**-1.37**
RE/TA	-5.89	-	-5.85	0.04	-8.02	-2.17	-9.78	-1.75	-15.09	**-5.32**
EBIT/TA	-0.95	-	-0.64	0.31	-1.26	**-0.62**	-1.21	0.05	-1.32	-0.12
MC/TL	5.04	-	4.52	-0.52	3.70	-0.82	4.54	0.84	1.87	**-2.67**
S/TA	1.42	-	1.43	0.01	1.36	-0.07	1.35	-0.01	1.86	**0.51**

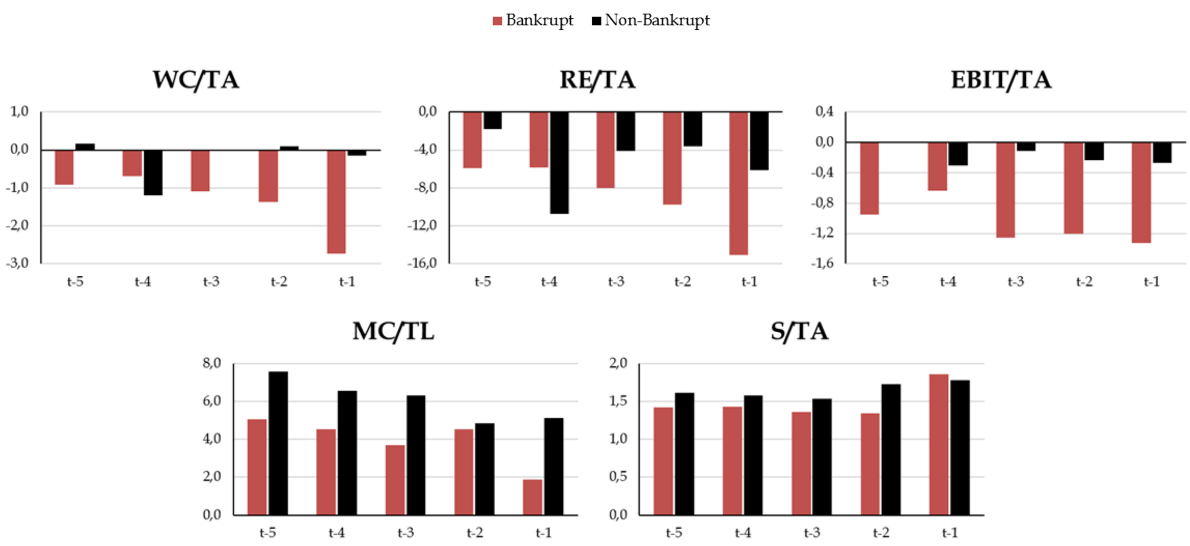
Non-Bankrupt Group

	T_{-5}		T_{-4}		T_{-3}		T_{-2}		T_{-1}	
Variable	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]
WC/TA	0.17	-	-1.20	**-1.37**	0.01	1.12	0.10	0.09	-0.14	-0.24
RE/TA	-1.80	-	-10.75	**-8.95**	-4.12	6.63	-3.61	0.51	-6.09	-2.48
EBIT/TA	0.00	-	-0.30	**-0.30**	-0.11	0.19	-0.23	-0.12	-0.27	-0.04
MC/TL	7.57	-	6.56	-1.01	6.32	-0.24	4.86	**-1.46**	5.13	0.27
S/TA	1.61	-	1.57	-0.04	1.54	-0.03	1.72	**0.18**	1.78	0.06

[1] Change from previous period

*Numbers in bold represents the largest yearly change in the ratios

Figure 5. Development of mean variables over time (as reported numbers)



5.1.2. Recognizing off-balance sheet debt

As the purpose of this study to a large extent consists of comparing the accuracy of various bankruptcy prediction models using as reported and recasted accounting numbers, we have calculated new values for the predictive variables based on the methodology outlined in Section 4.3.

First, the mean off-balance sheet debt for the respective groups have been calculated[11] and are presented in Table 6 and illustrated in Figure 6. The bankrupt firms clearly use off-balance sheet financing to a greater extent than non-bankrupt firms. This is consistent with the notion that firms that are financially constrained make particular use of leasing, since it provides firms with greater operational flexibility and is easier to finance (Zhang, 2011). Whereas the pension obligations for the bankrupt group consistently increase as the firms move closer to default, the use of operating leases appears to have a more inconsistent pattern, opposite to what we can see for the matching sample. The relatively large difference between the amount of pension obligations between the groups are also notable: the pension obligations for an average bankrupt firm is more than twenty times as high as for the average matching firm one year prior to default.

Table 6. Off-balance sheet debt ($U.S. million)

Bankrupt Group

Year	Capitalized Leasing[1]	Pension Obligations	Total off-balance sheet financing
T_{-1}	466.5	95.8	562.3
T_{-2}	547.0	59.0	606.0
T_{-3}	574.0	57.1	631.1
T_{-4}	576.3	25.8	602.1
T_{-5}	391.5	-40.7	350.8

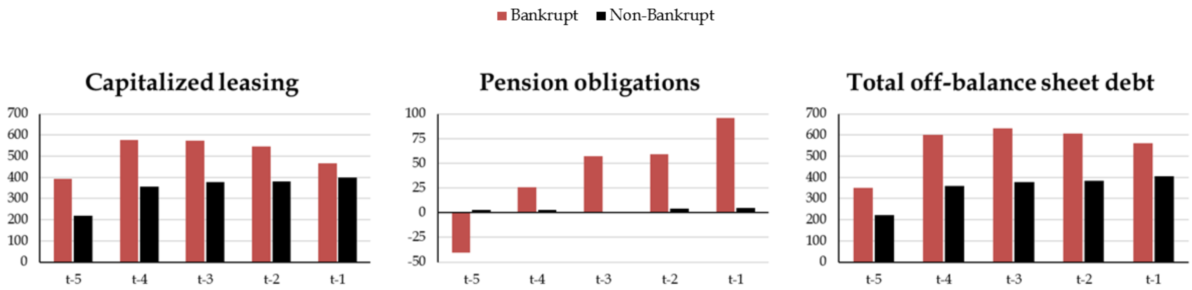
Non-Bankrupt Group

Year	Capitalized Leasing[1]	Pension Obligations	Total off-balance sheet financing
T_{-1}	399.6	4.7	404.3
T_{-2}	380.6	3.9	384.5
T_{-3}	376.9	0.6	377.5
T_{-4}	356.8	2.6	359.4
T_{-5}	220.2	2.7	222.9

[1] Calculated using the perpetuity method

[11] The value of capitalized operating lease obligations is calculated using the perpetuity method (see Appendix C).

Figure 6. Development of off-balance sheet debt over time ($U.S. million)



5.1.3. The impact of financial adjustments

A comparison between the mean financial items based on actual and recasted accounting numbers for the two groups are presented in Table 7 and illustrated in Figure 7 and Figure 8. Note that the calculation of capitalized operating lease debt is based on the perpetuity method of Lim et al (2003), as discussed in section 4.3 (see Appendix C for an illustrative example).

For both groups, the largest difference in mean values when using recasted instead of reported accounting numbers occurs in total assets and total liabilities. This is mainly attributable to the capitalization of operating lease debt. Although the bankrupt firms utilize leasing to a larger extent than non-bankrupt firms, the inflation of the balance sheet is larger for the matching group in relative terms.[12]

At first glance, the reader might be surprised that working capital becomes positive for the bankrupt group when using recasted figures. However, recall that we adjust current liabilities by removing short-term interest-bearing debt, which in this case results in positive working capital for the average bankrupt firm. When using adjusted financials, EBIT (and consequently retained earnings) improves for both groups. This is attributable to the adjustment of lease interest (derived from the capitalized operating lease debt), as well as adjustments for interest related to pension benefit obligations.

[12] For the bankrupt and non-bankrupt group, total liabilities increase on average by 82.0% and 95.7% respectively.

The predictors presented in Table 5 (Section 5.1.1) can be further dissected by looking at the mean values of the financial items presented in Table 7. Indeed, the falling trend in WC/TA for bankrupt firms is almost solely explained by decreasing working capital, whereas total assets remain fairly constant. As indicated by our interpretation of Table 5, the RE/TA-ratio falls due to increased cumulative losses for the bankrupt firm, whereas the non-bankrupt group displays improved cumulative profitability.

Here, a clarification might be in place. The attentive reader may wonder how it is that positive retained earnings results in a negative RE/TA-ratio. A firm with substantial positive retained earnings will have significant impact on the average value of the sample (skewing it towards a positive mean value). However, the absolute size of retained earnings becomes irrelevant when deriving the RE/TA-ratio, where the size effect diminishes. Hence, the mean RE/TA-ratio can be negative despite on average positive retained earnings (the same argument goes for EBIT/TA).

The development of EBIT for the bankrupt group is volatile and always negative, whereas EBIT for the matching group is positive for all the years. It is hardly surprising that it is the failing firms that display negative earnings, as they later file for bankruptcy. As displayed in Table 5, the MC/TL-ratio is decreasing for both groups. For the bankrupt firms, this is explained by falling market values and increasing liabilities. The theoretical justification for the fall in market value can, as already explained, be attributable to traders discounting the imminent bankruptcy. An interesting fact is that the market seems to be discounting the default risk as early as three years prior to bankruptcy, as illustrated by the sharp drop in MC in Figure 7. It is also evident that the defaulting firms display a sudden rise in the amount of total liabilities in the period closest to bankruptcy. There could be many reasons for this, and although it would be interesting, it is not within the scope of this study to investigate why. For the non-bankrupt firms, the fall in MC/TL is explained by increasing liabilities accompanied by fairly constant market values.

Table 7. Mean item comparison - as reported vs. recasted numbers ($U.S. million)

Bankrupt Group

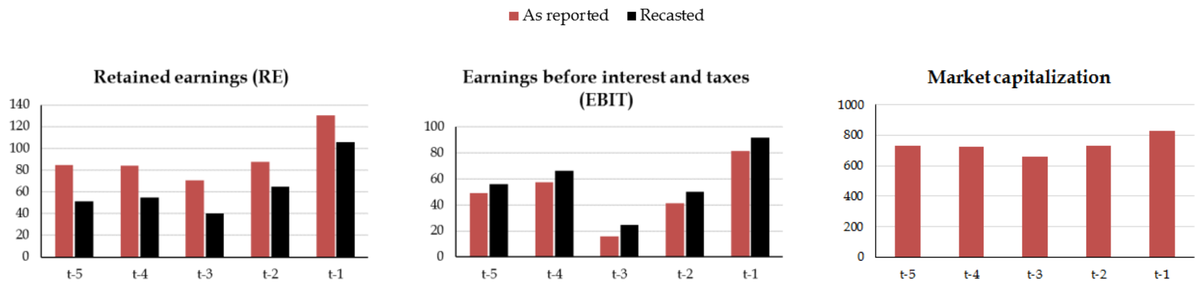
	WC		TL		TA		RE		EBIT		MC
Year	Reported	Recasted	Reported	Recasted	Reported	Recasted	Reported	Recasted	Reported	Recasted	-
T_{-1}	-75.0	97.9	904.8	1467.2	822.9	1289.4	-62.5	-48.2	-41.9	-31.3	270.0
T_{-2}	82.2	121.4	689.4	1295.5	645.6	1192.7	55.2	29.0	-60.5	-52.8	180.1
T_{-3}	102.8	116.0	619.1	1250.2	657.1	1231.1	138.0	113.1	-1.1	8.8	183.1
T_{-4}	113.3	129.9	630.2	1232.3	717.5	1293.8	168.4	129.4	-78.6	-71.3	437.9
T_{-5}	120.1	142.4	651.9	1057.7	871.1	1317.6	270.5	244.2	-2.2	2.4	545.8

Non-Bankrupt Group

	WC		TL		TA		RE		EBIT		MC
Year	Reported	Recasted	Reported	Recasted	Reported	Recasted	Reported	Recasted	Reported	Recasted	-
T_{-1}	219.5	228.6	428.5	832.6	760.7	1160.3	130.6	105.9	81.8	91.8	828.8
T_{-2}	169.1	208.9	424.7	809.1	749.5	1130.1	87.9	64.7	41.2	50.1	732.6
T_{-3}	183.6	213.3	383.6	763.5	686.1	1065.4	70.7	40.3	16.0	24.7	660.0
T_{-4}	182.2	205.0	320.7	680.1	633.2	990.0	84.1	54.8	57.8	66.2	726.3
T_{-5}	173.1	193.6	270.3	493.3	574.6	794.9	84.6	51.3	49.3	56.2	732.5

Figure 7. Impact of off-balance sheet debt - Bankrupt Group

Figure 8. Impact of off-balance sheet debt - Non-Bankrupt Group



As highlighted by bold figures in Table 8, three out of five predictors for the bankrupt group has the largest change one period prior to bankruptcy when recognizing off-balance sheet financing. For the matching firms, all predictive variables display the largest change in T_{-4}. As previously discussed it is hard to explain why T_{-4} display these values. For illustrative purposes, the development of the recasted predictive variables are depicted in Figure 9.

Table 8. Mean variables and annual change (recasted numbers)

Bankrupt Group

	T_{-5}		T_{-4}		T_{-3}		T_{-2}		T_{-1}	
Variable	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]
WC/TA	0.04	-	-0.02	-0.06	-0.07	-0.05	-0.05	0.02	-0.27	**-0.22**
RE/TA	-1.44	-	-2.54	-1.11	-3.72	-1.17	-3.20	0.51	-6.30	**-3.10**
EBIT/TA	-0.21	-	-0.24	-0.02	-0.27	**-0.03**	-0.28	-0.01	-0.29	-0.01
MC/TL	5.38	-	3.84	-1.54	5.18	1.34	2.35	**-2.83**	1.11	-1.24
S/TA	0.67	-	0.64	-0.03	0.52	-0.12	0.46	-0.06	0.65	**0.19**

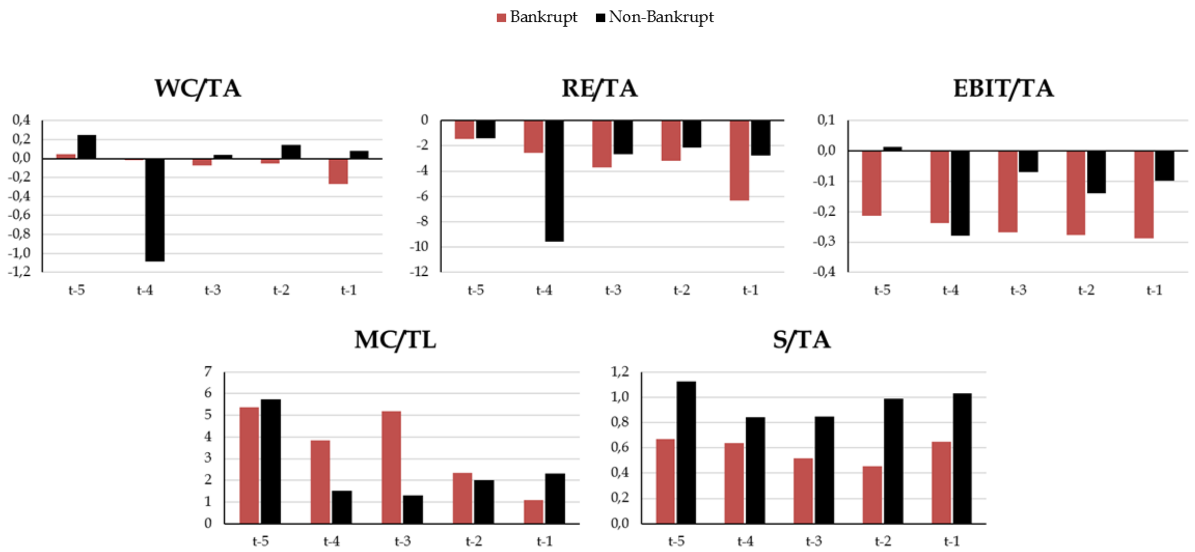
Non-Bankrupt Group

	T_{-5}		T_{-4}		T_{-3}		T_{-2}		T_{-1}	
Variable	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]
WC/TA	0.25	-	-1.08	**-1.33**	0.04	1.12	0.14	0.10	0.08	-0.06
RE/TA	-1.42	-	-9.56	**-8.14**	-2.63	6.93	-2.14	0.49	-2.74	-0.60
EBIT/TA	0.01	-	-0.28	**-0.29**	-0.07	0.21	-0.14	-0.07	-0.10	0.04
MC/TL	5.75	-	1.51	**-4.24**	1.31	-0.20	2.02	0.71	2.33	0.31
S/TA	1.12	-	0.84	**-0.28**	0.85	0.01	0.99	0.14	1.03	-0.04

[1] Change from previous period

*Numbers in bold represents the largest yearly change in the ratios

Figure 9. Development of mean variables over time (recasted numbers)



5.2. Results from bankruptcy prediction models

Consistent with Begley et al. (1996) and Hillegeist et al. (2004), we find that several of the coefficients estimated when applying our model on reported financials differ substantially from the coefficients presented in earlier studies. Solely based on these results, we suggest caution when using accounting numbers to estimate bankruptcy probabilities as the association between the predictive variables and bankruptcy probabilities obviously are not stable over time.

According to Model I, only MC/TL (using reported and recasted figures) is statistically significant.[13] This is not unique for our study, e.g. Shumway (2001) also struggles with insignificant variables. While this makes it hard to statistically justify any predictability of the insignificant variables, there is little to be done about it. There is no possibility to alter the data since we cannot "create" more bankrupt firms, and as already stated, the limited time frame precludes us from including a larger number of matching firms. Furthermore, the predictive variables are those of previous research, which do not automatically mean that they are the most relevant for our sample. It is therefore not surprising that a logistic regression analysis based

[13] See table 9.

on these given explanatory variables yields suboptimal results. One could also question if these variables are suitable for predicting bankruptcies in more recent years. Perhaps, the characteristics of today's firms have changed and other predictors would consequently suit our sample better. Another potential reason for not achieving statistical significance for most of the predictors is the probable existence of multicollinearity between the variables.

However. the main reason for including the insignificant predictors is that the purpose of this study is not to develop an "optimal" bankruptcy prediction model: as already stipulated, we primarily aim to evaluate existing models. Therefore, our ambition is not to develop a new robust prediction model per se.

5.2.1. Coefficients of Model I and Model II

The sign of the coefficients in Table 9 tells us that firms with higher working capital, earnings and sales relative to total assets are less likely to fail. Larger firms, as measured by market value of equity, with lower liabilities, are also less likely to go bankrupt. Higher cumulative earnings were expected to result in a lesser likelihood of default. However, when applying Model I on the data, retained earnings appear to have a small effect on the probability of default and this effect is in the opposite direction of what we expected to find.

An interesting finding is that when using recasted data, the size of the coefficients increases substantially. For example, EBIT/TA increases nine times (in absolute value) when using adjusted financial data instead of reported. This tells us that the variables based on adjusted data have a larger effect on the estimation of bankruptcy, which is reasonable. By using a variable based on total assets to predict the likelihood of bankruptcy, while not adjusting for off-balance sheet debt, the variable could be misleading as total assets are underestimated. It is clear that including off-balance sheet debt increases the impact of the predictive variables.

Table 9. Re-estimated coefficients from Model I

	As reported			Recasted		
Variable	Coefficient	Std.error	p-value	Coefficient	Std.error	p-value
Intercept	0.672	0.574	0.242	1.179	0.529	0.026
WC/TA	-0.046	0.170	0.789	-0.061	0.727	0.934
RE/TA	0.002	0.029	0.939	0.014	0.060	0.810
EBIT/TA	-0.409	0.710	0.565	-4.111	2.819	0.145
MC/TL	-0.252	0.115	0.029	-1.162	0.446	0.009
S/TA	-0.071	0.211	0.735	-0.478	0.445	0.283

As discussed in Section 4.2.3, researchers have made use of a time factor when calculating probabilities of default. Consistent with Shumway (2001) we include the logarithm of the firm's trading age, since it is a good measure of how long the firm has been a viable enterprise. In Model II, the original predictive variables are therefore complemented with an age factor.

The inference from Table 10 reveals that adding age does not make the regression that much stronger and it does not make any real improvements to the statistical significance of the coefficients. As for Shumway (2001), the log of age is not statistically significant, indicating that there appears to be little duration dependence in bankruptcy probability. Consistent with our findings in Model I, the size of the coefficients increase when using adjusted data. The signs are the same as above, except for the coefficient for WC/TA, which becomes positive when using adjusted data. As before, only MC/TL in Model II is the only statistically significant variable.

The lack of statistically significant variables is similar to the findings of Shumway (2001), who concluded that half of the variables used by Altman and Zmijevski were statistically unrelated to bankruptcy probabilities. The fact that MC/TL is the only statistically significant variable could possibly indicate that the previously used accounting ratios are poor predictors in failure-forecasting contexts, and that market-driven variables are more related to default probabilities.

Table 10. Re-estimated coefficients from Model II

	As reported			Recasted		
Variable	Coefficient	Std.error	p-value	Coefficient	Std.error	p-value
Intercept	2.124	1.453	0.144	2.775	1.532	0.070
WC/TA	-0.018	0.161	0.913	0.145	0.741	0.845
RE/TA	0.0003	0.030	0.990	0.011	0.061	0.859
EBIT/TA	-0.415	0.720	0.565	-4.435	2.863	0.121
MC/TL	-0.251	0.114	0.028	-1.197	0.460	0.009
S/TA	-0.089	0.215	0.678	-0.559	0.476	0.240
LN(AGE)	-0.550	0.500	0.271	-0.601	0.528	0.255

5.2.2. Predictive accuracy of the models

In Table 11 the predictive accuracy of the models, both the conventional and Model I and Model II, is displayed, where the cut-off score used for the conventional models is 2.675. As stated by e.g. Altman (1968), his bankruptcy prediction model is accurate for up to two years prior to bankruptcy, with diminishing predictability for more distant time periods. The reader should keep this in mind as we mainly focus our interpretation on the first two periods prior to default.

As can be seen, the highest accuracy is obtained when applying the coefficients of Begley et al. (1996), with a correct classification of 73.2% one year prior to bankruptcy, and 71.4% two years prior. For the same period, the coefficients of Hillegeist et al. (2004) generate the lowest predictive accuracy. Interestingly, even though his model was developed as early as 1968, the use of Altman's coefficients results in the second-best prediction accuracy using reported financial statement data. Thus, Altman's model is still surprisingly accurate despite its age.

When applying our own coefficients, derived from our logistic regression, our models perform mediocre in terms of predictive ability. Model I, without the age factor, outperforms Model II. Even though we do not focus on the most distant periods, it is notable that Model I and II has the best performance in T_{-4} and T_{-5} using reported data. The fact that our models, using reported data, performs better in the most distant time periods is surprising. Arguably, predicting bankruptcies further away from the actual event should be harder. However, by looking at the results based on recasted data in Table 11, it can be observed that when adjusting the financial statements, this pattern is reversed.

Indeed, Model I and II now has the highest predictive accuracy one period prior to default. Contrarily, when using adjusted financials, the predictive ability of the conventional models worsens. This is interesting considering the large number of practitioners that advocate the necessity of adjustments to obtain a better analytical foundation. Applying the conventional models on our sample, this is apparently not the case. Only when applying the adjusted data on our models, the predictive accuracy becomes better. Going forward, we will keep this in mind.

Table 11. Five-year predictive accuracy of studied models (in %) - Perpetuity method

As reported

Year	Altman	Begley et al.	Hillegeist et al.	Shumway 62-83'	Shumway 62-92'	Model I	Model II
T_{-1}	71.4	**73.2**	53.6	55.4	55.4	66.1	64.3
T_{-2}	67.9	**71.4**	51.8	51.8	50.0	66.1	62.5
T_{-3}	66.1	67.9	48.2	50.0	51.8	60.7	**69.6**
T_{-4}	64.3	69.6	55.4	51.8	51.8	71.4	**75.0**
T_{-5}	67.9	62.5	51.8	55.4	50.0	71.4	**75.0**

Recasted

Year	Altman	Begley	Hillegeist	Shumway 62-83'	Shumway 62-92'	Model I	Model II
T_{-1}	64.3	67.9	48.2	51.8	51.8	73.2	**76.8**
T_{-2}	58.9	**71.4**	48.2	50.0	50.0	64.3	69.6
T_{-3}	55.4	**67.9**	48.2	50.0	50.0	62.5	58.9
T_{-4}	57.1	67.9	50.0	50.0	50.0	**69.6**	**69.6**
T_{-5}	60.7	**73.2**	48.2	51.8	48.2	71.4	64.3

*Numbers in bold represents the highest yearly predictability between the models

5.2.3. Dissection of the predictive accuracy

Consistent with previous bankruptcy prediction studies, and for illustrative purposes, we chose to display the Type-I and Type-II classification errors in Table 12. This "accuracy matrix" is set up as illustrated in the chart below.

	Predicted Group Membership	
Actual Group Membership	Bankrupt	Non-Bankrupt
Bankrupt	Hit	Type-I error (Miss)
Non-Bankrupt	Type-II error (Miss)	Hit

The actual group membership is the group to which each observed firm in our data sample is classified into, based on whether or not they go bankrupt (28 firms are classified as bankrupt and 28 are classified as non-bankrupt, as explained in Section 3). The bankruptcy prediction models attempt to correctly classify these firms as bankrupt or non-bankrupt, resulting in a predicted group membership. In the chart above, correct classifications ("Hit") indicates that the model have been successful in its classification. Thus, the sum of the diagonal elements equals the total number of correct predictions, and by dividing with the total number of firms (58 in our case) we obtain the predictive accuracy. This accuracy percentage is actually analogous to the coefficient of determination (also known as "goodness of fit") in regression analysis (Altman, 1968). The Type-I and Type-II errors ("Miss") arises when the models misclassify the firms in our sample. The Type-I error represents bankrupt firms that are misclassified as non-bankrupt, whereas the Type-II error represents non-bankrupt firms incorrectly classified into the bankrupt group.

Table 12 shows the resulting Type-I and Type-II errors one period prior to bankruptcy when the models are applied on unadjusted data. Based on reported accounting numbers, Model II display the highest Type-I error rate (25.0%), whereas both of Shumway's (2001) models have the highest Type-II error rate (89.3%). The model developed by Hillegeist et al. (2004) has the highest overall error rate (46.4%) and, as presented in Table 12, Begley's et al. (1996) model has the highest prediction accuracy (73.2%). By comparing the results presented in Table 12 with previous studies, we observe an increase in the Type-I and Type-II error rate for some of the models. For example, Altman's (1968) original model generated Type-I and Type-II error rates of 6% and 3% respectively, whereas the Type-I and Type-II error rate based on our sample is 14% and 43% respectively. Thus, we see a dramatic increase in Type-I and Type-II errors when Altman's (1968) original model is used on more recent data. Note that the Type-I errors are lower for all the conventional models compared to Model I and Model II and that all models (including Model I and Model II) have surprisingly high Type-II errors. Table 12 also show the Type-I and Type-II errors when recasted data is applied to the models instead. When recasted accounting numbers are applied, the overall error rate increases for all the conventional models. In fact, all the conventional models have Type-II errors well above 50%, indicating that the recasted data substantially increase the probability that a non-bankrupt firm is misclassified as a bankrupt firm. Whereas the predictive accuracy of the conventional models deteriorates when recasted data is used, Model I and Model II display higher accuracy due to a decrease in the number of misclassifications. As a result, both our estimated models now have higher accuracy than the conventional models (73.2% and 76.8% respectively), which is mostly attributable to the decrease in Type-II errors.

Table 12. Predictive ability of models, one period prior to bankruptcy (T_{-1}) – Perpetuity method

As reported numbers

		Altman			Begley et al.			Hillegeist et al.			Shumway 62-83′			Shumway 62-92′			Model I			Model II		
	N	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error
Type-I	28	24	85.7	14.3	26	92.9	7.1	26	92.9	7.1	28	100.0	0.0	28	100.0	0.0	23	82.1	17.9	21	75.0	25.0
Type-II	28	16	57.1	42.9	15	53.6	46.4	4	14.3	85.7	3	10.7	89.3	3	10.7	89.3	14	50.0	50.0	15	53.6	46.4
Total	56	40	71.4	28.6	41	73.2	26.8	30	53.6	46.4	31	55.4	44.6	31	55.4	44.6	37	66.1	33.9	36	64.3	35.7

Recasted numbers

		Altman			Begley et al.			Hillegeist et al.			Shumway 62-83′			Shumway 62-92′			Model I			Model II		
	N	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error
Type-I	28	28	100.0	0.0	27	96.4	3.6	26	92.9	7.1	28	100.0	0.0	28	100.0	0.0	22	78.6	21.4	24	85.7	14.3
Type-II	28	8	28.6	71.4	11	39.3	60.7	1	3.6	96.4	1	3.6	96.4	1	3.6	96.4	19	67.9	32.1	19	67.9	32.1
Total	56	36	64.3	35.7	38	67.9	32.1	27	48.2	51.8	29	51.8	48.2	29	51.8	48.2	41	73.2	26.8	43	76.8	23.2

Based on the high presence of both Type-I and Type-II errors throughout the models, and consequently the relatively low prediction accuracy, we have considered various measures to improve the results. One potential problem is the method used for capitalizing operating lease debt. As mentioned in Section 4.3, there are different methods for estimating the value of leases. If our initial choice of method (the perpetuity method) calculates the value of operating lease debt too aggressively, the financial ratios will potentially be misleading.

Therefore, we will apply an alternative method to estimate the value of leases, namely the multiple method. This method is particularly popular in the investment banking community and is widely used by credit institutes.[14] Details of the multiple-based calculations for capitalizing leases are presented in Appendix C.

5.3. Results from using an alternative leasing method

Even though Lim et al. (2003) finds that the perpetuity method is the best estimator of future lease commitments, we chose to also apply the multiple method since it is expected to yield lower lease values, which consequently would lead to less inflated balance sheets. This change in methodology will affect all the predictors and thereby potentially improve the predictive accuracy of the models.

The new estimated values of operating lease debt and total off-balance sheet obligations for the respective groups are presented in Table 13 Panel A. In Panel B, a comparison between the two lease methods are summarized. Note that the value of pension obligations remains unaffected.

As can be seen, the choice of method has a significant impact on the estimated value of operating leases and as expected, the multiple approach consistently yield lower leasing estimates. By applying the multiple method instead of the perpetuity method, the average total off-balance sheet financing decrease by approximately \$300-470 million for the bankrupt firms and \$170-330 million for the non-bankrupt firms over the studied period. Looking solely at the period closest to bankruptcy, the

[14] For example, both Moody’s and McKinsey advise the use of multiples to estimate the value of operating leases.

total off-balance sheet debt is reduced by 66% and 80% for the bankrupt and non-bankrupt group respectively. It is therefore safe to say that the choice of method is important when recognizing off-balance sheet lease obligations.

Table 13. Off-balance sheet debt ($U.S. million) - Multiple method

Panel A. Off-balance sheet debt under the multiple method ($U.S. million)

Bankrupt Group

Capitalized Leasing

Year	Perpetuity Method	Multiple Method	Difference
T_{-1}	466.5	93.8	372.7
T_{-2}	547.0	103.4	443.6
T_{-3}	574.0	104.2	469.8
T_{-4}	576.3	101.4	474.9
T_{-5}	391.5	87.0	304.5

Total off-balance sheet financing

Year	Perpetuity Method	Multiple Method	Difference
T_{-1}	562.3	189.6	372.7
T_{-2}	606.0	162.4	443.6
T_{-3}	631.1	161.3	469.8
T_{-4}	602.1	127.2	474.9
T_{-5}	350.8	46.3	304.5

Non-Bankrupt Group

Capitalized Leasing

Year	Perpetuity Method	Multiple Method	Difference
T_{-1}	399.6	76.4	323.2
T_{-2}	380.6	70.1	310.5
T_{-3}	376.9	67.3	309.6
T_{-4}	356.8	64.3	292.5
T_{-5}	220.2	50.9	169.3

Total off-balance sheet financing

Year	Perpetuity Method	Multiple Method	Difference
T_{-1}	404.3	81.1	323.2
T_{-2}	384.5	74.0	310.5
T_{-3}	377.5	67.9	309.6
T_{-4}	359.4	66.9	292.5
T_{-5}	222.9	53.6	169.3

Panel B. Comparison of lease estimation models

Bankrupt Group

Year	Capitalized Leasing[1]	Pension Obligations	Total off-balance sheet financing
T_{-1}	93.8	95.8	189.6
T_{-2}	103.4	59.0	162.4
T_{-3}	104.2	57.1	161.3
T_{-4}	101.4	25.8	127.2
T_{-5}	87.0	-40.7	46.3

Non-Bankrupt Group

Year	Capitalized Leasing[1]	Pension Obligations	Total off-balance sheet financing
T_{-1}	76.4	4.7	81.1
T_{-2}	70.1	3.9	74.0
T_{-3}	67.3	0.6	67.9
T_{-4}	64.3	2.6	66.9
T_{-5}	50.9	2.7	53.6

[1] Calculated using the perpetuity method

Naturally, the multiple method alters the recasted numbers presented in Section 5.1.3 Table 7, and the effect of this change on each line item can be seen in Table 14. Working capital and retained earnings remain unaffected[15] for both groups, but total assets and total liabilities are consistently lower under the multiple approach because of the downward adjustment of the leasing values. EBIT worsens under the multiple method for all years and for both groups. The fall in EBIT is an expected result as the lower leasing value naturally results in a lower lease interest.[16] As the trend of the mean financial items presented below remain unchanged (albeit with new values) relative to that of Table 7, we refer to Section 5.1 for further inferences.

Table 14. Mean item comparison under the different leasing methods ($U.S. million)

Bankrupt Group

	WC		TL		TA		RE		EBIT	
Year	Perpetuity	Multiple	Perpetuity	Multiple	Perpetuity	Multiple	Perpetuity	Multiple	Perpetuity	Multiple
T_{-1}	97.9	97.9	1467.2	1094.5	1289.4	916.7	-48.2	-48.2	-41.9	40.9
T_{-2}	121.4	121.4	1295.5	851.9	1192.7	749.1	29.0	29.0	-60.5	-63.7
T_{-3}	116.0	116.0	1250.2	780.5	1231.1	761.3	113.1	113.1	-1.1	-2.2
T_{-4}	129.9	129.9	1232.3	757.3	1293.8	818.9	129.4	129.4	-78.6	-82.4
T_{-5}	142.4	142.4	1057.7	753.2	1317.6	1013.1	244.2	244.2	-2.2	-6.9

Non-Bankrupt Group

	WC		TL		TA		RE		EBIT	
Year	Perpetuity	Multiple	Perpetuity	Multiple	Perpetuity	Multiple	Perpetuity	Multiple	Perpetuity	Multiple
T_{-1}	228.6	228.6	832.6	509.4	1160.3	837.1	105.9	105.9	91.8	83.5
T_{-2}	208.9	208.9	809.1	498.6	1130.1	819.5	64.7	64.7	50.1	42.5
T_{-3}	213.3	213.3	763.5	454.0	1065.4	755.8	40.3	40.3	24.7	17.5
T_{-4}	205.0	205.0	680.1	387.7	990.0	697.5	54.8	54.8	66.2	59.4
T_{-5}	193.6	193.6	493.3	323.9	794.9	625.5	51.3	51.3	56.2	51.0

[15] Regardless of the leasing interest derived, the impact on net income, and subsequently retained earnings, will be the same for both methods since the lease interest is only reallocated on the income statement. Therefore, EBIT is affected, whereas net income is not. For obvious reasons, working capital remain unaffected.

[16] Lease interest is derived by multiplying the assumed cost of secure debt with the capitalized lease value, and as the multiple method yields a lower lease value, the lease interest under this method is lower. Consistent with the methodology used by Moody’s, we reclassify the implicit lease interest as a financial expense by removing its impact on EBIT. Consequently, by removing a lower lease interest, the improvement in EBIT is lower when applying the multiple method.

As presented in Table 15, the largest change in the predictive variables for the bankrupt group occurs in the closest period prior to bankruptcy, with the exception of EBIT/TA, and the largest drop occurs in RE/TA. It can be hypothesized that this sharp drop is explained by considerable losses of the failing firms in the period closest to default, which ultimately forces the firms into liquidation. Compared to the annual changes in the predictors under the perpetuity method (see Table 8), the changes one year prior to bankruptcy under the multiple method appear to be more dramatic for all variables. An interesting note is that the largest drop in the MC/TL-ratio for the failing group now occurs in T_{-1}, instead of during T_{-2} under the perpetuity method. For the matching firms, the largest annual change still occurs in T_{-4} for all variables.

Table 15. Mean variables and annual change (recasted numbers) - Multiple method

Bankrupt Group

	T_{-5}		T_{-4}		T_{-3}		T_{-2}		T_{-1}	
Variable	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]
WC/TA	-0.16	-	-0.11	0.05	-0.12	-0.01	-0.27	-0.15	-0.88	**-0.61**
RE/TA	-3.01	-	-4.07	-1.06	-5.93	-1.86	-5.47	0.46	-9.24	**-3.77**
EBIT/TA	-0.47	-	-0.41	0.06	-0.70	**-0.29**	-0.60	0.10	-0.64	-0.04
MC/TL	4.40	-	3.61	-0.79	2.56	-1.05	3.49	0.93	1.28	**-2.21**
S/TA	0.94	-	0.99	0.05	0.84	-0.15	0.80	-0.04	1.12	**0.32**

Non-Bankrupt Group

	T_{-5}		T_{-4}		T_{-3}		T_{-2}		T_{-1}	
Variable	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]	Ratio	Change[1]
WC/TA	0.29	-	-1.03	**-1.32**	0.07	1.10	0.19	0.12	0.05	-0.14
RE/TA	-1.66	-	-10.08	**-8.42**	-3.67	6.41	-3.06	0.61	-4.44	-1.38
EBIT/TA	0.01	-	-0.29	**-0.30**	-0.10	0.19	-0.20	-0.10	-0.18	0.02
MC/TL	6.45	-	2.56	**-3.89**	2.93	0.37	3.31	0.38	3.58	0.27
S/TA	1.38	-	1.20	**-0.18**	1.20	0.00	1.38	0.18	1.41	0.03

[1] Change from previous period

*Numbers in bold represents the largest yearly change in the ratios

5.3.1. Comparing the predictive accuracy of the lease methods

In Table 16, we present the predictive accuracy of the models based on the two different types of lease-estimation methods. Recall that the period of interest is T_{-1} and T_{-2}.

As in the case when unadjusted accounting numbers are used, the highest prediction accuracy under the multiple method is achieved by the model of Begley et al. (1996), which correctly predicts 73.2% and 71.4% of the bankruptcies for T_{-1} and T_{-2} respectively. Consistent with the results presented in Table 12, Hillegeist's et al. (2004) model has the lowest accuracy (48.2% for T_{-1} and T_{-2}). An interesting result is that the predictive ability of Model I and Model II worsens under the multiple method compared to the perpetuity method, whereas the accuracy of the conventional models improves or remain unchanged. Another discovery is that unadjusted accounting numbers seems to generate the highest predictive accuracy for the conventional models, which yet again goes against the argument that adjusted financial statements constitutes a superior analytical foundation compared to as reported financial statements.

Table 16. Five-year predictive accuracy of studied models (in %) - Multiple method

Perpetuity method

Year	Altman	Begley	Hillegeist	Shumway 62-83'	Shumway 62-92'	Model I	Model II
T_{-1}	64.3	67.9	48.2	51.8	51.8	73.2	**76.8**
T_{-2}	58.9	**71.4**	48.2	50.0	50.0	64.3	69.6
T_{-3}	55.4	**67.9**	48.2	50.0	50.0	62.5	58.9
T_{-4}	57.1	67.9	50.0	50.0	50.0	**69.6**	**69.6**
T_{-5}	60.7	**73.2**	48.2	51.8	48.2	71.4	64.3

Multiple method

Year	Altman	Begley et al.	Hillegeist et al.	Shumway 62-83'	Shumway 62-92'	Model I	Model II
T_{-1}	71.4	**73.2**	51.8	53.6	51.8	69.6	67.9
T_{-2}	62.5	**71.4**	51.8	50.0	50.0	64.3	69.6
T_{-3}	64.3	**67.9**	50.0	50.0	50.0	64.3	60.7
T_{-4}	64.3	67.9	51.8	53.6	51.8	**73.2**	**73.2**
T_{-5}	67.9	69.6	48.2	51.8	50.0	**71.4**	67.9

*Numbers in bold represents the highest yearly predictability between the models

The predictive accuracy (in terms of Type-I and Type-II errors) of the models using unadjusted and recasted data based on the multiple approach and the perpetuity method is outlined in Table 17. As we had hoped, both the Type-II error rate and the predictive accuracy improves for all the conventional models (except for Shumway 62-92′, which is unaffected) when using the multiple approach to estimate the value of leases. Unfortunately, for Model I and Model II the Type-II error rate increases, and despite the reduction in Type-I errors the predictive accuracy deteriorates for both our models.

Under the multiple method, Model II displays the highest Type-I error rate (21.4%), whereas the Shumway (2001) 62-92′ model has the highest Type-II error rate (96.4%). The Shumway 62-92′ model also has the highest overall error rate along with the model developed by Hillegeist et al. (2004) (48.2%). The highest prediction accuracy is attributable to Begley's et al. (1996) model (73.2%), closely followed by Altman's (1968) model (71.4%). Consequently, both Altman's and Begley's model outperform Model I and Model II when a more conservative lease valuation method is applied to our sample.

Table 17. Predictive ability of revisited models, one period prior to bankruptcy (T_{-1})

As reported numbers

		Altman			Begley et al.			Hillegeist et al.			Shumway 62-83'			Shumway 62-92'			Model I			Model II		
	N	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error
Type-I	28	24	85.7	14.3	26	92.9	7.1	26	92.9	7.1	28	100.0	0.0	28	100.0	0.0	23	82.1	17.9	21	75.0	25.0
Type-II	28	16	57.1	42.9	15	53.6	46.4	4	14.3	85.7	3	10.7	89.3	3	10.7	89.3	14	50.0	50.0	15	53.6	46.4
Total	56	40	71.4	28.6	41	73.2	26.8	30	53.6	46.4	31	55.4	44.6	31	55.4	44.6	37	66.1	33.9	36	64.3	35.7

Perpetuity method

		Altman			Begley et al.			Hillegeist et al.			Shumway 62-83'			Shumway 62-92'			Model I			Model II		
	N	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error
Type-I	28	28	100.0	0.0	27	96.4	3.6	26	92.9	7.1	28	100.0	0.0	28	100.0	0.0	22	78.6	21.4	24	85.7	14.3
Type-II	28	8	28.6	71.4	11	39.3	60.7	1	3.6	96.4	1	3.6	96.4	1	3.6	96.4	19	67.9	32.1	19	67.9	32.1
Total	56	36	64.3	35.7	38	67.9	32.1	27	48.2	51.8	29	51.8	48.2	29	51.8	48.2	41	73.2	26.8	43	76.8	23.2

Multiple method

		Altman			Begley et al.			Hillegeist et al.			Shumway 62-83'			Shumway 62-92'			Model I			Model II		
	N	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error	N Correct	% Correct	% Error
Type-I	28	28	100.0	0.0	26	92.9	7.1	26	92.9	7.1	28	100.0	0.0	28	100.0	0.0	23	82.1	17.9	22	78.6	21.4
Type-II	28	12	42.9	57.1	15	53.6	46.4	3	10.7	89.3	2	7.1	92.9	1	3.6	96.4	16	57.1	42.9	16	57.1	42.9
Total	56	40	71.4	28.6	41	73.2	23.8	29	51.8	48.2	30	53.6	46.4	29	51.8	48.2	39	69.6	30.4	38	67.9	32.1

5.4 Summarizing our results

We find that the predictive variables, except for sales relative to total assets, are significantly different between the bankrupt and matching group, revealing that failing firms have characteristics that distinguish them from surviving firms. Another distinguishing factor between the groups is that the failing firms experience the largest financial deterioration in the period closest to default.

Looking at the individual predictors, only market capitalization relative to total liabilities (MC/TL) is statistically significant when predicting bankruptcies using our logistic models. Whereas previous studies have differed in the statistical significance of the predictors, market capitalization has generally been deemed to be reliable when forecasting business failures. Thus, we argue that market capitalization persists as a viable indicator of impending bankruptcies as the default risk is typically incorporated into the market value of the enterprise. In fact, traders appear to discount the bankruptcy risk as early as three fiscal years prior to failure.

Regarding the statistical weakness of the other predictors, we partly refer to the argument of Hillegeist et al. (2004), that accounting numbers (which reflect past performance) may not be particularly informative when assessing the future health of a given firm. As bankruptcy predictions are forward looking by nature, using numbers reflecting past performance to predict defaults will likely limit the predictive capability of bankruptcy-estimation models. Furthermore, by not deriving new predictors, but simply make use of those presented in previous research, there is a risk that the predictors do not fit our sample. Consistent with Begley et al. (1996), we also wish to highlight that there are problems when applying established bankruptcy prediction models on recent data, an inference derived from our models underperforming the predictive accuracy achieved by earlier studies. These problems are likely due to measurement errors and biases stemming from the ever-changing business environment.

Further, as stated by Zhang (2011), failing firms appear to make greater use of off-balance sheet debt, which is mainly attributable to an extensive use of operating leases. Due to the effect on the financial statements when recognizing off-balance sheet debt, as well as other adjustments, the predictive ability of the models differ substantially compared to when applying them on reported numbers.

For the conventional models, recasted numbers results in lower predictive accuracy because of a substantial increase in Type-II errors. However, looking solely at the Type-I errors for the conventional models when using recasted data, the models appear highly accurate. Therefore, we hypothesize that when recasting the data, the characteristics of the non-bankrupt firms are altered so that they resemble that of defaulting firms (due to the inflated balance sheet). As the matching firms to a larger extent resembles the defaulting firms, conventional models now fail to successfully distinguish between the groups. Therefore, we believe that the high presence of Type-II misclassifications stems from the design of the conventional models. Contrary, Model I and Model II both show a higher predictive accuracy when using recasted numbers, as a result of an improvement in the Type-II errors.

We wish to highlight the importance of recognizing the impact on the predictors depending on the choice of lease-estimation method. Of the two methods outlined in this study, the perpetuity method results in the highest predictive accuracy for Model I and Model II, whereas the multiple method is most suitable for the conventional models. However, the conventional models perform best when applied to reported data. Given that we find the highest overall predictive accuracy of all the models under the perpetuity method in Model II, one could question the simplified multiple method often employed by the investment banking community and credit rating institutes.

6. Conclusion

This study seeks to assess whether it is possible to improve the accuracy of bankruptcy prediction models by using recasted financial statements instead of as reported. Based on our results, we advocate that when using the conventional models of Altman (1968), Begley et al. (1996), Shumway (2001) and Hillegeist et al. (2004) on recent data, financial statements should not be recasted. Solely based on these findings, we conclude that financial adjustments are not necessary for mentioned bankruptcy prediction models. Using reported data, the conventional models are more likely to successfully foresee imminent business failures as compared to adjusted data. For recasted numbers, the coefficients derived in Model II should instead be applied, where an age factor is included. As a bi-product of our study, we advocate the use of the perpetuity method relative to the multiple approach when capitalizing operating lease debt, since the former method yields the best accuracy when predicting bankruptcies based on recasted data in our models. As a concluding remark, we recognize that the necessity of using recasted financials may very well persist in other financial areas, but it is not as apparent within the field of bankruptcy prediction models.

With these conclusions in mind, we believe that our study has made several valuable contributions within the field of predicting imminent business failures. For further investigations, we recognize the potential problem of basing our logistic models (Model I and Model II) on a limited data set. Therefore, we advocate that future research should be based on a larger sample of matching firms, which potentially would result in a more robust and accurate bankruptcy prediction model. With a larger sample, the statistical inferences would arguably be more reliable and less biased.

In this study, we make use of a cut-off score of 2.675 as the discriminating value for the conventional models. Since Altman (2000) also advocates the use of a lower cut-off score of 1.81, future research could assess whether this cut-off score would result in better classification accuracy, or if another cut-off score would be more appropriate for today's firm.

Consistent with Altman, we have limited this study to only include U.S. manufacturing and retail firms. Given this restraint, general inferences might be erroneous due to the risk of country and industry bias. Thus, a valuable contribution to this study (and perhaps bankruptcy-prediction theory in general) would be to investigate other economies and businesses.

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Appendix A

Typical adjustments made by rating agencies and recommended by leading textbooks

Adjustment categories	Moody's (2006)	S&P (2006)	Wild et al. (2006)	Stickney et al. (2006)	White et al. (2003)
Unfunded/underfunded pensions	x	x	x	x	x
Operating leases	x	x	x	x	x
Capitalized interest	x	x	x	-	x
Stock-based compensation	x	-	-	x	x
Hybrid securities	x	x	-	-	-
Securitizations	x	x	x	-	-
Inventory on LIFO cost basis	x	x	x	x	x
Unusual and nonrecurring – Income statement	x	x	-	x	x
Unusual and nonrecurring – Cash flows	x	-	-	-	-
Nonstandard adjustments	x	x	x	x	x
Allocating restructuring charges to prior periods	-	-	x	-	x

Source: Batta et al. (2012)

Appendix B

Complete list of companies included in the study

Company name	Matching firm	Industry	Year of Bankruptcy
Aéropostale, Inc.	Zumiez Inc.	5600 Apparel and accessory stores	2016
Cosi Inc.	Chanticleer Holdings, Inc.	5800 Eating and drinking places	2016
Hampshire Group, Limited	Crown Crafts, Inc.	2200 Textile mill products	2016
Hancock Fabrics Inc.	Nutrisystem, Inc.	5900 Miscellaneous retail	2016
Nuo Therapeutics, Inc.	Scientific Industries, Inc.	3800 Measuring, analyzing, and control instruments	2016
OxySure Therapeutics, inc.	Procyon Corporation	3800 Measuring, analyzing, and control instruments	2016
Quantum Fuel Systems Technologies Inc.	ZAP	3700 Transportation equipment	2016
Sanomedics, Inc.	Reflect Scientific, Inc.	3800 Measuring, analyzing, and control instruments	2016
ScripsAmerica, inc.	ICTV Brands, inc.	5900 Miscellaneous retail	2016
SunEdison, Inc.	Jabil Circuit, Inc.	3600 Electronic and other electrical equipment and components	2016
Verso Corporation	KapStone Paper and Packaging Corporation	2600 Paper and allied products	2016
Xenonics Holdings, Inc.	China Carbon Graphite Group, Inc.	3600 Electronic and other electrical equipment and components	2016
Abakan Inc.	Smith-Midland Corporation	3200 Stone, clay, glass, and concrete products	2015
Cache, inc.	Gordmans Stores, inc.	5600 Apparel and accessory stores	2015
Interphase Corp.	AG&E Holdings Inc.	3500 Industrial and commercial machinery and computer equipment	2015
Positron Corporation	Precision Optics Corporation, Inc.	3800 Measuring, analyzing, and control instruments	2015
Crumbs Bake Shop, inc.	Bowlin Travel Centers, inc.	5400 Food stores	2014
dELiA*s, Inc.	Christopher & Banks Corporation	5600 Apparel and accessory stores	2014
Kid Brands, Inc.	Summer Infant, Inc.	3900 Miscellaneous manufacturing industries	2014
Tandy Brands Accessories, Inc.	Talon International, Inc.	2300 Apparel and other finished products made from fabrics	2014
Exide Technologies	Skyworks Solutions, inc.	3600 Electronic and other electrical equipment and components	2013
Hoku Corporation	Cirrus Logic, Inc.	3600 Electronic and other electrical equipment and components	2013
Ormet Corporation	Northwest Pipe Company	3300 Primary metal industries	2013
School Specialty, Inc.	PC Connection, Inc.	5900 Miscellaneous retail	2013
CDEX Inc.	Medizone International, Inc.	3800 Measuring, analyzing, and control instruments	2012
Eastman Kodak Company	KLA-Tencor Corporation	3800 Measuring, analyzing, and control instruments	2012
Imaging3, Inc.	Non-Invasive Monitoring Systems, Inc.	3800 Measuring, analyzing, and control instruments	2012
Reddy Ice Holdings, Inc.	Synutra International, Inc.	2000 Food and kindred products	2012

Appendix C

Estimating lease values using the Hancock Fabrics Inc. annual report for 2015

For fiscal year 2015, Hancock Fabrics reported an operating lease rental expense of \$22.3 million and a minimum lease rental commitment for 2016 of \$19.5 million.

1) The perpetuity method

The perpetuity approach averages the lease rental expense for 2015 (\$22.3 million) and the minimum payment for 2016 (\$19.5 million) and then divides by the effective yield of AA-rated corporate bonds for that particular year (2.56%). In the case of Hancock Fabrics, this yields a perpetuity value estimate of

$$V = \frac{\$22.3 + \$19.5}{2} * \frac{1}{0.0256} = \$816.4\, million$$

Note that the discount rate used (AA-rated U.S. corporate bonds) varies over time and therefore affects the approximated lease values.

2) The multiple method

The multiple approach calculates the value of operating leases as the current year rental expense multiplied with an industry specific multiple. The multiple used is derived from the methodology used by Moody's when estimating the value of operating leases.

Industry	Multiple of Rent Expense
Manufacturing	6
Retail	8

Excerpt from Moody's guideline for rent expense multiples for adjustment to capitalize operating leases.

As Hancock Fabrics is classified as a retail company (SIC code 5900) a multiple of 8 is used to estimate the value of operating leases. The multiple approach thereby yields an estimated value of operating leases of

$$V = \$22.3 * 8 = \$174.4\, million$$

The two methods yield significantly different estimates of the value of operating leases: the perpetuity method yields an operating lease value almost 5 times as high as the multiple approach.